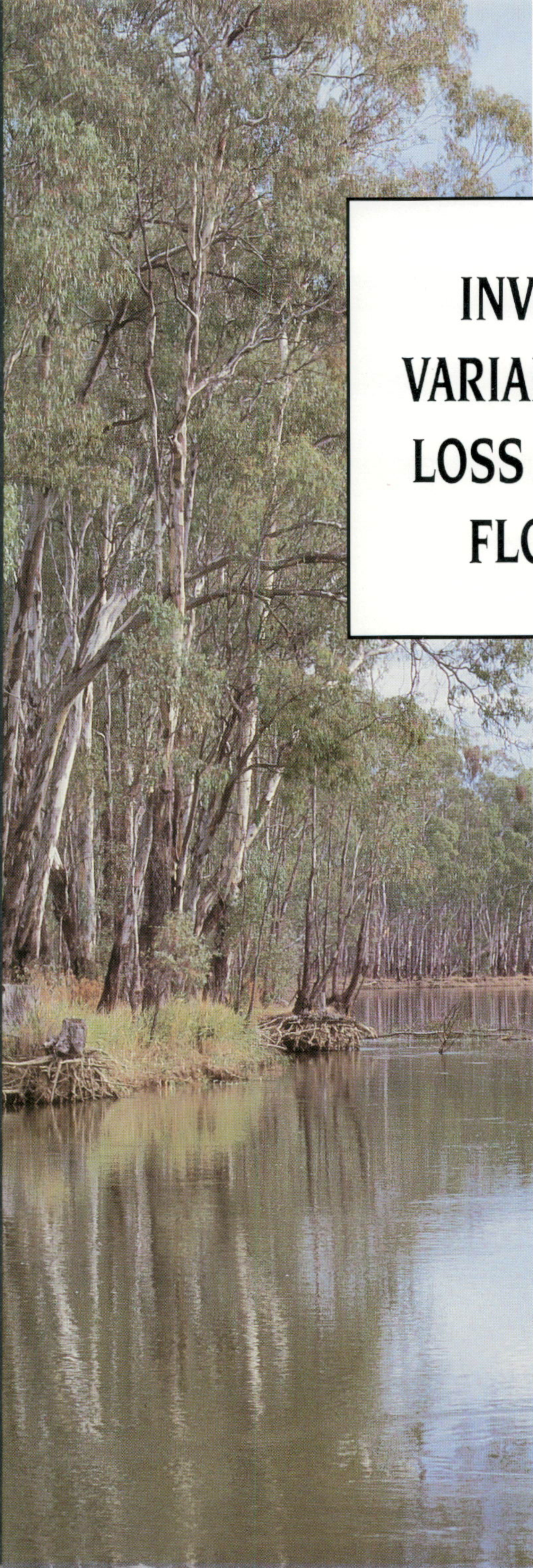

INVESTIGATION OF A VARIABLE PROPORTIONAL LOSS MODEL FOR USE IN FLOOD ESTIMATION

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PREFACE

A major aim of the CRC Project "Improved Loss Modelling for Design Flood Estimation and Flood Forecasting" was to reduce the uncertainties inherent in current procedures for estimating runoff generation from storm rainfall. The establishment of a large integrated database of rainfall and runoff observations was a key component of the project, since the development and testing of new loss models relied heavily on observed catchment behaviour.

The work reported here deals with the investigation of a variable proportional loss model to describe the change in runoff producing areas observed in catchments during storms. It also examines the use of pre-storm baseflow as a practical and reliable indicator of the antecedent wetness of a catchment.

The research has produced a significant advance in the empirical knowledge of losses and their role in design and real-time flood estimates. Parts of the work can already be used in the early estimation of real time flood response, before updating procedures, using observed data.

Russell Mein
Leader, Flood Hydrology Program
CRC for Catchment Hydrology

SUMMARY

This report presents some of the outcomes from a major research project "Improved Loss Modelling for Design Flood Estimation and Flood Forecasting" undertaken by the CRC for Catchment Hydrology. It details the development and application of a variable proportional loss (VPL) model, intended for use in real time flood forecasting and design flood estimation. The method is based on the assumption that the size of the saturation areas of the catchment increases as the rain progresses, resulting in an increased proportion of rainfall contributing to runoff as the storm progresses.

The development of the VPL model was based on the analysis of storm events for 20 Victorian catchments. This led to development of a relationship for volumetric runoff coefficient (event) as a function of pre-storm baseflow and storm rainfall. On a catchment basis, this relationship can best be represented by a 4-parameter logistic function.

The relationship allows for determination of 'initial loss' and *progressive* runoff coefficients, knowing the pre-storm baseflow. The estimated loss parameters were consistent and behaved satisfactorily for the catchments analysed.

A single parameter loss function was developed to use on a regional basis after ascertaining that the loss of accuracy caused in simplifying the relationship is not significant. The baseflow index (the fraction of the total streamflow which is baseflow) was found to be very significant in explaining the variability in the only parameter of this generalised loss function.

Suitability of the proposed VPL model for real-time flood forecasting was investigated for a number of test catchments. The rainfall excess hyetographs determined from the VPL model were routed using the calibrated RORB model; recorded and predicted hydrographs were then compared. It was concluded that the proposed loss model can be adopted satisfactorily in real-time flood forecasting within the context of uncertainties associated with the procedure. The successful application lies primarily in the ability of the loss model to predict runoff coefficients accurately.

For design flood estimation, further work is required before the variable proportional loss model can be applied.

ACKNOWLEDGMENTS

The authors would like to express appreciation to the members of the Project Reference Panel (Rory Nathan, Erwin Weinmann, Tom McMahon, Leon Soste, Jim Elliott, and Sri Srikanthan) for the guidance and valuable suggestions offered at various stages of the study.

The assistance of the Bureau of Meteorology and the (former) Rural Water Corporation in provision of hydrometric data was a key component of this project.

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1. INTRODUCTION

1.1 Purpose

This report documents the development and application of a 'variable proportional loss model', intended for both real-time flood forecasting and design flood estimation. The method is based on the assumption that the size of the saturation areas of the catchment increases as the rain progresses, resulting in an increasing proportion of rainfall contributing to runoff during the storm. In particular, it looks at the linking of proportional losses to the indicators of initial catchment wetness such as pre-storm baseflow.

The work reported here covers part of the work for Project D1 of CRC for Catchment Hydrology - "Improved Loss Modelling for Design Flood Estimation and Flood Forecasting". A CRC working document 'Development and Testing of a Variable Proportional Loss Model' (Siriwardena et al., 1997) gives further details of the methods and data.

1.2 Background

The 'initial loss/continuing loss' and 'initial loss/proportional loss' models are currently recommended for flood estimation and forecasting purposes in Australia. In the 'initial loss/continuing loss model', no rainfall is assumed to occur until a given initial loss capacity is satisfied, and the rainfall excess is the residual left after subtracting a constant rate of continuing loss. In the 'initial loss/proportional loss' model, losses are assumed to be a constant factor of rainfall, once initial loss is satisfied. Both models are gross approximations of the processes which contribute to the total loss from rainfall.

This study is an attempt to incorporate the concept of saturation areas (source areas) in to loss modelling, as suggested in the studies by NERC (1975), Mein and O'Loughlin (1991) and Mag and Mein (1994). NERC (1975) described a variable proportional loss model, derived on a regional basis, in which the proportional runoff factor is defined as a function of the antecedent wetness index, storm rainfall, and catchment characteristics such as an index of soil properties and the proportion of catchment urbanised. Mein and O'Loughlin (1991) postulated and developed a relationship for a proportional runoff factor, on a catchment basis, as a function of pre-storm baseflow and storm rainfall, for the estimation of progressive losses in real-time flood forecasting. In Mag and Mein (1994), this latter approach was developed further and demonstrated on a test catchment.

The Mein and O'Loughlin (1991) approach can be used to develop a relationship for volumetric runoff coefficient as a function of pre-storm baseflow and rainfall depth, on a catchment basis. This method gives progressively higher runoff factors as the storm progresses, hence, is considered to be more representative of physical processes than the previously mentioned simple loss models. However, the method is not appropriate when modelling events with insignificantly small pre-storm baseflow.

1.3 Guide to the Report

The aim of this study was to develop relationships ('saturation curves') for volumetric runoff coefficients as a function of pre-storm baseflow (or alternative soil moisture index) and storm rainfall, for a number of catchments. The type of catchments for which the proposed loss model is suitable was investigated. Generalised prediction equations for catchment losses were developed as a function of antecedent conditions and catchment characteristics based on pooled data. For a number of test catchments, the rainfall excess determined from the proposed loss model was routed using the 'RORB' runoff routing model (Laurenson and Mein, 1995) and compared with the observed hydrographs in order to assess the applicability of the proposed model for flood forecasting.

This report begins with a review of previous work related to the study. Chapter 3 then describes the catchments and data used in this study and the methodology adopted in the development of relationships ('saturation curves') for volumetric runoff coefficient. The results for individual catchments are presented in Chapter 4 and the relative merits of the methodology are discussed. Chapter 5 describes a regional study of the derivation of generalised prediction equations for loss parameters as a function of antecedent conditions and catchment characteristics, based on pooled data.

The next chapters deal with the practical applications of the proposed loss model. In Chapter 6, the applicability of the proposed loss model for real-time flood forecasting is examined by routing the rainfall excess determined from the proposed loss model using the 'RORB' model and comparing the modelled and recorded hydrographs. A preliminary evaluation of the suitability of the proposed loss model for design application is presented in Chapter 7. The summary of the results and conclusions drawn from the study are presented in Chapter 8.

2. PREVIOUS WORK ON EMPIRICAL ANALYSIS OF LOSSES

2.1 Preamble

The difference between storm rainfall and the volume of flood runoff (ie. 'loss') has a major influence on the magnitude and shape of the resultant flood hydrograph. Here, loss for an event is defined as the amount of precipitation that does not appear as direct runoff; it includes moisture intercepted by vegetation, percolated into soil or retained by surface storage. As these loss components depend on topography, soils, vegetation and climate, the rainfall losses exhibit both temporal and spatial variability during an event.

Nandakumar et. al (1995) present a review of approaches used to estimate the amount of rainfall which becomes runoff during storm events. Their concern was with loss estimation for use in both real-time flood forecasting and calculation of design floods used to size hydraulic structures. The purpose of the review was to highlight the deficiencies in the current state-of-art and to indicate the most promising areas of research for CRC Project D1 "Improved Loss Modelling for Design Flood Estimation and Flood Forecasting". The loss models they identified which have direct relevance to this study are briefly discussed below.

2.2 Empirical Models for Determining Losses

Estimation of Initial Loss

The 'initial loss/continuing loss' and 'initial loss/proportional loss' models have been widely adopted for flood estimation and forecasting purposes. As initial loss is related to the antecedent catchment wetness, various empirical models have been proposed to predict initial loss from different soil moisture indices. The most common moisture index is the antecedent precipitation index (API), defined as :

$$API_0 = P_0 + P_1K + P_2K^2 + \dots\dots\dots\dots + P_nK^n \qquad (2.1)$$

where K = a recession factor less than unity

P_n = daily rainfall n days antecedent to the storm event

A number of investigations have found that the recession parameter, K, needs to be varied seasonally to allow for the seasonal variation of evapotranspiration; K is expected to be high in winter and low in summer. Cordery (1970) also established that the recession constant (K) used in API computation can be functionally related to monthly temperature, monthly evaporation or even to an arbitrary sine curve function. Yang and Laurenson (1985) used both API and the beginning discharge of a storm (baseflow) for derivation of empirical relationships for initial loss.

Cordery (1970), using rainfall and runoff records for 14 catchments (catchment areas ranging from 0.06 - 250 km^2) in NSW, developed an exponential relationship to predict initial loss in the following form :

$$IL = IL_{max}(N)^{API} \qquad (2.2)$$

where IL = initial loss

N = a constant less than unity

For each catchment, he derived optimised monthly K values and established the best form of functional relationship giving optimum K values. This was achieved by optimising the parameters of the functional relationship (used to define the monthly K values) to obtain the highest correlation coefficient for Equation 2.2. The average values of K obtained for different catchments ranged from 0.85 to 0.96.

Mein et al. (1995), based on the analysis of nine Victorian catchments, found that pre-storm baseflow is the slightly better and more consistent indicator (in comparison to API) of the antecedent catchment wetness, with respect to derivation of empirical relationships for initial loss.

Estimates of Total Loss and Its Distribution

The Flood Studies Report (NERC, 1975) recommends a technique for distributing losses; it relies on prior knowledge of the total losses during the storm, estimated using a prediction equation. Analysis of UK data led to the recommendation in the Flood Studies Report (NERC, 1975) to use Equation 2.3 for predicting total percentage runoff in a storm.

$$PR = 0.22(CWI\text{-}125) + 0.1(P\text{-}10) + SPR \tag{2.3}$$

in which
- PR = percentage of rainfall which becomes direct runoff
- CWI = a catchment wetness index (defined in Equation 2.5 below)
- P = storm rainfall (mm)
- SPR = standard percentage runoff for the catchment, determined from an index of soil properties and the proportion of the catchment urbanised.

Equation 2.3 is not a representation of physical processes, although it does consider that losses are distributed throughout the storm and dependent on the changing state of the catchment (NERC, 1975).

NERC (1975) proposed a short term (5 day) antecedent precipitation index (API_5) given by:

$$API_5 = 0.5^{1/2}[P_{d\text{-}1} + 0.5\,P_{d\text{-}2} + (0.5)^2 P_{d\text{-}3} + (0.5)^3 P_{d\text{-}4} + (0.5)^4 P_{d\text{-}5}] \tag{2.4}$$

This API is used in conjunction with the soil moisture deficit, estimated from the rainfall and actual evaporation, to calculate an antecedent wetness index (CWI) given by:

$$CWI = 125 + API_5 - SMD \tag{2.5}$$

where SMD is the soil moisture deficit.

The total storm loss is estimated in advance from Equation 2.3 and then distributed throughout the duration of the storm. The Flood Studies Report (FSR) gives a technique for distribution which varies the percentage of rainfall lost in each time period, in inverse proportion to a measure of catchment wetness applying at the start of that time period. The measure of catchment wetness is progressively updated following each rainfall increment.

Oddie et al. (1982) applied the FSR method with the unit hydrograph flood model to obtain flood hydrographs for two catchments in Victoria, and found good agreement with observed and simulated flows. When total storm losses were estimated using Equation 2.3, however, CWI failed to indicate sufficient variation with real changes in catchment wetness. This was attributed to the fact that the antecedent condition plays a more dominant role in Australian rainfall-runoff processes than in the UK.

Approaches Based on Source Area

Mein and O'Loughlin (1991) proposed a methodology for real-time flood forecasting which makes use of the size and location of the saturated area on a catchment (ie. the source areas) to determine the proportion of the rainfall that becomes runoff on a catchment during flood events. During the storm, these saturated areas increase in size, as a function of cumulative rainfall. They proposed the use of the TOPOG model to indicate the extent and position of saturated areas on a catchment for any level of rainfall excess. The catchment behaviour, predicted by the TOPOG model, can be represented by a family of characteristic 'S' curves, relating the present saturated area to the pre-storm baseflow and progressive rainfall (as shown later in Section 3.2).

In an update of the work presented by Mein and O'Loughlin (1991), Mag and Mein (1994) investigated this particular relationship on the Burra Creek catchment, located near Canberra by plotting the relationship between volumetric runoff coefficient (equal to surface runoff divided by storm rainfall), pre-storm baseflow and rainfall. With 100 percent runoff assumed from the saturated areas, the percent saturated area can be taken as equal to the volumetric runoff coefficient. Their work showed that the shape of the 'S' curves obtained using volumetric runoff coefficient is generally consistent with that produced by TOPOG for the proportion of saturated area as a function of pre-storm baseflow and subsequent rainfall.

Approaches Based on Empirical Relationships

Drobot and Iorgulescu (1991) illustrated how a simplified version of the SSARR model (Rockwood, 1968) is used to compute storm rainfall excess; it is based on a non-linear relationship between the runoff coefficient C, the soil moisture index U and the average rainfall intensity I over a catchment. The analysis of empirically obtained runoff coefficient curves for given rainfall intensities, I, at selected durations, indicated a relationship of the logistic type between the variables C, U and I; hence, the following expression was proposed for the runoff coefficient C:

$$C(U,I) = \frac{K(I)}{1+a(I).\exp[-b(I).U]} \tag{2.6}$$

where $K(I)$ represents the ceiling value of the curve for intensity I, and $a(I)$ and $b(I)$ are parameters for the same curve. The expression for the ceiling value $K(I)$ can be obtained from physical considerations. This equation is an example of the type based on assumed relationships between loss, and the factors which influence it.

Summary

The above examples illustrate several ways to predict losses from event rainfall. In the following chapters, the method based on saturation curves is developed further, since this seems to have the greatest potential for both real-time and design applications.

3. METHODOLOGY USED TO DERIVE EVENT LOSSES

3.1 Catchments and Data Used

3.1.1 Catchments Selected for the Study

Eight Victorian catchments were used in a preliminary study of the variable proportional loss model (Siriwardena and Mein, 1995 & 1996); twelve additional catchments were included for this study to better represent different climatological and topographical regimes. The drainage area of the selected catchments ranged from 32 to 609 km^2, (including three catchments of drainage area greater than 300 km^2), so as to test the methodology for moderately large catchments. The mean annual rainfall of the selected catchments ranges from 550 to 1900 mm. The list of catchments selected for this study is given in Table 3.1; Figure 3.1 shows their locations. This figure shows a reasonably good coverage of Victoria with the exception of the northern and western parts of the State; the latter is due to the non-availability of suitable gauged catchments in this region.

The selected catchments are part of a database of 67 Victorian catchments assembled by Hill (1994). The primary concern in the selection for this study was the availability of concurrent streamflow and rainfall pluviographic data (at least 15 years). There was also a need for adequate daily rainfall data, depending on the size of the catchment and nature of rainfall regime. An attempt was made to select catchments of different sizes in different rainfall and topographical regimes.

Table 3.1 : Study catchments

Catchment	Gauging Station	Catchment Area (km^2)	Annual Rainfall (mm)
Aire River @ Wyelangta	235219	89.8	1900
Avon River @ Beazley's Bridge	415224	259	565
Axe Creek @ Longlea	406214	234	625
Boggy Creek @ Angleside	403226	108	1090
Cobbannah Creek @ near Bairnsdale	224209	106	840
Goodman Creek @ above Lerderderg tunnel	231219	32.3	800
Holland Creek @ Kelfeera	404207	451	920
La Trobe River @ Noojee	226222	62.2	1480
Lerderderg River @ u/s Goodman Creek Jn.	231211	234	985
Lerderderg River @ Sardine Ck.	231213	153	1020
Moe River @ Darnum	226209	214	1050
Seven Creeks @ Euroa Township	405237	332	925
Snobs Creek @ Snobs Ck. Hatchery	405257	50.7	1650
Spring Creek @ Fawcett	405261	62.6	750
Sugarloaf Creek @ Ash Bridge	405240	609	710
Tallagatta Creek @ McCallums	401220	464	1000
Tarwin River East Branch @ Mirboo	227228	44.3	1140
Wanalta Creek @ Wanalta	405229	108	480
Warrambine Creek @ Warrambine	233223	57.2	670
Wattle Creek @ Navarre	415238	141	555

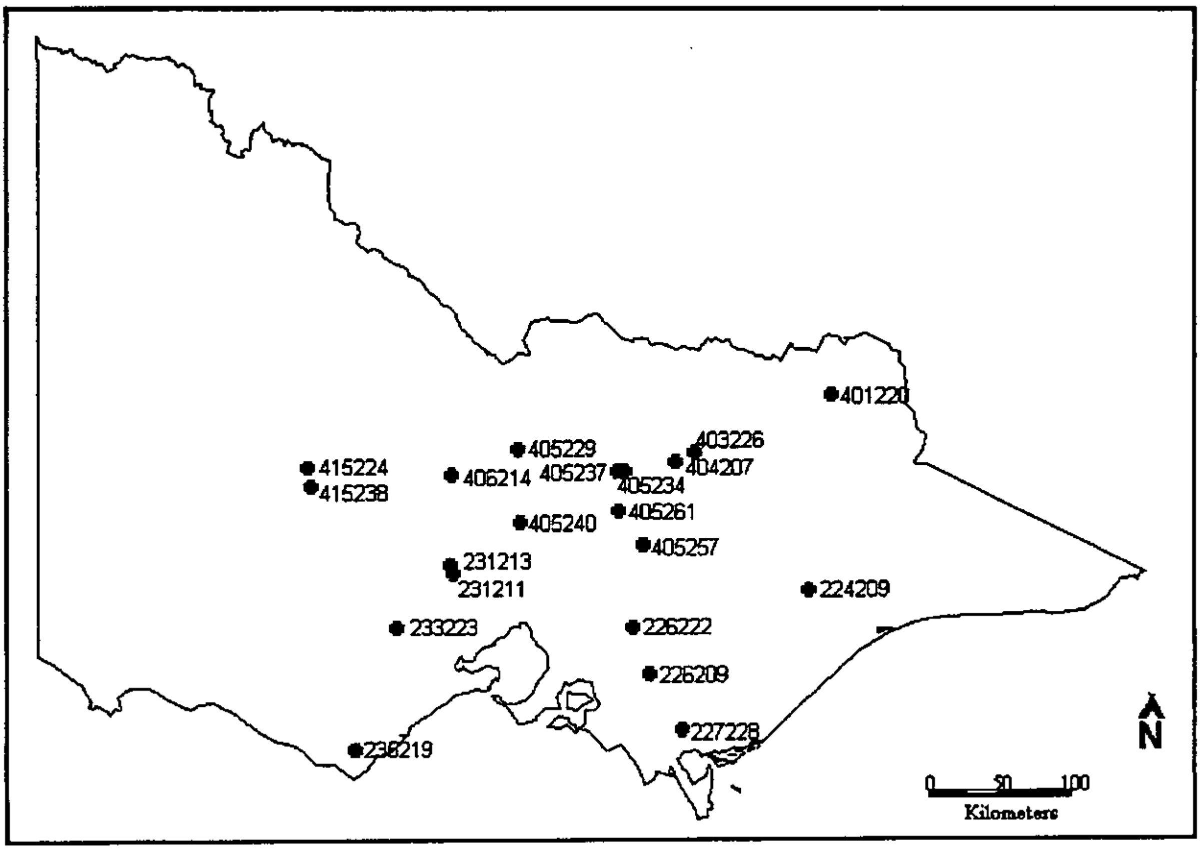


Figure 3.1 : Location of study catchments

3.1.2 Selection of Events for Modelling

The selection of events for each catchment was made from the pluviograph, streamflow, and rainfall data stored in the HYDSYS data archiving system. An emphasis was made to include storm events of a range of magnitudes representing a wide range of antecedent wetness conditions. To achieve this, the following approach was used :

1. Select all events having flood peaks above a certain threshold value, such that the number of events is approximately equal to 5 times the number of years of data.
2. Select a representative rainfall station for the catchment (eg. centrally located and having continuous data) and extract largest storm events for 24 and 48 hour durations, such that the number of events is equal to approximately 5 times the years of data.
3. Select all storm events in (2) which produce any runoff. Note that some events are coincidental with those in (1).
4. Screen the selected events, and discard any unsuitable events for loss modelling (timing errors, accumulated rainfall, multiple peaked hydrographs, zero baseflow events etc).
5. Arbitrarily add events to more fully represent extremely wet and dry conditions by inspecting the streamflow time series plots on log scale.

This strategy ensured the inclusion of events that produced the largest flood events and the largest storm events that produced significant runoff. For the 20 catchments analysed, 25 to

80 events were selected, depending on the length of the pluviograph record and availability of suitable events for modelling.

3.2 Procedure Adopted in Development of Saturation Curves

3.2.1 Separation of Baseflow

Lyne and Hollick (1979) introduced a recursive digital filter technique to separate the streamflow hydrograph into quick and slow response components, representing surface runoff and baseflow respectively. Although the separation procedure does not account for differences in physical processes, the method provides a quick, convenient and consistent methodology for separation of baseflow provided that sensible model parameters (filter factor, number of passes and time interval) are chosen.

The application of this technique has been discussed by O'Loughlin et al. (1982) and Nathan and McMahon (1990). Using daily data, Nathan and McMahon (1990) compared the performance of a master recession curve technique, the smoothed minima technique developed by Institute of Hydrology (1980), and the recursive digital filter technique (Lyne and Hollick 1979) with different filter parameters for five catchments (4-210 km^2). They concluded that the digital filter technique with a filter factor 0.925 and three passes (two forward and one reverse) would give the optimum results compared to the other two techniques. O'Loughlin et al. (1982) used the same parameters with a 1 hour time interval. Mag and Mein (1994) showed that results obtained from the digital filtering technique with these parameters, and those obtained from 'manual' subtraction of baseflow, were not significantly different.

The HYBASE sub-program in the HYDSYS data archiving system uses a digital filter technique for baseflow separation. In this study, continuous baseflow separation for all streamflow records was carried out using HYBASE, with default parameters of filter factor of 0.925, 3 passes (representing three forward and three reverse passes) and a 60 minutes time step.

3.2.2 Antecedent Wetness Index Adopted in the Study

During a pilot study, Mein et al. (1994) found that, for a set of eleven catchments, pre-storm baseflow is the better and more consistent indicator of antecedent wetness than the antecedent precipitation index (*API*) for the estimation of initial loss. For *API*, uncertainties in the value of the adopted recession parameter (*K*) significantly decrease the reliability of estimated *API* values. Siriwardena et al. (1997) also found that the pre-storm baseflow is the better indicator than the *API* for development of saturation curves for Spring Creek (405261) catchment. Based on above work, the pre-storm baseflow (expressed in mm/day for comparison for different catchments) was adopted in this study.

Pre-storm baseflow can be considered equal to the observed pre-storm streamflow if the antecedent period has been dry. In the case where surface runoff from a previous event is still occurring, this will need to be subtracted from the observed streamflow to obtain the baseflow component. For the events analysed in this study, pre-storm baseflow was found to be equal or nearly equal to the observed pre-storm streamflow. This allows direct use of observed pre-storm streamflow in deriving losses.

3.2.3 Fitting Saturation Curves

For the selected storm events, the Thiessen weighted storm rainfall was estimated from the pluviograph and daily rainfall stations located in and around the catchment. Volumetric runoff coefficients (equal to the surface runoff divided by storm rainfall) were plotted against the observed pre-storm baseflow on a semi-log plot (ie. baseflow in log scale). If 100 percent runoff is assumed from the saturated areas, the percent saturated area can be assumed equal to the volumetric runoff coefficient. Each data point on the graph was labelled with the corresponding storm rainfall for that event. If any trend exists, curves corresponding to different levels of storm rainfall can be subjectively drawn (Mein and O'Loughlin, 1991). However, when the number of data points are large, and if there is a considerable 'noise' in the distribution of data points, it is preferable to fit a mathematical function.

Siriwardena et al. (1997) examined three different functions and concluded that a logistic function of the form of Equation 3.1 was preferred.

$$r.o.c. = (1-d)+\frac{1}{1/d+a.BF^{b}.RAIN^{c}} \qquad (3.1)$$

where BF = baseflow in mm/day
$RAIN$ = storm rainfall in mm
a, b, c, d are coefficients determined by regression.

The advantage of the logistic functions given in Equations 3.1 is that runoff coefficient reaches an upper bound of 1.0 and produces the postulated 'S' shape. If the optimised parameter 'd' is greater than 1.0, then the lower bound of Equation 3.1 becomes a negative value. In this case, for any pre-storm baseflow (BF), when $r.o.c.$ becomes zero, Equation 3.1 gives a finite positive value for $RAIN$, which is 'initial loss'. Thus, Equation 3.1 provides adequate flexibility for the modelling of initial loss.

3.2.4 Interpretation of the Fitted Curves

Once the curves are plotted for any level of pre-storm baseflow, the corresponding initial loss and runoff coefficient can be estimated from the vertical line which cuts the curves of storm rainfall (Figure 3.2). The corresponding volumetric runoff coefficients reflect average runoff coefficients for the corresponding storm depth, and therefore need some manipulation to derive the variation of loss rate through a storm.

The value of the interpolated storm rainfall curve which produces zero runoff at the particular pre-storm baseflow level may be taken as initial loss. For the purpose of using the fitted curves as a variable proportional loss model, the runoff coefficients at incremental storm rainfall depths need to be calculated. For example, the runoff coefficient for the incremental rainfall from 40 to 60 mm ($r.o.c._{40\text{-}60}$) may be calculated as:

$$\mathrm{r.o.c.}_{40-60} = \frac{60\times r_{60} - 40\times r_{40}}{(60-40)} \qquad (3.2)$$

where r_{60} and r_{40} are the volumetric runoff coefficients for total rainfall of 60 and 40 mm respectively (see Figure 3.2).

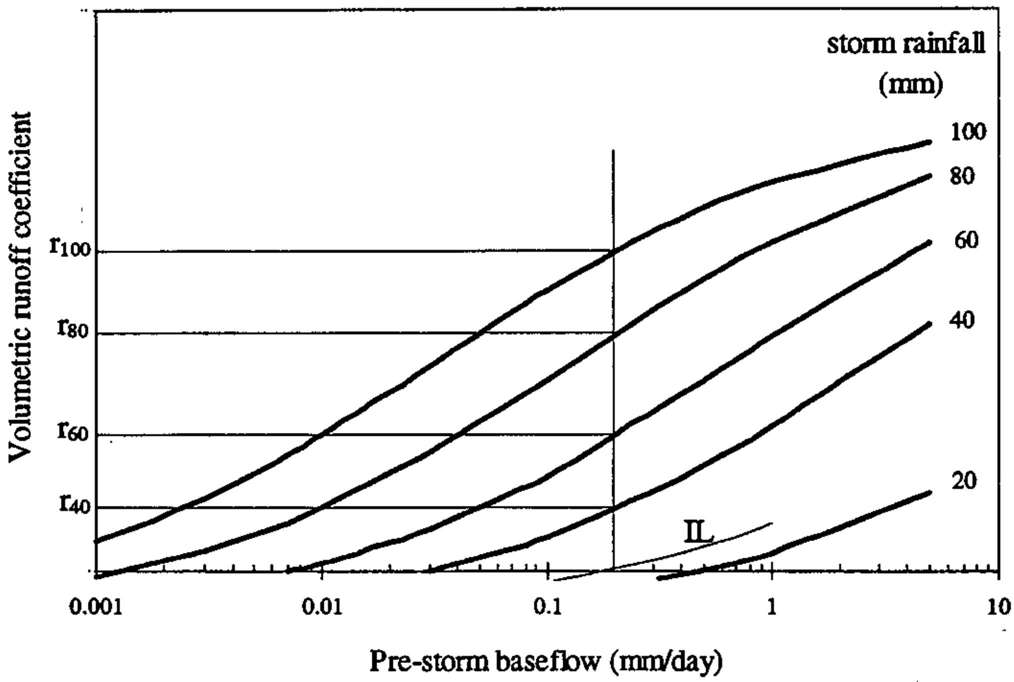


Figure. 3.2 : Estimation of loss parameters (after Mein and O'Loughlin, 1991)

Knowing the fitted mathematical function, incremental runoff coefficients at a range of pre-storm baseflow levels can be easily tabulated. The values of calculated incremental runoff coefficients would be expected to increase gradually as the storm progresses.

4. RESULTS OBTAINED WITH THE VARIABLE PROPORTIONAL LOSS MODEL

4.1 Development of Saturation Curves for Individual Catchments

In the development of saturation curves for a catchment, the volumetric runoff coefficient is defined as a function of pre-storm baseflow and total storm rainfall. As the pre-storm baseflow is representative of antecedent catchment wetness, the volumetric runoff coefficient is expected to increase with the pre-storm baseflow. Similarly, the larger the storm event, the larger the area that contributes to surface runoff; hence, higher volumetric runoff coefficients. The fitted mathematical relationship for runoff coefficient can be graphically presented as a family of curves for a range of storm rainfall as shown in Figure 3.2.

Relationships for runoff coefficient were developed for each catchment using a logistic type of function (Equation 3.1). During the fitting process for some of the catchments, a few data points which did not appear to fit with the trend of the remaining data were considered as 'outliers' and eliminated (up to a maximum of 3 events). A plot of volumetric runoff coefficient against pre-storm baseflow (in log-scale), with data points labelled with corresponding storm rainfall for the Tarwin River catchment is given in Figure 4.1. The saturation curves fitted by the logistic type function (Equation 3.1) for an appropriate range of storm rainfall are also shown in this figure. Similar plots for other catchments are given in Siriwardena et al. (1997). If the pre-storm baseflow is known, these relationships can be used to estimate the volumetric runoff coefficient for a given storm rainfall depth, and provide the basis for estimation of progressive incremental runoff factors. The volumetric runoff coefficient, pre-storm baseflow and storm rainfall for the selected events used for calibration of curves for each catchment are also given in Siriwardena et al. (1997).

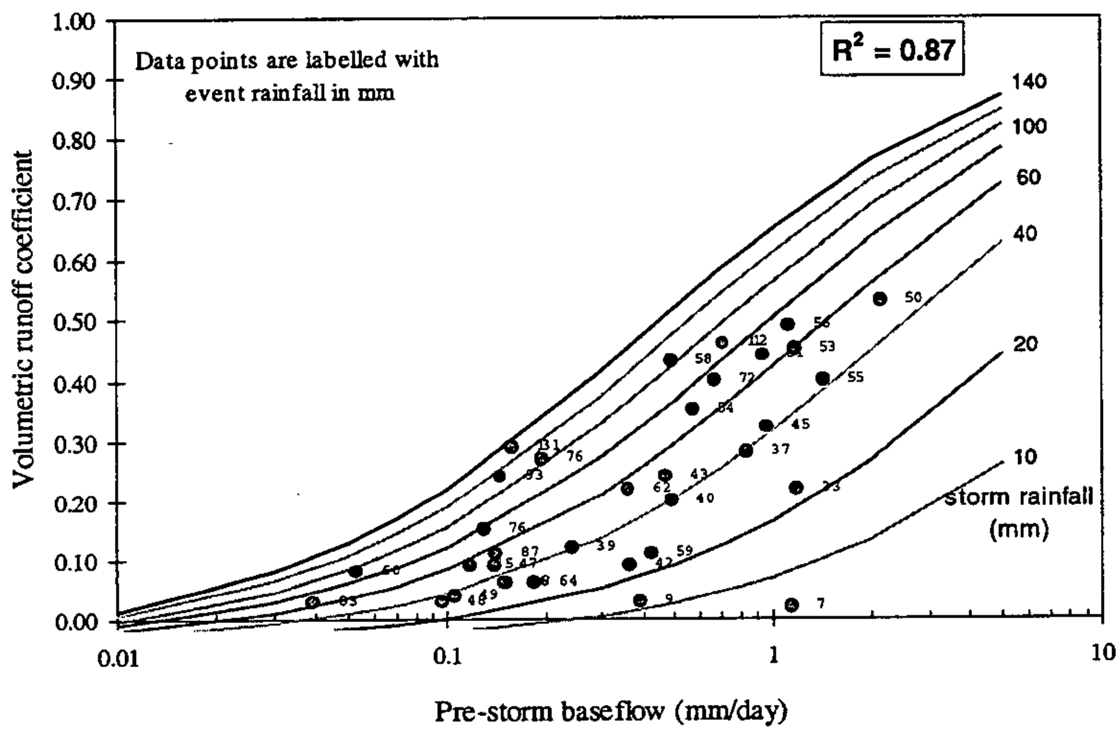


Figure 4.1 : Fitted saturation curves for Tarwin River East at Mirboo

4.2 Evaluation of Results for Different Catchments

Logistic type relationships (Equation 3.1) were derived for all catchments except for the La Trobe River for which no satisfactory relation was found to exist. It should be noted that, for catchments which experience cease-to-flow conditions for a major period of time (eg. Avon, Wanalta, Wattle), only the non-zero events could be used in the analysis. The optimised regression parameters, the coefficient of determination (R^2) and the standard error of estimate (SEE) of the fitted relationships are given in Table 4.1.

The regression coefficient *d* is directly related to the 'initial loss'. It was found that *d* is either 1.0, or slightly greater than 1.0, for many catchments, and greater than 1.10 for only 3 out of 19 catchments tested. This indicates that for many catchments, 'initial loss' is small. The Lerderderg River (@ Sardine Ck.) is an exception, with a high value of *d* (2.14).

As it can be seen from Table 4.1, the coefficient of determination (R^2) varies from 0.05 to 0.91 for the test catchments, representing varying levels of suitability for the methodology adopted. Satisfactory results were obtained for a majority of catchments having R^2 values greater than 0.70 (15 out of 19 catchments). Of these, 8 catchments had R^2 values greater than 0.85.

The hydrologic behaviour of the La Trobe catchment was found to be different from the rest of the catchments; runoff coefficients remained very low for all events. The pre-storm baseflow of this catchment was always high; its small range in value precludes the fitting of the curves. A simpler loss model, such as an average runoff coefficient for all ranges of pre-storm baseflow, would be adequate for this type of catchment.

The 'noise' in the processed data used for Snobs Creek (R^2 = 0.39) was so high that the saturation curves for different storm rainfall were not significantly different. Wanalta Creek, Warrambine Creek and Aire River were not satisfactorily modelled, as the R^2 of the fitted relationships falls within the range of 0.40 to 0.60.

The standard error of estimate (SEE) is a good indicator of the accuracy of the predictor variable. Table 4.1 shows that the SEE of the runoff coefficients derived from the fitted relationship varied from 0.017 to 0.108 for the catchments tested. It might be noted that there is no direct relationship between the R^2 and SEE; for example, the R^2 of the fitted relationship for Snobs Creek was only 0.39, but the SEE of the predicted runoff coefficient was low (0.033). This is because the hydrologic behaviour of the catchment is such that the runoff coefficients of the events used in calibration were less than 0.21. On the other hand, the fitted relationship for Cobbannah Creek can be considered as good (R^2 = 0.80), but the SEE of the predicted runoff coefficient was high (0.11), as the events used in calibration had a range of runoff coefficients extending up to 0.75.

The SEE expressed as a percentage of the mean runoff coefficient of the events would be more useful. Table 4.1 shows that SEE as a percentage of the mean ranges from 26 to 49 percent. It should be noted, however, that selection of many events of low runoff tends to lower the computed 'mean' for many catchments. As a consequence, the computed SEE expressed as a percentage of the mean is higher.

Table 4.1 : Regression parameters and performance indices for the fitted logistic function (Equation 3.1)

	Catchment	Station Code	Regression parameters for logistic function				R^2	Standard Error	
			a	*b*	*c*	*d*			as a % of mean
1	Aire River @ Wyelangta	235219	586	-0.73	-1.06	1.00*	0.58	0.089	49%
2	Avon River @ Beazley's Bridge	415224	5.64	-0.32	-0.69	1.12	0.77	0.075	30%
3	Axe Creek @ Longlea	406214	21.9	-0.73	-0.86	1.00*	0.88	0.045	28%
4	Boggy Creek @ Angleside	403226	134	-0.71	-0.73	1.01	0.87	0.030	32%
5	Cobbannah Ck. @ near Bairnsdale	224209	334	-0.61	-1.54	1.04	0.80	0.105	36%
6	Goodman Ck. @above Lerderderg tunnel	231219	517	-0.62	-1.71	1.00*	0.75	0.066	42%
7	Holland Creek @ Kelfeera	404207	86.0	-0.74	-0.92	1.02	0.91	0.037	30%
8	La Trobe River @ Noojee	226222	-	-	-	-	0.05	0.026	38%
9	Lerderderg R. @ u/s Goodman Ck. Jn.	231211	1089	-0.48	-1.64	1.03	0.88	0.054	40%
10	Lerderderg River @ Sardine Ck.	231213	1.27	-0.22	-0.51	2.14	0.71	0.100	38%
11	Moe River @ Darnum	226209	11.6	-0.60	-0.44	1.06	0.83	0.041	28%
12	Seven Ck. @ Euroa Township	405237	104	-0.96	-0.90	1.00*	0.90	0.035	29%
13	Snobs Creek @ Snobs Ck. Hatchery	405257	24.1	-0.44	-0.14	1.00*	0.39	0.033	41%
14	Spring Creek @ Fawcett	405261	257	-0.86	-1.70	1.00*	0.79	0.085	38%
15	Sugarloaf Creek @ Ash Bridge	405240	16.8	-0.74	-0.80	1.02	0.91	0.046	26%
16	Tallagatta Ck. @ McCallums	401220	209	-0.95	-0.86	1.00*	0.88	0.017	36%
17	Tarwin R. East Branch @ Mirboo	227228	93.4	-0.77	-1.07	1.04	0.87	0.061	28%
18	Wanalta Creek @ Wanalta	405229	37.9	-0.29	-1.06	1.00*	0.45	0.083	34%
19	Warrambine Ck. @ Warrambine	233223	4.65	-0.22	-0.72	1.32	0.42	0.108	37%
20	Wattle Creek @ Navarre	415238	21.9	-0.42	-0.89	1.01	0.68	0.068	40%

* Set to 1.0 (optimised value being slightly less than 1.00)

The availability of data for large rainfall events plays a dominant role on the shape and accuracy of the fitted curves at the high end. In general, the saturation curves derived for catchments in low rainfall areas are only reliable up to a moderate event rainfall (eg. 100 mm) due to the lack of points.

A direct comparison of the predicted and observed runoff coefficients for the Tarwin River is shown in Figure 4.2. Such plots are useful in assessing the accuracy of the prediction equation as well as observing any trends and biases in the distribution. Similar plots for other catchments are given in Siriwardena et al. (1997).

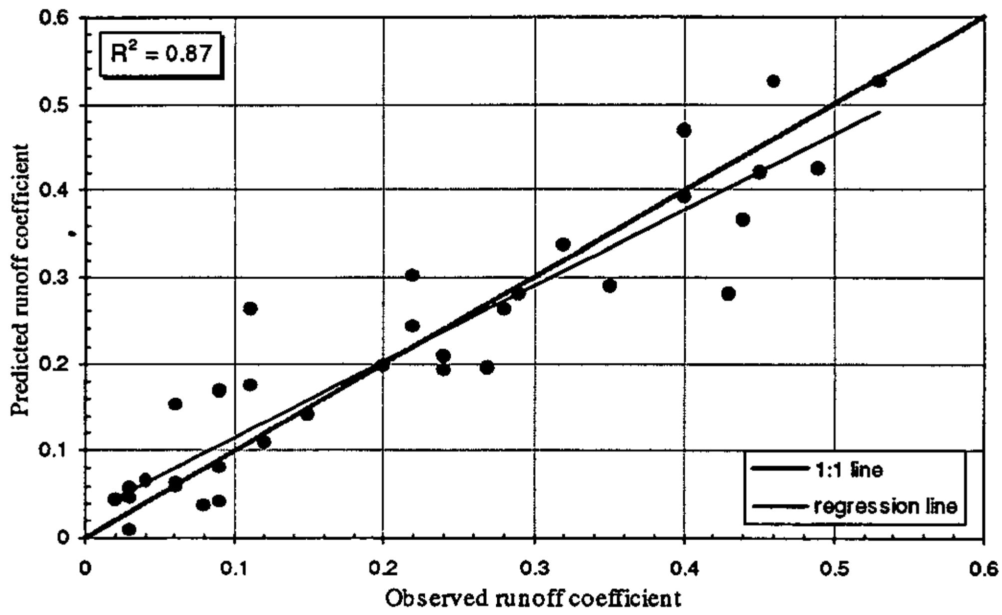


Figure 4.2 : Comparison of actual and predicted runoff coefficient for Tarwin River

Table 4.2 summarises the accuracy of the predicted runoff coefficients for all streams. This table shows the percentage of the predicted values that are within 20 percent and 50 percent of the calculated runoff coefficients. The table also shows the percentage of the predicted values those are within ± 0.05 and ± 0.10 of the calculated runoff coefficients.

The percentage error may not be a good indicator, especially for lower ranges of runoff coefficients; and therefore, the percentage of predicted runoff coefficients being within ±0.05 could be considered as an improved performance measure for the loss model. Using this measure, the Seven Creeks, Boggy Creek, Tallagatta Creek and Holland Creek produced the best results, with more than 85% of the predicted values being within ±0.05. The R^2 of the fitted relationship for these catchments is also more than 0.85. Cobbannah Creek, Lerderderg River (@ Sardine Ck.) and Warrambine Creek are the worst representatives, with less than 50% of the predicted values being within ±0.05.

Overall, the proposed variable proportional loss model based on saturation curves could be satisfactorily applied for more than 75% of the catchments analysed in this study. However, it was also shown that the methodology is not suitable for certain type of catchments, as discussed in Chapter 5.

Table 4.2 : Accuracy of predicted runoff coefficients

Catchment	R^2	Percentage of predicted runoff coefficient being within:			
		20 %	50 %	± 0.05	± 0.10
Aire River @ Wyelangta (235219)	0.58	45 %	80 %	62 %	87 %
Avon River @ Beazley's Bridge (415224)	0.77	70 %	88 %	61 %	85 %
Axe Creek @ Longlea (406214)	0.88	51 %	76 %	77 %	99 %
Boggy Creek @ Angleside (403226)	0.87	38 %	75 %	92 %	100 %
Cobbannah Ck. @ Bairnsdale (224209)	0.80	47 %	70 %	41 %	76 %
Goodman Ck. @ u/s Lerder. tunnel (231219)	0.75	29 %	68 %	62 %	94 %
Holland Creek @ Kelfeera (404207)	0.91	34 %	71 %	86 %	100 %
La Trobe River @ Noojee (226222)	0.05	-	-	-	-
Lerderderg R. @ u/s Goodman Ck. (231211)	0.88	41 %	59 %	69 %	100 %
Lerderderg River @ Sardine Ck. (231213)	0.71	45 %	72 %	31 %	79 %
Moe River @ Darnum (226209)	0.83	49 %	77 %	77 %	100 %
Seven Creeks @ Euroa Township (405237)	0.90	55 %	95 %	87 %	97 %
Snobs Ck. @ Snobs Ck. Hatchery (405257)	0.39	-	-	-	-
Spring Creek @ Fawcett (405261)	0.79	30 %	61 %	50 %	80 %
Sugarloaf Creek @ Ash Bridge (405240)	0.91	42 %	71 %	78 %	97 %
Tallagatta Creek @ McCallums (401220)	0.88	51 %	81 %	99 %	100 %
Tarwin R. East Branch @ Mirboo (227228)	0.87	59 %	70 %	65 %	94 %
Wanalta Creek @ Wanalta (405229)	0.45	56 %	86 %	50 %	81 %
Warrambine Creek @ Warrambine (233223)	0.42	45 %	82 %	36 %	73 %
Wattle Creek @ Navarre (415238)	0.68	43 %	72 %	54 %	89 %

4.3 Application of the Variable Proportional Loss Model

To apply the variable proportional loss model to an event, incremental runoff coefficients at progressive rainfall increments need to be calculated from the derived relationship for storm average runoff coefficients, as explained in Section 3.2.4. The incremental runoff coefficients calculated in this way are given in Siriwardena et al. (1997) for all catchments.

An example plot of progressively calculated incremental runoff coefficients (at 5 mm intervals) for Tarwin River is shown in Figure 4.3.

The incremental runoff coefficient is expected to increase gradually and approach a value of 1.0 as the storm rainfall increases (Figure 4.3). Although the average storm runoff coefficient is constrained to be less than 1.0 by the type of function used in the fitting procedure, it does not guarantee that the incremental runoff coefficients are also constrained. As a consequence, for a few catchments it was found that the incremental runoff coefficients asymptotically approach a value slightly greater than 1.0, especially at higher pre-storm baseflows. For practical purposes, truncating these values to 1.0 would not make a significant difference.

It is important to note that the 'initial loss' estimated from the proposed loss model is not comparable to the initial loss attributed to conventional loss models. The latter are conceptually lumped models, having an initial loss followed by a constant proportional loss or continuing loss rate. The proposed variable proportional loss model simulates the concept of saturation areas, having a progressively increased runoff coefficient to model the contribution from the increasing 'saturation areas' as the storm progresses. This is considered to be more representative of the physical processes than conventional loss models. In this model, the rainfall up to the commencement of runoff (zero runoff coefficient) can be regarded as 'initial loss' but it is small in comparison to the initial loss for the conventional loss models.

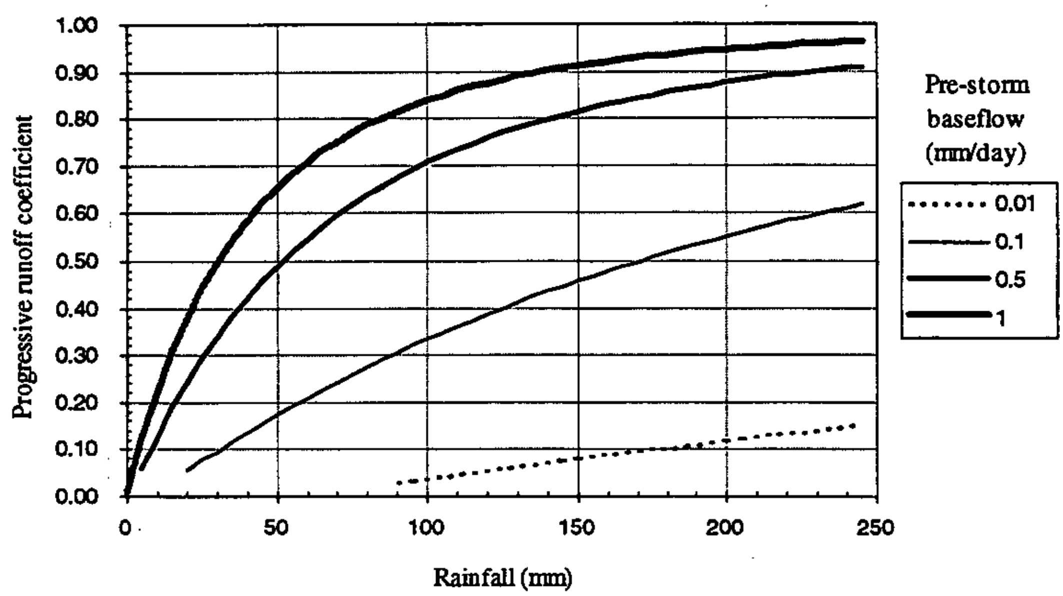


Figure 4.3 : Progressive (incremental) runoff coefficients for Tarwin River for different pre-storm baseflow levels

The application of the variable proportional loss model to compute rainfall excess is illustrated in Figure 4.4. In this example, the rainfall excess is calculated from the progressive runoff coefficient, which increases from zero to 0.56 (equivalent to an average storm runoff coefficient of 0.25). A deficiency in this procedure is the inability to account for the changes in the catchment wetness (and in turn, progressive runoff coefficients) during the rainless periods within a storm.

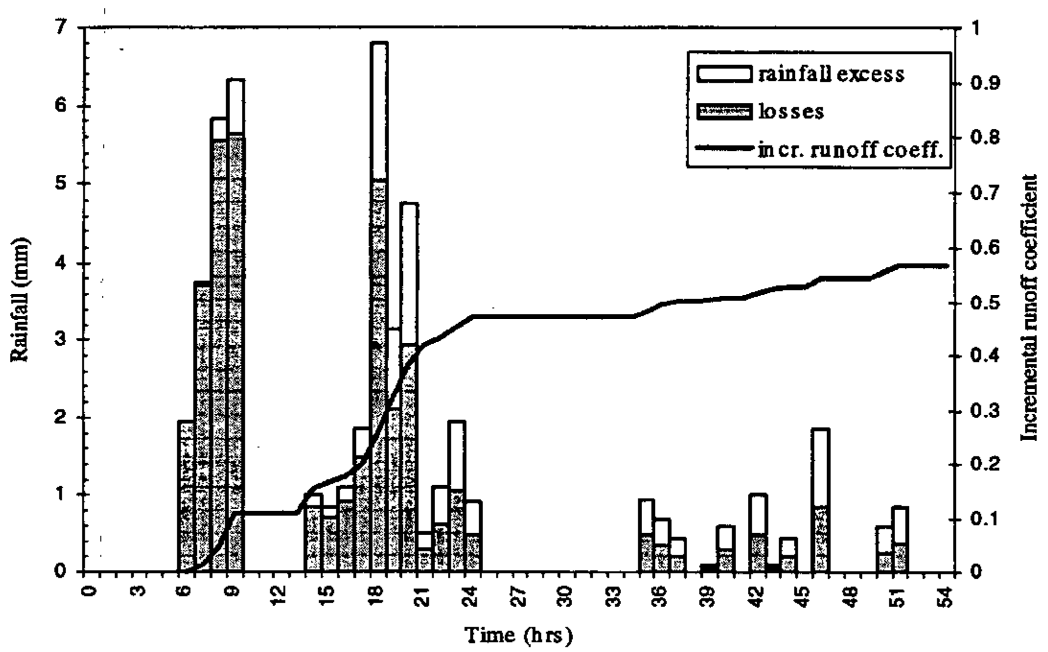


Figure 4.4 : Application of proposed loss model to storm events: Spring Creek (20/09/1976) (note the increase in proportional runoff coefficient as the storm progresses)

The following procedure can be used to convert a storm hyetograph to a rainfall excess hyetograph:

(i) Calculate the cumulative storm rainfall up to the end of each time interval;
(ii) Calculate the average storm runoff coefficients corresponding to the cumulative storm rainfall at end of each time interval using the fitted relationship (Equation 3.1) for known pre-storm baseflow;
(iii) Multiply the average runoff coefficients in step (ii) by the cumulative storm rainfall in step (i) to obtain the cumulative *excess* rainfall at the end of each time interval;
(iv) Calculate the difference between rainfall excess totals at subsequent time intervals to determine the excess rainfall hyetograph.

The above procedure avoids the need for direct computation of incremental runoff coefficients, and provides a convenient method to determine the rainfall excess hyetograph. It is important however to check that the incremental runoff coefficients are sensible (ie. values not exceeding 1.0) before applying the procedure.

4.4 Overview of the Adopted Procedure for Loss Modelling

4.4.1 Factors Affecting the Fitted Relationships

The reliability of the fitted relationship depends upon the accuracy of the derived event parameters of the largest rainfall events used for calibration. As only a few such rainfall events are available for the calibration of the curves, the data points corresponding to individual large rainfall events play a dominant role on the shape and accuracy of the curves. For the development of consistent curves, a uniform distribution of data points covering a range of rainfall is desirable. It was often observed that the 'outliers' stem from "complexities" in the data, such as the inclusion of double or multi-peaked storms.

The use of reliable storm data in the calibration of the curves is vital in getting satisfactory results from this methodology. Inconsistencies in the positions of some storms in relation to the curves ('noise' in plotted data) could be caused by a number of factors.

- Uncertainty in the estimation of catchment rainfall, due to inadequate spatial coverage of rainfall stations (pluviograph as well as daily read), could cause a considerable 'noise' in the distribution of data; hence an adverse effect on the final results. This is important when there is a strong rainfall gradient across the catchment (eg. Boggy Creek), as well as when modelling events caused by of thunderstorms. The uncertainty in the weighted catchment storm rainfall has a two-fold effect: both volumetric runoff coefficient and assigned storm rainfall (label) are in error. The calculated runoff coefficient, especially for small events, is very sensitive to the value of rainfall used.

- The intensity of rainfall is known to have an effect on the results. An intense burst may result in a higher runoff coefficient compared to a storm having distributed rainfall (less intense) with the same amount of rainfall, under similar antecedent conditions. This may be due to infiltration-excess overland flow being generated.

- Spatial variation in rainfall will result in inconsistencies in the results. For example, a partial area storm occurring closer to the catchment outlet, may produce a higher runoff coefficient compared to a storm having uniform rainfall over the catchment with same amount of rainfall, under similar antecedent conditions.

- Measurement errors in the data and errors in estimation will increase uncertainties in the fitted curves, eg. rating table extrapolation.

- The estimation of the baseflow at the start of the event could be in error, due to the influence of recent antecedent rainfall on the catchment.

In addition to the above, although the selected data generally covers a wide range of baseflows, the availability of few storms of large magnitudes restricts the adequate definition of the fitted curves at the high-rainfall end.

4.4.2 Advantages and Disadvantages of Proposed Loss Model

The proposed method for loss modelling has advantages over the conventional procedures with respect to the subjectivity in separation of initial loss and timing errors in streamflow and rainfall data, as only volumetric runoff coefficient, pre-storm baseflow and storm rainfall are involved in the analysis. Hence, this method is less subjective and less susceptible to timing errors in the data.

One of the disadvantages of the proposed method is that the relationship only holds when pre-storm baseflow exists (a zero baseflow could be representative of a wide range of catchment wetness). As a consequence, this method has only a limited applicability for streams which are dry for a major part of the year (eg. Wanalta, Warrambine).

The relationship developed to estimate the volumetric runoff coefficient is not explicit in time; hence application of the loss model to a storm event requires some manipulation to transform the cumulative function to be time variant. This can be conveniently carried out using a small computer program or worksheet.

The method does not account for the depletion of soil moisture (catchment wetness) during the rainless periods of a storm. The inclusion of the depletion of soil moisture is an area which requires further work.

4.4.3 Applicability for Flood Forecasting and Design Purposes

This method would seem to have direct applicability in real-time flood forecasting. With established 'saturation curves' for the catchment, and knowing the baseflow at the onset of the storm, the initial loss and the variable proportional runoff factors can be estimated progressively as explained in Chapter 3. Then, the calculated rainfall excess can be applied to a routing model to predict the flood hydrograph. This may be continued until the rising limb of the observed hydrograph is formed. Corrective measures may then have to be taken to match the hydrographs. The suitability of the proposed loss model for flood forecasting is evaluated in Chapter 6.

This method can also be applied for design purposes if the mean or median value of pre-storm baseflow (event), or any design level of antecedent condition, is known. It may be noted that this loss model is based on the analyses of complete storms. In contrast, the design rainfalls given in ARR87 are not. This incompatibility impairs the direct applicability of the proposed loss model in application for design purposes.

5. DEVELOPMENT OF THE LOSS MODEL ON A REGIONAL BASIS

5.1 Catchment Characteristics Selected for Regional Analyses

An understanding of the factors that affect rainfall losses is desirable to explain observed differences in rainfall losses between different catchments. Such an understanding would give an insight in the choice of characteristics, and the likely predictive success of the selected variables.

The catchment characteristics relevant for this study can be classified into several categories.

- *Climatic factors*
- *Morphometric characteristics*
- *Soil characteristics and geology*
- *Land use*

A range of physical characteristics was derived for each of the study catchments. These characteristics were estimated from 1:100,000 topographical maps and other published information (eg, DCNR, 1994). A description of these characteristics is listed below.

AREA: *Catchment area in (km^2)*

Drainage area measured with a planimeter from a 1:100,000 map.

ANNRAIN: *Mean annual catchment rainfall (mm)*

Thiessen weighted mean annual rainfall using stations having more than 40 years of data.

MARUN: *Mean annual runoff (mm)*

Mean annual runoff measured at the gauging station, expressed as a depth in mm.

WETDAY: *Number of wet days per year*

Defined as average number of rainy days (0.2 mm rainfall as threshold) at a representative long-term daily rainfall station. For large catchments (eg. >150 km^2) weighted average of a number of representative stations was estimated.

PET: *Potential evapotranspiration (mm)*

Nathan and Pamminger (1995) have prepared a set of maps for Victoria showing mean potential evapotranspiration rates for each month of the year as well as for the whole year. These maps are based on the use of Morton's (1983) complementary procedure for estimation of regional evapotranspiration. The PET was estimated for each catchment from the isohyetal map for average annual potential evapotranspiration given in the above report.

BFI: *Baseflow index*

Baseflow index is defined as the ratio of baseflow volume to the total volume of streamflow on long-term basis (Nathan and Weinmann, 1993). It should be noted that this index is sensitive to the method used for separation of baseflow. For this study, BFI was calculated by separating the baseflow using the HYBASE program with 24 hour time interval, filter factor of 0.925 and a single pass, consistent with the findings of Nathan and McMahon (1991).

NFI: *No-flow index*

No-flow index is defined by the percentage of time in which the catchment ceases to flow, or falls below a measurable quantity. In this study 1 percent of the long term mean flow was taken as the measure of cease-to-flow conditions as defined by Nathan and Weinmann (1993). Hourly flow rates were used to calculate the index.

BVI: Baseflow variability index

This index is a measure of variability of baseflow and was calculated from the continuous separated baseflow series by the following formula:

$$BFI = \frac{\textit{Baseflow exceeded 25\% of time} - \textit{Baseflow exceeded 75\% of time}}{\textit{Baseflow exceeded 50\% of time}}$$

Note that this index is undefined for streams for which cease-to-flow conditions prevail for most of the time (eg. NFI > 0.30)

SHAPE1, SHAPE2 : Catchment shape factor

Two catchment shape factors were considered.

SHAPE1 :- Defined as the catchment perimeter divided by the area, where the catchment perimeter is the total length of the watershed divide. The units are in km^{-1}.

SHAPE2 :- Defined as the catchment perimeter divided by the perimeter of the circular catchment of same catchment area. This is a dimensionless index.

$^{20}I_2$, $^{20}I_{48}$ *: Rainfall intensity for 20 year return period and 2 h and 48 h durations. (mm/hr)*

Rainfall intensities were calculated from the IFD curves given in Chapter 2 of ARR(1987) at the centroid of the catchment. As the indices are point specific, they are only approximate for large catchments.

IRATIO : Ratio of rainfall intensities of 48 h and 2 h durations for 20 year return period.

This is the ratio of rainfall intensities derived for 48 hour and 2 hour durations for 20 year return period. IRATIO = $^{20}I_{48}$ / $^{20}I_2$

S1085 : Slope of the central 75 percent of the mainstream length

The stream slope was defined as the mainstream slope (expressed as a percentage) between the 10 and 85 percentiles of mainstream length upstream from the catchment outlet, ie. the slope of the approximately central 75 percent of mainstream length.

FCOV, FCOVW : Percentage of catchment covered by dense/medium forest

The percentage of catchment covered by forest was determined from 1:100,000 topographic maps using a planimeter, based on the area designated as dense, medium and scattered forest or scrub. Parameters were:

FCOV :- The percentage of catchment covered by dense and medium forest and also dense and medium scrub.

FCOVW :- This is a weighted measure taking into account all types of forest cover. Weights of 3, 2, and 1 were given for dense, medium and scattered respectively.

$$\text{FCOVW} = \frac{3 \cdot \text{DENSE} + 2 \cdot \text{MEDIUM} + 1 \cdot \text{SCATTERED}}{3}$$

Hence, if the catchment is covered by 100% dense forest, FCOVW = 100%

If the catchment is covered by 100% scattered forest, FCOVW = 33.3%

The derived catchment parameters for the study are given in Table 5.1. The above list is devoid of a suitable soil parameter as no suitable measure of the hydrologic properties of soils at the catchment scale could be found.

Table 5.1 : Catchment parameters derived for regional study

Station Code	Drainage Area (km^2) AREA	M.annual Rainfall (mm) ANNRAIN	M.annual Runoff (mm) MARUN	Annual PET (mm) PET	Number of wet days WET	Baseflow Index BFI	No-flow Index NFI	Baseflow variability Index BVI	Shape Factor 1 $(km)^{-1}$ SHAPE1	Shape Factor 2 SHAPE2	20 yr/2hr. rainfall (mm/hr) $^{20}I_2$	20 yr/48hr. rainfall (mm/hr) $^{20}I_{48}$	Intensity ratio $^{20}I_{48}/^{20}I_2$ IRATIO	main stream slope(%) S1085	Forest cover (%) FCOV	Weighted forest cover (%) FCOVW
224209	106.0	840	146.5	1025	129	0.14	0.42	5.88	0.40	1.17	25.69	3.80	0.148	1.26	99.5	99.5
226209	214.0	1050	246.7	980	201	0.48	0.00	1.92	0.36	1.48	20.57	2.76	0.134	0.30	5.4	8.3
226222	62.2	1480	477.9	980	162	0.81	0.00	0.52	0.53	1.17	22.44	3.52	0.157	0.81	98.8	98.8
227228	44.3	1140	333.5	1000	190	0.41	0.00	1.74	0.69	1.29	22.43	3.36	0.150	0.91	39.2	59.5
231211	234.0	985	122.7	1100	181	0.32	0.25	3.05	0.36	1.54	23.45	3.14	0.134	1.65	94.3	96.1
231213	153.0	1020	219.5	1100	139	0.41	0.14	3.54	0.35	1.22	23.40	3.07	0.131	0.87	90.1	93.2
231219	32.3	800	64.5	1080	144	0.13	0.39	-	0.84	1.35	23.21	3.06	0.132	2.40	85.0	85.6
233223	57.2	670	38.8	1075	102	0.09	0.33	-	0.59	1.25	20.72	2.24	0.108	1.02	0.0	0.0
235219	89.8	1900	877.5	1050	216	0.58	0.00	1.61	0.49	1.32	21.86	3.67	0.168	0.94	76.7	68.1
401220	464.0	1000	182.0	1150	132	0.60	0.01	2.59	0.23	1.37	24.17	2.73	0.113	0.86	72.7	80.7
403226	108.0	1090	308.3	1130	114	0.55	0.05	3.27	0.56	1.63	23.14	2.52	0.109	1.50	59.6	72.3
404207	451.0	920	221.7	1125	156	0.45	0.05	3.02	0.24	1.45	25.51	3.41	0.134	1.29	60.5	71.3
405229	108.0	480	9.4	1160	96	0.08	0.73	-	0.43	1.25	21.88	2.21	0.101	0.15	51.7	50.6
405237	332.0	925	254.7	1110	130	0.47	0.01	2.52	0.25	1.26	25.54	3.24	0.127	0.83	18.2	39.6
405240	609.0	710	146.6	1080	158	0.29	0.16	4.00	0.22	1.54	22.11	2.68	0.121	0.51	60.0	55.0
405257	50.7	1650	666.1	1025	156	0.72	0.00	1.31	0.92	1.84	23.05	2.60	0.113	4.12	92.0	92.0
405261	62.6	750	142.3	1055	97	0.25	0.16	5.40	0.55	1.23	21.87	2.80	0.128	1.16	10.5	23.5
406214	234.0	625	82.8	1160	136	0.25	0.20	7.31	0.31	1.35	21.73	2.39	0.110	0.63	39.0	47.4
415224	259.0	565	45.8	1110	114	0.09	0.66	-	0.28	1.29	21.79	2.19	0.100	0.35	24.8	30.9
415238	141.0	555	51.6	1100	138	0.15	0.50	-	0.39	1.31	22.26	2.41	0.108	0.42	27.1	40.0

5.2 Applicability of the Proposed Loss Model for Different Types of Catchments

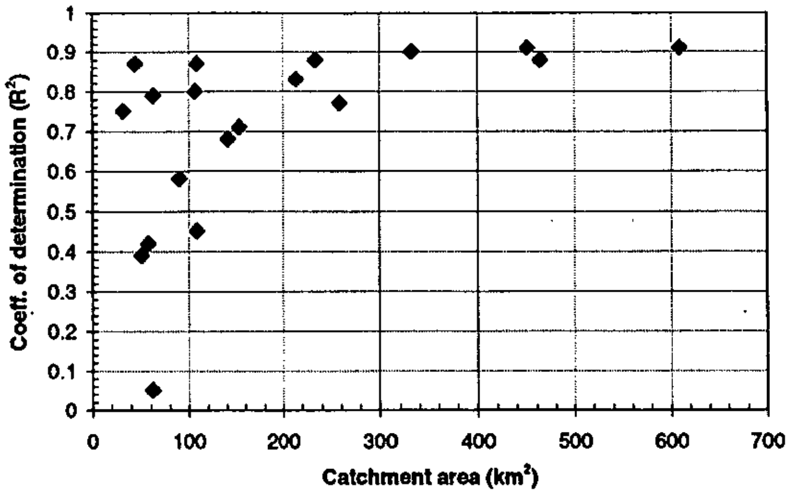
The importance of catchment characteristics in explaining runoff coefficient was investigated using the coefficient of determination (R^2) and standard error (SEE) as performance indices. It should be noted that R^2 and, more specifically, SEE cannot be considered as sufficiently robust parameters to compare model performance for different catchments. For example, the same 'noise' in the runoff coefficients for a 'low runoff' catchment affects (ie. reduces) the R^2 considerably more than for a 'high runoff' catchment. Similarly, SEE is also shown to be highly related to the range of runoff coefficients used in the calibration; hence, some standardisation such as expressing as a percentage of the mean is required for comparison of the performance of different catchments. The stability of R^2 is also adversely affected by the presence of outliers. The R^2 and SEE plotted against selected catchment characteristics are shown in Figures 5.1 and 5.2.

Figure 5.1(a) appears to give an impression that the R^2 increases as the catchment area increases. Such results must be interpreted carefully, as catchments of smaller areas (<100 km^2) have been drawn from different rainfall regimes which have diverse characteristics, whereas the large catchments have predominantly low rainfalls. The only conclusion that can be made is that the proposed methodology can satisfactorily be applied for large catchment areas (eg. Sugarloaf Creek, Tallagatta Creek, Holland Creek), despite the likely spatial variability of the storm rainfalls over such large catchments.

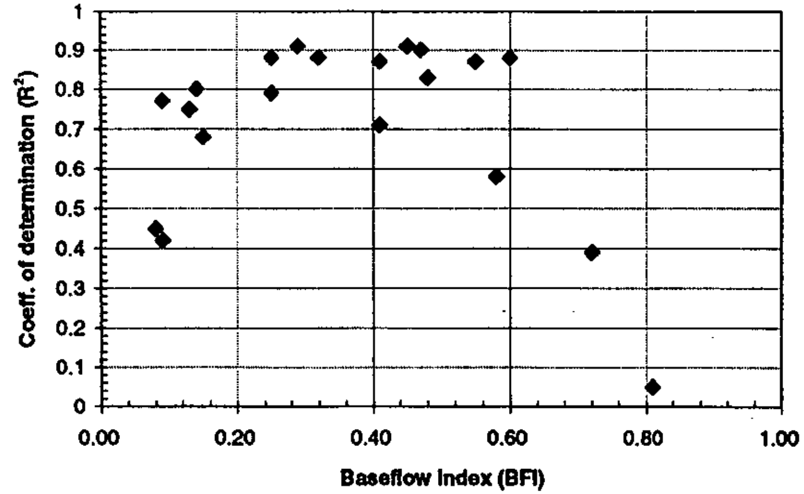
The runoff responding to a storm event is partly due to surface runoff and partly due to sub-surface flow (baseflow). Apart from the antecedent moisture conditions, the relative magnitude of the surface runoff depends on the rainfall characteristics and the physical characteristics of the catchment. For example, a catchment which has thick porous soil may produce less surface runoff, but more sub-surface flow. Baseflow indices such as baseflow index (BFI) and baseflow variability index (BVI) provide convenient and simple indicators of catchment behaviour in this regard.

As it can be seen from Figure 5.1(b), there is no general trend in the plot of R^2 of the fitted curves against BFI, although two catchments with BFIs greater than 0.60 (Snobs Creek, La Trobe River) show distinctly low R^2 for the fitted curves. Similarly, the same two catchments have the lowest BVI [Figure 5.1(d)], in which the tendency to have low R^2 (when BVI is less than 1.5) is evident. Figure 5.1(b) indicates that good relationships have been obtained for the catchments having BFI in the range of 0.20-0.60.

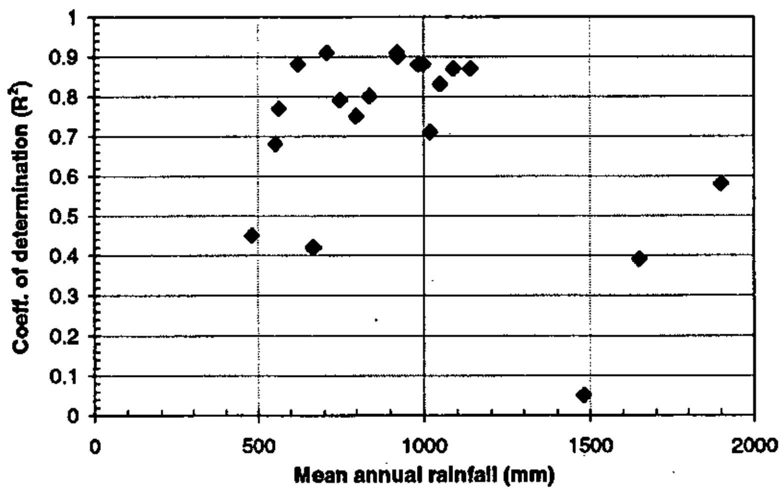
Figure 5.1(c) examines trends in R^2 of the fitted curves with respect to the mean annual rainfall. The wet catchments (mean annual rainfall greater than 1300 mm) show a tendency to have a low R^2, compared with the R^2 values of the rest of the catchments. Incidentally, both La Trobe River and Snobs Creek are located in high rainfall areas. Wanalta Creek and Warrambine Creek exhibit cease-to-flow conditions for a major period of time, and hence the low R^2 associated with these catchments may be due to the lack of suitable events for modelling.



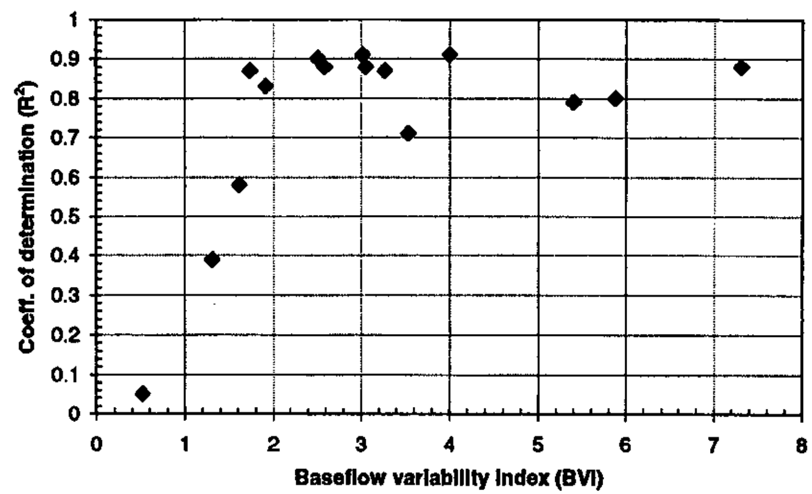
(a) Catchment area



(b) Baseflow index

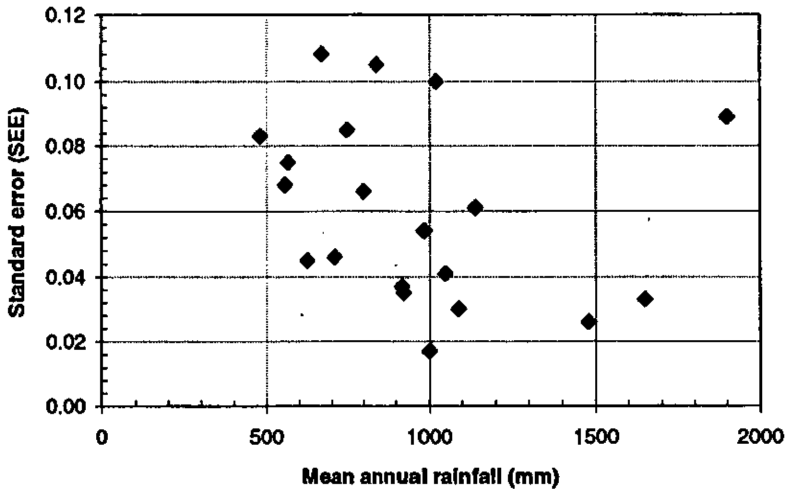


(c). Mean annual rainfall

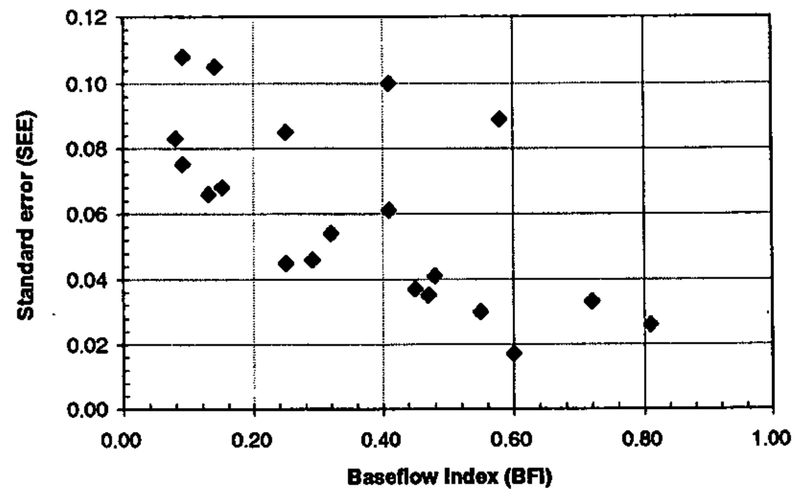


(d). Baseflow variablity index

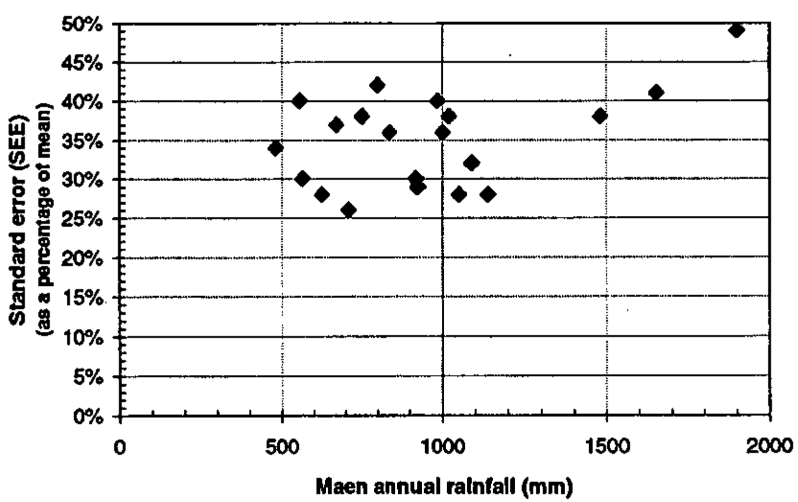
Figure 5.1 : Plot of coeff. of determination (R^2) against catchment characteristics



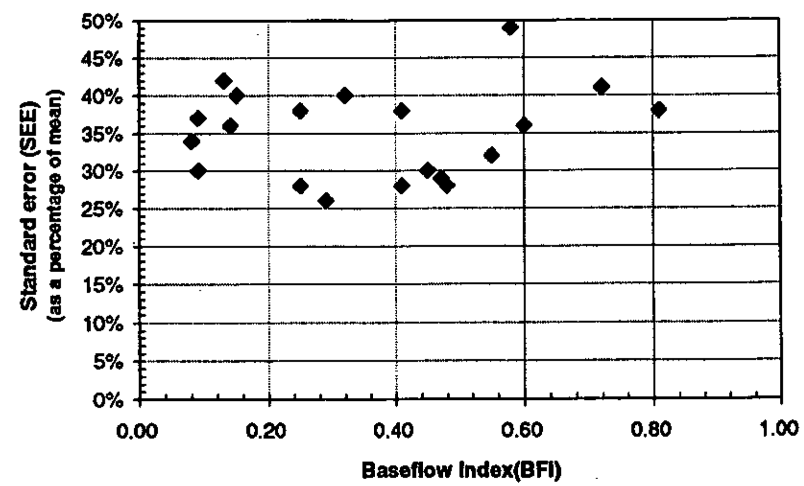
(a) Standard error against mean annual rainfall



(b) Standard error against baseflow index (BFI)



(c) Standard error (as a % of mean) against mean annual rainfall



(d) Standard error (as a % of mean) against baseflow index (BFI)

Figure 5.2 : Plot of standard error estimate (SEE) against catchment characteristics

Figure 5.2 indicates that there is a slight tendency for a decrease in SEE with mean annual rainfall and baseflow index. This may be viewed as a result of low runoff coefficients associated with the catchments having high BFI and mean annual rainfall rather than the performance of the fitted curves. When SEE is expressed as a percentage of the mean, no significant relationship is shown either with the mean annual rainfall or BFI. This shows the limitation of the SEE in evaluating the performance of the fitted curves in relation to catchment characteristics.

The La Trobe River has the highest BFI (0.81) and lowest BVI (0.52), and has a mean annual rainfall of 1480 mm. As the R^2 of the fitted curves for this catchment is only about 0.05, it is of particular interest to review the results with respect to rainfall and flow characteristics of the catchment. Time series plots of rainfall and streamflow show that the La Trobe River exhibits very strong baseflow characteristics, with 81 percent of the streamflow coming from sub-surface flow; the baseflow remains high throughout the year. As a consequence, the runoff coefficients of the events used in calibration of 'saturation curves' were all below 0.15. The variability of the baseflow over the year is also low. This could be attributed to the relatively even spread of rainfall over the year. As there are no prolonged rainless periods, there are no events for calibration which have low pre-storm baseflow; the latter are important in defining the fitted curves. Snobs Creek with runoff coefficients less than 0.20, also shows a hydrologic behaviour similar to that of La Trobe River. Although the results can be partially explained with respect to the baseflow characteristics, it is important to understand the physical catchment characteristics that explain the hydrologic behaviour of the catchments.

The low R^2 of the fitted curves for the La Trobe River and Snobs Creek is considered to be due to the low runoff coefficients (< 0.20), and the small range in pre-storm baseflow. The 'noise' in the data precludes an adequate fit for a logistic function. A simpler model would be adequate for this type of catchment.

In conclusion, a catchment having BFI greater than 0.60, a BVI less than 1.5, or a mean annual rainfall greater than 1300 mm, can be considered as likely indications for strong baseflow conditions; for these, the 'saturation curves' of the type proposed in this study would not likely be fitted satisfactorily. More research is needed to strength these recommended guidelines, however.

5.3 Regionalisation

5.3.1 Basis for Regional Relationship

Chapter 4 described a methodology for derivation of prediction equations for volumetric runoff coefficient for individual catchments, as a function of pre-storm baseflow and storm rainfall. The methodology has been applied for 20 Victorian catchments, located in different rainfall regimes and having different catchment characteristics. The catchments also provide a reasonably good coverage over much of Victoria (Figure 3.1). It was shown in Section 5.2 that the response to rainfall is highly dependant on the physical characteristics of the catchment and the climatic parameters, in addition to antecedent wetness.

A basic assumption made in this study is that all catchments can be considered to be of one homogeneous region, ie. differences in hydrological response can be attributed solely to the catchment characteristics and climatic factors. This leads to the concept of one generalised prediction equation for volumetric runoff coefficient for all catchments, inclusive of catchment and climatic parameters in addition to antecedent wetness index and storm rainfall. The prediction equation is of the form:

r.o.c. = f (antecedent wetness index, storm rainfall, catchment and climatic parameters)

5.3.2 Prediction Equations on Regional Basis

Prediction equations on a regional basis can be derived by:

(i) Pooling the event data and fitting one general equation of suitable form. The catchment parameters are taken as same for all events for any particular catchment;

(ii) Estimating regression parameters as a function of catchment and climatic parameters (eg. the regression parameters of *a*, *b*, *c* and *d* in Equation 3.1).

Pooling the data as proposed in (i) could cause a significant bias in the results, as the number of events used for different catchments is not the same (they range from 25-80 events). Hence, regional estimation of regression parameters was adopted in this study.

In Chapter 4, the four parameter logistic function given in Equation 3.1 were fitted to event data for each catchment to obtain prediction equations for runoff coefficient (Table 4.1). It is not feasible to establish regional relationships for all four parameters due to parameter inter-dependency. As an approximation it is possible to fix certain parameters that show less variability over the range of catchments analysed. This will reduce the accuracy of the prediction equation, but the parameter estimates would be more suitable for regionalisation.

An inspection of Table 4.1 reveals that the parameter *d* is very close to 1.0 for all catchments except for the Lerderderg River (@ Sardine Ck.). Hence, parameter *d* in the regional equation was fixed at an average value for the catchments tested (with Lerderderg River omitted as an outlier). Similarly parameters *b* and *c* were also fixed at their average values as they are relatively stable (less variable) than parameter *a*. The function is now reduced to a single parameter model with only the parameter *a* left to be optimised. The simplified function is shown in Equation 5.1.

$$r.o.c. \;=\; -0.035 + \frac{1}{0.966 + a.\,BF^{-0.60}.\,RAIN^{-0.96}} \qquad (5.1)$$

This simplified function (Equation 5.1) was re-fitted to all catchments and the optimised values for the parameter *a* are given in Table 5.2. In this table the R^2 and SEE of the fitted relationships are also compared with those obtained from the original four parameter model.

Table 5.2 : Optimised *a* parameter for 1-parameter regionalisation equation.

Station	One parameter model			4 parameter model	
Code	Parameter *a*	R^2	SEE	R^2	SEE
227228	71.2	0.84	0.066	0.87	0.061
224209	27.7	0.71	0.114	0.80	0.105
415224	8.2	0.61	0.086	0.77	0.075
226222	476	-	-	0.05	0.026
231213	48.6	0.67	0.101	0.71	0.100
233223	7.6	0.28	0.150	0.42	0.108
405237	128	0.85	0.042	0.90	0.035
405261	24.8	0.74	0.093	0.79	0.085
405229	10.3	0.30	0.134	0.45	0.083
231211	69.3	0.76	0.071	0.88	0.054
226209	95.2	0.70	0.055	0.83	0.041
405240	31.6	0.88	0.053	0.91	0.046
235219	288	0.57	0.089	0.58	0.089
403226	280	0.78	0.038	0.87	0.030
401220	248	0.70	0.026	0.88	0.017
404207	102	0.90	0.040	0.91	0.037
405257	572	-	0.053	0.39	0.033
406214	31.7	0.84	0.050	0.88	0.045
231219	23.8	0.55	0.084	0.75	0.066
415238	15.7	0.57	0.076	0.68	0.068

It is to be expected that R^2 would be reduced and SEE increased when the number of parameters of the function are fixed with average values. The acceptability of the reduced function (Equation 5.1) for the regional analysis depends on the ability of the model to fit the data satisfactorily, with only a small reduction in R^2. The reduction in R^2 is only marginal for those catchments whose parameter values of *b* and *c* are close to the average values, but up to 20 percent for other catchments. The catchments having unsatisfactory relationships with the original function (4-parameter model) showed a greater reduction in R^2. For seven catchments, the R^2 has been reduced by more than 15 percent.

Based on the above results, it was concluded that the simplified function (Equation 5.1) is adequate for use in a regional analysis. With this model, the regional variability of runoff coefficients is attributed to the variation of the parameter *a*. A 'low runoff' catchment is represented by a large value of parameter *a* and vice-versa for a 'high runoff' catchment. The success of the regional model depends on the ability to predict the parameter *a* from the catchment and climatic parameters.

5.3.3 Selection of Catchment Parameters for Regional Equations

Table 5.1 presents a list of catchment and climatic parameters considered to be useful for derivation of a regional model for loss parameters. The development of a regional equation would be based on the following criteria:

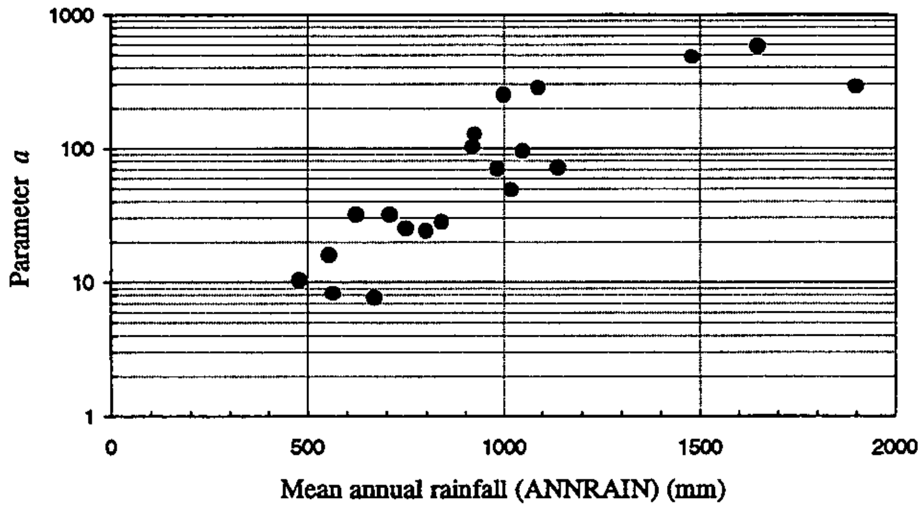
- Only the parameters highly correlated with the dependant variable would be used;
- The selected parameters should themselves be nearly independent (uncorrelated);
- The parameters should be easily obtained. For example, the mean annual rainfall (ANNRAIN) may be used in preference over the mean annual runoff (MARUN) as the MARUN can only be estimated for gauged catchments. Similarly, baseflow characteristics (BFI, BVI) can only be estimated for gauged catchments, unless they can be estimated from regional equations;
- The number of parameters used in the regional equation is limited to allow for an adequate degree of freedom in the fit. As only 20 catchments are used in the regional study, the number of parameters involved in the regional equations should not exceed about three.

Table 5.3 shows the correlation of parameter *a* with various catchment characteristics. This table indicates that mean annual rainfall (ANNRAIN), mean annual runoff (MARUN), and baseflow index (BFI) are correlated to a significant degree with the parameter *a* (with $R^2 > 0.60$), whereas shape factor (SHAPE2), forest cover (FCOV), and mean stream slope (S1085) show only a poor correlation (R^2 = 0.20 - 0.30). However, some of the 'low' correlated parameters can still be useful in improving the overall fit of a regional equation.

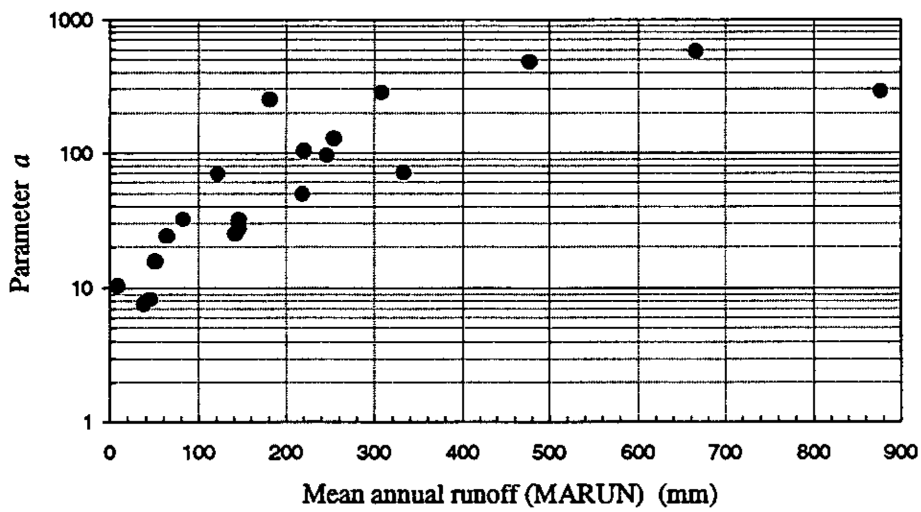
Table 5.3 : Correlation of parameter *a* against catchment characteristics

Catchment characteristic	Coeff. of det. (R^2)
AREA	0.03
ANNRAIN	0.67
MARUN	0.63
WET	0.10
PET	0.12
BFI	0.77
BVI	0.30
SHAPE1	0.16
SHAPE2	0.21
${}^{20}I_2$	0.01
${}^{20}I_{48}$	0.05
IRATIO	0.06
S1085	0.30
FCOV	0.21
FCOVW	0.21

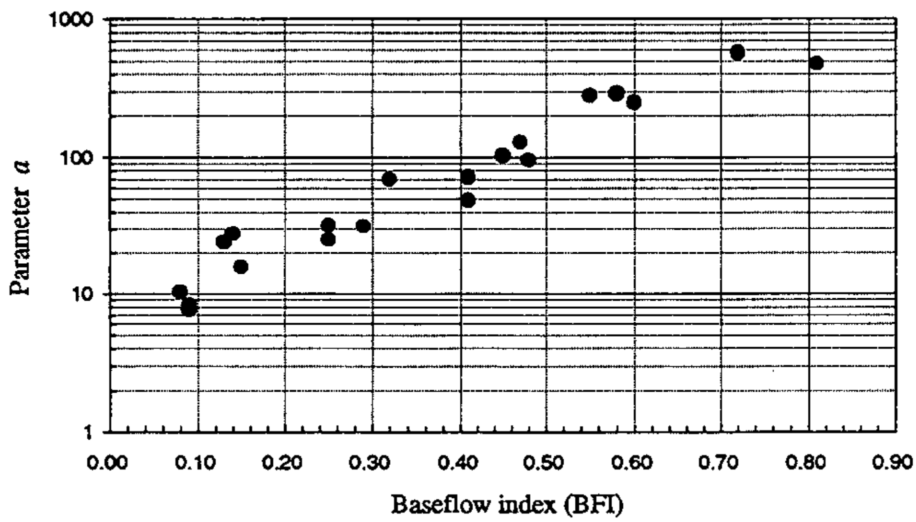
Plots of parameter *a* against a number of useful catchment characteristics are shown in Figure 5.3. The relationship between parameter *a* and catchment parameters such as mean annual rainfall (ANNRAIN), mean annual runoff (MARUN), and baseflow index (BFI) are shown to be highly non-linear. The catchments with higher ANNRAIN, MARUN, or BFI exhibit lower runoff (higher losses), in response to increase in parameter *a*. Figure 5.3 indicates that the increase in shape factor (SHAPE2), forest cover (FCOV), or stream slope (S1085) tend to result in a reduction in runoff coefficient, although the relationships are not very significant.



(a) Plot of parameter a against mean annual rainfall (ANNRAIN)

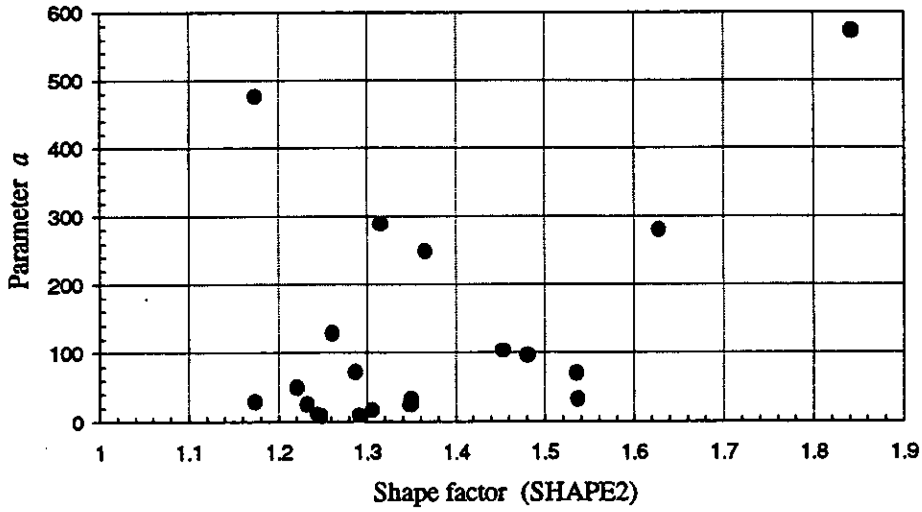


(b) Plot of parameter a against mean annual runoff (MARUN)

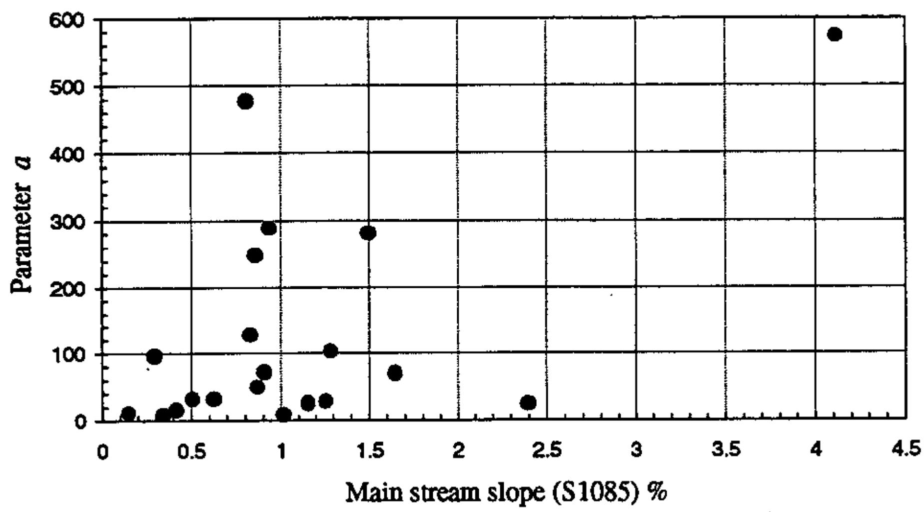


(c) Plot of parameter a against baseflow index (BFI)

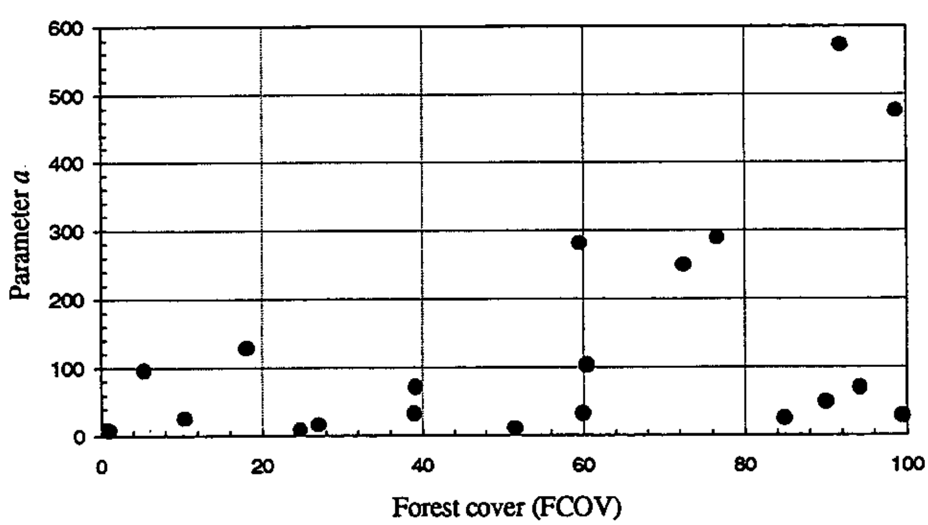
Figure 5.3 : Plot of parameter a against catchment characteristics



(d) Plot of parameter a against shape factor (SHAPE2)



(e) Plot of parameter a against main stream slope (S1085)



(f) Plot of parameter a against forest cover (FCOV)

Figure 5.3 (cont.) : Plot of parameter a against catchment characteristics

Cross correlation coefficients (correlation matrix) of the catchment parameters considered for this study are shown in Table 5.4; it is necessary that the catchment parameters used in the regional equation to be nearly independent (uncorrelated). The table indicates that, for example, baseflow index (BFI) and mean annual rainfall (ANNRAIN) should not be used in combination as they are highly correlated (R^2=0.76). As both ANNRAIN and BFI are highly correlated with the independent variable a ($R^2 \approx 0.70$), they are considered as primary dependant variables to derive alternative prediction equations for parameter a. Parameter BFI can be used to derive relationships for gauged catchments, whereas ANNRAIN would be the suitable alternative for ungauged catchments. With due consideration to the independence of parameters (Table 5.4) and the correlation associated with parameter a (Table 5.3), SHAPE2, S1085 and FCOV were selected as secondary parameters. The weighted forest cover (FCOVW) has not led to an improvement in correlation with the parameter a; hence, the simpler measure of forest cover (FCOV) has been used in the regionalisation procedures.

Table 5.4 : Correlation matrix of catchment parameters

	AREA	RAIN	MARUN	WET	PET	BFI	BVI	SHAPE1	SHAPE2	I20_2	I20_48	IRATIO	S1085	FCOV1	FCOVW
AREA	1.00														
RAIN	-0.25	1.00													
MARUN	-0.23	0.97	1.00												
WET	0.06	0.66	0.61	1.00											
PET	0.41	-0.52	-0.47	-0.53	1.00										
BFI	0.05	0.83	0.78	0.49	-0.35	1.00									
BVI	0.17	-0.69	-0.58	-0.49	0.39	-0.77	1.00								
SHAPE1	-0.77	0.39	0.35	0.06	-0.45	0.13	-0.28	1.00							
SHAPE2	0.20	0.31	0.30	0.26	0.02	0.38	-0.11	0.25	1.00						
I20_2	0.30	0.07	0.02	-0.07	0.21	0.18	0.06	-0.21	0.00	1.00					
I20_48	-0.06	0.56	0.49	0.55	-0.48	0.40	-0.26	0.03	-0.24	0.56	1.00				
IRATIO	-0.20	0.65	0.59	0.70	-0.65	0.42	-0.34	0.13	-0.25	0.21	0.93	1.00			
S1085	-0.31	0.46	0.39	0.09	-0.20	0.32	-0.17	0.72	0.62	0.27	0.13	0.04	1.00		
FCOV	-0.05	0.48	0.37	0.28	-0.08	0.38	-0.27	0.19	0.18	0.47	0.52	0.41	0.46	1.00	
FCOVW	-0.04	0.45	0.34	0.25	-0.04	0.42	-0.27	0.18	0.17	0.59	0.56	0.40	0.48	0.97	1.00

5.3.4 Regional Prediction Equations for Parameter '*a*'

BFI and ANNRAIN were separately linked with shape factor (SHAPE2), main stream slope (S1085), and forest cover (FCOV) to form different combinations of prediction equations for parameter a, both in linear and non-linear forms. As the R^2 associated with the fitted functions of linear form is comparatively low, the equation of non-linear form was considered for further study. The R^2 and SEE associated with the prediction equations derived using different combinations of catchment characteristics are given in Table 5.5.

It should also be noted that the prediction equation for parameter a developed by combining BFI and ANNRAIN has not resulted in an improvement in R^2, showing the effect of cross-correlation between the two parameters.

Table 5.5 : Regression analyses for estimation of parameter *a* from catchment characteristics

Regression equation :

$$a = a + b(\mathrm{VAR1})^c\,(\mathrm{VAR2})^d\,(\mathrm{VAR3})^e$$

VAR1	VAR2	VAR3	R^2	SEE
BFI	-	-	0.91	52.5
BFI	S1085	-	0.98	26.9
BFI	SHAPE2	-	0.98	27.3
BFI	FCOV	-	0.91	51.8
BFI	S1085	SHAPE2	0.98	26.7
BFI	S1085	FCOV	0.98	27.7
BFI	SHAPE2	FCOV	0.98	25.3
ANNRAIN	-	-	0.67	98.2
ANNRAIN	S1085	-	0.74	90.3
ANNRAIN	SHAPE2	-	0.74	91.0
ANNRAIN	FCOV	-	0.69	101.7
ANNRAIN	S1085	SHAPE2	0.75	92.1
ANNRAIN	S1085	FCOV	0.74	93.0
ANNRAIN	SHAPE2	FCOV	0.76	90.3
ANNRAIN	BFI	-	0.93	46.1

Gauged Catchments

The non-linear relationship between parameter *a* and BFI has an R^2 of 0.91, indicating the strong influence of BFI. The relationship can further be improved by inclusion of either S1085 or SHAPE2 in the regional equation. As the inclusion of the third parameter (FCOV) has not yielded any significant improvement, the prediction equation for parameter *a* can be best represented by the following alternative two parameter models having R^2 of 0.98, and SEE of 26.9 and 27.3 respectively.

$$a = 2.68 + 860.8\,(\mathrm{BFI})^{2.42}\,(\mathrm{S1085})^{0.28} \tag{5.2}$$
$$R^2 = 0.977,\ \mathrm{SEE} = 26.9$$

$$a = 7.55 + 719.5\,(\mathrm{BFI})^{2.80}\,(\mathrm{SHAPE2})^{1.13} \tag{5.3}$$
$$R^2 = 0.976,\ \mathrm{SEE} = 27.3$$

Equations 5.2 and 5.3 provide similarly good prediction for parameter *a*. However, by virtue of its marginal improvement in R^2 and SEE, Equation 5.2 is adopted here. Knowing the BFI and S1085, the parameter *a* can be estimated from Equation 5.2 for any catchment and this may be substituted in Equation 5.1 to obtain the storm runoff coefficient for the given pre-storm baseflow and storm rainfall total. Alternatively, the regional equation based on BFI and shape factor (Equation 5.3) can also be used in conjunction with Equation 5.1. The disadvantage of these equations is that they can only be used for gauged catchments, unless the BFI is estimated from a regional equation.

In Figure 5.4, predicted values of parameter *a* using Equation 5.2 are compared with those used for fitting the prediction equation.

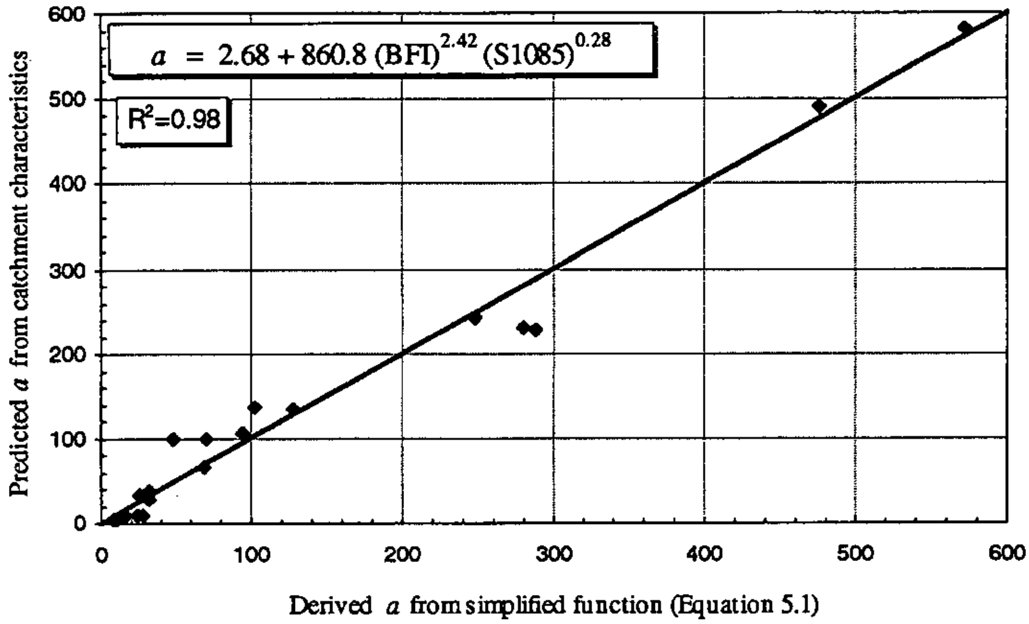


Figure 5.4 : Comparison of parameter a predicted (Equation 5.2) against derived, for *gauged catchments*

The applicability of the regional equation when the BFI is greater than 0.60 is doubtful, as the R^2 of the fitted curves for such catchments was found to be low. However, the magnitude of the predicted runoff coefficients is expected to be in the same order as the observed. The predicted parameter a values for both La Trobe River and Snobs Creek are very large, indicating low runoff coefficients.

Ungauged Catchments

It should be emphasised that Equations 5.2 or 5.3 cannot be applied directly for ungauged catchments, unless BFI is estimated from a regional equation. Nathan et al. (1995) derived such an equation from direct analyses of streamflow data from 195 catchments, and showed that BFI can be estimated as a linear combination of seven catchment parameters (catchment area, elevation, potential evapotranspiration, forest cover, fraction of catchment underlain by sandstones, mean annual rainfall and mainstream length). The R^2 of the fitted equation was 0.72. Lacey (1996) developed a procedure for prediction of BFI for ungauged catchments using an index based upon the native vegetation and underlying geology from analyses of BFI and catchment properties for 114 catchments in Victoria..

Procedures for estimation of BFI given by Nathan et al. (1995) or Lacey (1996) can be used in conjunction with Equation 5.2 or 5.3, when applying the regional loss model for ungauged catchments.

Alternatively, a prediction equation for parameter a can be developed using ANNRAIN; the best relationship established is shown in Equation 5.4. This may be used in conjunction with Equation 5.1.

$$a = -57.1 + 0.004\,(\text{ANNRAIN})^{1.55}\,(\text{S1085})^{0.29} \qquad (5.4)$$

$$R^2 = 0.74, \ \text{SEE} = 91.0$$

The performance indices (R^2 and SEE) are inferior to those for gauged catchments (Equation 5.2). In Figure 5.5, parameter a values predicted from Equation 5.4 are compared with those used for fitting the function.

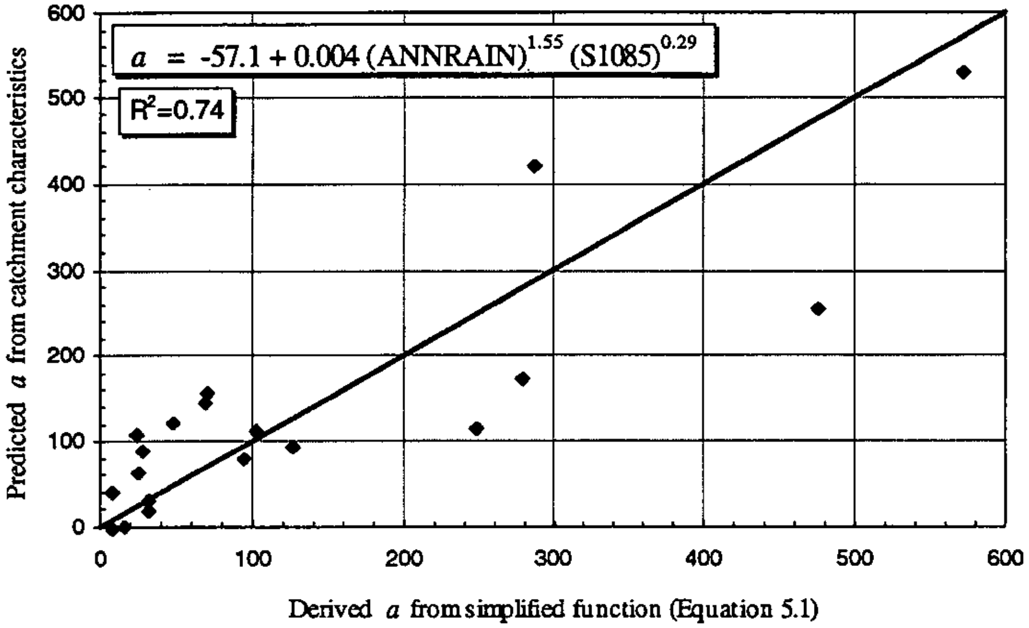


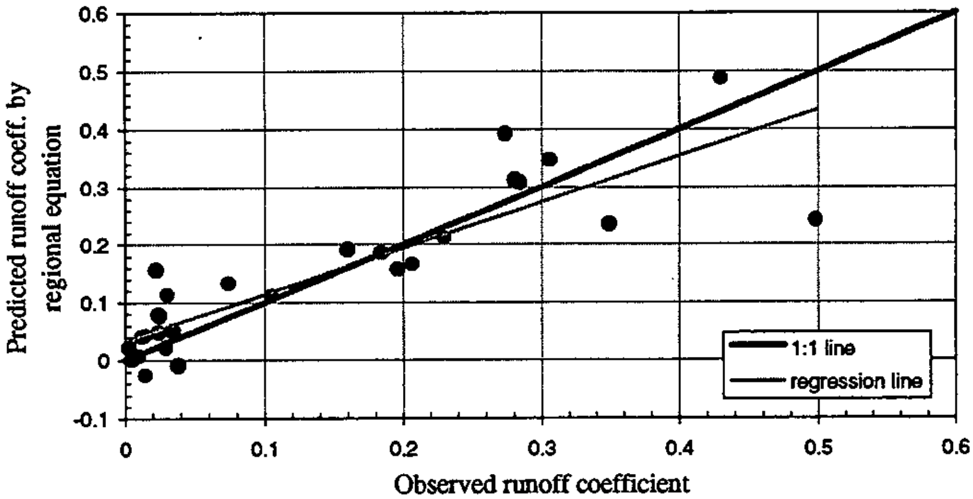
Figure 5.5 : Comparison of parameter a predicted (Equation 5.4) against derived, for *ungauged catchments*

For ungauged catchments, use of Equation 5.2 with BFI estimated from a regional equation may result in same order of accuracy as obtained from Equation 5.4, given that the R^2 of the prediction equation for BFI is in the range from 0.7 to 0.75 (Nathan et al. (1995). A representative value for BFI can also be estimated from a gauging station upstream or downstream or that from an adjacent catchment. In the absence of a representative value for BFI, Equation 5.4 is useful for ungauged catchments, to apply in conjunction with Equation 5.1.

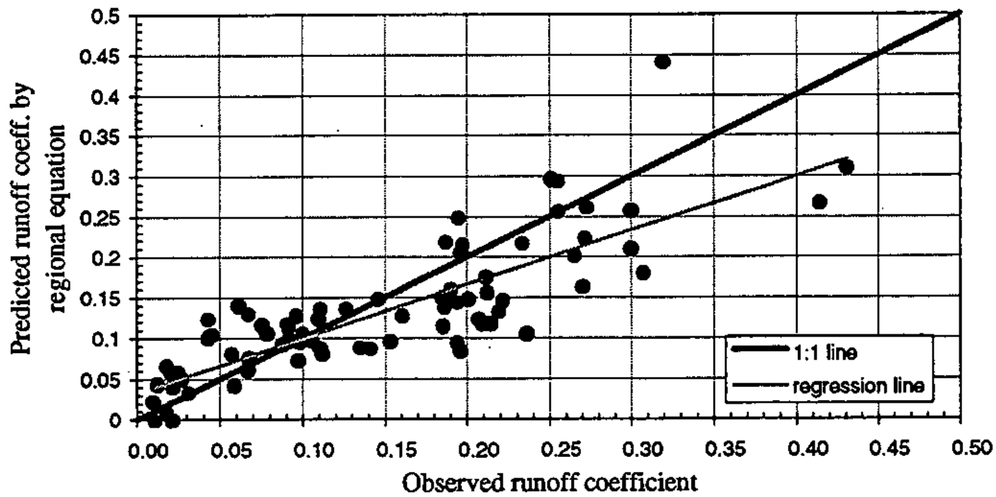
Testing model performance

The suitability of the regional model was investigated by comparing the event runoff coefficients predicted by the regional model (Equations 5.1 and 5.2) against observed runoff coefficients for three catchments as shown in Figure 5.6. The results generally appear to agree satisfactorily, given the uncertainty associated with the regionalisation procedure. For a particular catchment, the tendency to over-predict or under-predict the runoff coefficients as indicated by the regression line may be viewed as the result of under or over prediction of parameter a by the regional model (Equation 5.2) added to any tendencies introduced in simplification of the equation (Equation 5.1). The loss of accuracy during the regionalisation procedure eventuates in two stages; in generalisation of the loss function using average regression parameters (b, c, d) and in regionalisation of parameter a.

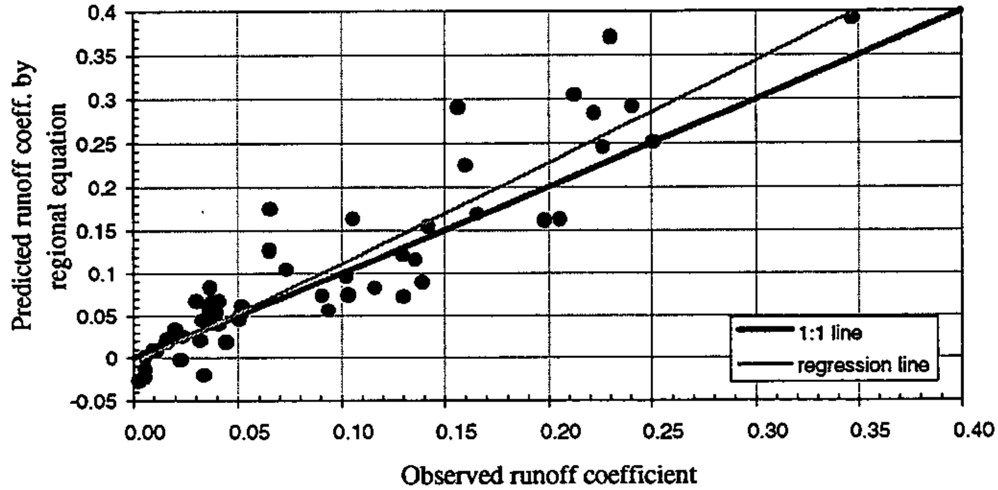
These results may be viewed with some caution, as those catchments have also been used in calibration of the regional equation.



(a) Lerderderg River @ u/s Goodman Creek (231211)



(b) Moe River @ Darnum (226209)



(c) Boggy Creek @ Angleside (403226)

Figure 5.6 : Comparison of runoff coefficients for complete storms against those predicted by the regional equation (Equation 5.1)

6. TESTING THE LOSS MODEL FOR REAL-TIME FLOOD FORECASTING USING RORB

6.1 Preamble

The importance of the loss model in prediction of runoff hydrographs was emphasised by Malone and Cordery (1989), who concluded that the loss model is more critical than the runoff routing model.

The suitability of the proposed variable proportional loss (VPL) model for application in real-time flood forecasting is investigated below, using the RORB runoff routing model. In the test, rainfall excess was estimated with the proposed loss model, and routed using RORB with calibrated parameters for the catchment, and the predicted and observed hydrographs compared. For successful application of the loss model in real time flood forecasting, the model should be able to predict the initial rise of the hydrograph accurately. *There was no fitting or calibration of rainfall-excess to match observed data.*

It should be stressed that this is a very stringent test; in most RORB calibrations, loss parameters are chosen to give the correct volume of runoff.

6.2 RORB Modelling with a Variable Proportional Loss Model

Seven catchments which were used in the calibration of the saturation curves were selected for testing the performance of the proposed loss model using the RORB model. These catchments, given in Table 6.1, have sizes ranging from 32 to 332 km^2, and chosen to cover a wide rainfall range (480 to 1900 mm). The coefficient of determination (R^2) of the fitted relationships for these catchments ranges from 0.45 (Wanalta Creek) to 0.90 (Seven Creeks) [see Section 4.2]. These values are useful in reviewing the results with respect to the adequacy of the fitted relationships.

For each catchment, 5-7 events were used to compare the modelled hydrographs (surface runoff) using the proposed loss model with the observed. The RORB data files for these catchments compiled by Hill et al. (1996b) were used with necessary modifications to accommodate the proposed loss model. The observed surface runoff hydrographs were determined by separating the baseflow using a digital filter technique (HYBASE) with the same parameters as used for determining surface runoff for events used for calibration of saturation curves (Section 3.2.1). This provides an equitable basis for comparing the predicted and observed hydrographs. The average calibrated k_c values for these catchments using initial loss/proportional loss model are shown in Table 6.1 (Hill et al., 1996b).

Rainfall excess hyetographs determined by the variable proportional loss model, were used as input for RORB, with zero losses being specified in the running of RORB itself. The rainfall excess hyetographs needed to be calculated for each sub-catchment area; this was carried out by a computer program which reads a conventional RORB data file and creates a data file suitable for RORB modelling, containing rainfall excess hyetographs and total rainfall excesses for each sub-area. These rainfall excess hyetographs were determined with the procedure given in Section 4.3, using *catchment specific loss model parameters* (Equation 3.1 and Table 4.1) and observed pre-storm baseflow values of the events under consideration.

Table 6.1 : Catchments selected for testing VPL model for real-time flood forecasting

Catchment	Catch. Area (km^2)	Annual Rainfall (mm)	Catchment average k_c IL / PL	No. of events modelled	R^2 of fitted curves
Avon R. @ Beazley's Bridge (415224)	259	565	14.1	6	0.77
Aire River @ Wyelangta (235219)	90	1900	12.3	4	0.58
Goodman Ck. abv Lerd. tunnel (231219)	32.3	800	4.8	6	0.75
Moe River @ Darnum (226209)	214	1050	16.3	6	0.83
Lerderderg R. @ Sardine Ck. (231213)	153	1020	12.7	4	0.71
Seven Ck. @ Euroa Township (405237)	332	925	14.9	6	0.90
Wanalta Ck. @ Wanalta (405229)	108	480	13.7	6	0.45

It needs to be emphasised again that the rainfall excess was <u>not</u> adjusted to equal to the value of surface runoff (volume balance), as the intention was to study the suitability of the loss model in predicting a hydrograph in real-time.

The RORB runs were made with the non-linearity parameter m fixed at 0.8, and using event optimised k_c values, and catchment average k_c values respectively, as determined by Hill et al. (1996b). It should be noted that these k_c values were determined for RORB with the initial loss and proportional loss model (IL / PL), and not with the loss model proposed here. This will have an (unknown) effect on the true optimum k_c.

The predicted and observed hydrographs for all events modelled by RORB using the catchment average k_c values are given in Siriwardena et al. (1997). Table 6.2 provides summary information such as actual and predicted runoff coefficients, percentage error in predicted runoff volume and peak discharge, error in time to peak etc.

6.2.1 Review of Results on a Catchment Basis

Avon River @ Beazley's Bridge (415224)

A feature of the modelled events for this catchment is the considerable time shifts between the modelled and observed hydrographs. This has been a consistent feature for this catchment; during screening for suitable events for calibration of 'S' curves, it was observed that many events had runoff which commenced after cessation of rainfall. This delayed catchment response cannot be satisfactorily modelled by the proposed or any other loss model.

In general, the peak discharge was satisfactorily modelled for the majority of the events. There appeared to be no bias in the prediction of runoff volume or peak discharge (equal chance of over or under prediction); under or over prediction of peak discharge is closely associated with the under or over prediction of runoff coefficient by the loss model. No reliable assessment on the initial rise can be made due to the excessive time shifts involved in the modelling. There is evidence of difficulty in re-producing multi-peaked hydrographs with the proposed loss model (eg. event on 24 Oct. 1975).

Table 6.2 : Comparison of observed against modelled hydrographs using RORB

Catchment	Event	Event k_c	Runoff coefficient		Runoff volume ($m^3 x 10^6$)			Peak discharge (m^3/s)					Error in time to peak (h)	Remarks
			Actual	Predicted	Actual	Predicted	% Error	Actual	Predicted		% Error			
									Event k_c	Catch. k_c	Event k_c	Catch. k_c		
	6/02/73	4.0												zero base flow; not modelled
Avon River	19/10/73	12.0	0.23	0.27	3.75	5.09	36%	90.1	107.8	93.9	20%	4%	-1	12 h. time shift, good match
(415224)	15/05/74	18.0	0.26	0.18	4.47	3.16	-29%	76.0	41.9	48.4	-45%	-36%	-1	modelled peak low
Catch. average	5/10/74	15.0	0.36	0.37	3.84	4.10	7%	72.5	81.9	86.3	13%	19%	-2	24 h. time shift
k_c = 14.1	24/10/75	12.0	0.54	0.51	7.69	7.28	-5%	83.0	69.6	63.4	-16%	-24%	-6	24 h. time shift, multi peaked
	28/09/79	13.5	0.46	0.52	6.06	7.21	19%	115.5	135.4	130.6	17%	13%	-4	18 h. time shift
	4/08/81	14.3	0.53	0.44	5.53	4.50	-19%	106.4	70.1	70.5	-34%	-34%	-5	modelled : early rise and low peak
	4/01/87	14.0	0.31	0.20	2.94	1.90	-35%	46.2	23.8	25.3	-49%	-45%	0	initial rise o.k., modelled peak low
Aire River	1/02/90	9.5	0.21	0.19	4.64	4.04	-13%	61.5	39.7	35.2	-35%	-43%	1	initial rise o.k., modelled peak low
(235219)	9/02/90	7.7	0.45	0.35	3.96	3.07	-22%	84.2	46.9	36.4	-44%	-57%	1	initial rise o.k., modelled peak low
Catch. average	11/06/91	13.5	0.74	0.20										Data errors ? not modelled
k_c = 12.3	15/12/91	12.2	0.27	0.27	4.41	4.39	0%	67.5	55.9	55.8	-17%	-17%	1	reasonably good match
	7/11/71	3.0	0.29	0.23	1.52	1.19	-22%	31.6	18.3	16.0	-42%	-49%	-	multi peaked; difficult to model
Goodman	6/02/73	1.5	0.16	0.15	5.97	5.83	-2%	31.0	36.8	26.7	19%	-14%	1	reasonably good match
Creek (231219)	14/10/76	3.2	0.37	0.53	0.83	1.22	46%	20.7	22.0	19.1	6%	-8%	3	fairly good match
Catch. average	3/07/78	5.7	0.54	0.12	0.64	0.17	-74%	27.1	6.3	7.2	-77%	-74%	3	modelled peak very low
k_c = 4.8	6/08/78	6.1	0.39	0.34	0.98	0.87	-12%	28.5	19.3	20.7	-32%	-27%	1	modelled peak low
	19/11/78	4.2	0.41	0.34	1.20	1.00	-17%	47.9	35.4	34.5	-26%	-28%	3	modelled peak low
Lerderderg	12/05/74	12.1	0.61	0.44	9.82	7.05	-28%	165.1	103.5	103.0	-37%	-38%	3	good match in shape, but low peak
River (231213)	20/09/76	11.0	0.40	0.41	5.02	5.08	1%	85.1	78.9	74.4	-7%	-13%	-2	modelled hg. rises early; peak o.k.
Catch. average	7/08/78	14.1	0.39	0.46	5.38	6.39	19%	77.2	83.9	90.4	9%	17%	1	good match
k_c = 12.7	4/10/79	13.4	0.42	0.46	4.18	4.57	9%	53.0	53.5	55.3	1%	4%	-2	modelled hg. rises early; peak o.k.

Table 6.2 (cont.): Comparison of observed against modelled hydrographs using RORB

Catchment	Event	Event k_c	Runoff coefficient		Runoff volume ($m^3 x 10^6$)			Peak discharge (m^3/s)					Error in time to peak (h)	Remarks
			Actual	Predicted	Actual	Predicted	% Error	Actual	Predicted		% Error			
									Event k_c	Catch. k_c	Event k_c	Catch. k_c		
	11/08/75	17.0	0.29	0.25	2.19	1.88	-14%	26.7	24.0	24.8	-10%	-7%	1	very good match
Moe River	17/09/75	10.1	0.26	0.31	2.21	2.60	18%	31.6	35.1	24.6	11%	-22%	0	fairly good match
(226209)	28/06/80	15.8	0.15	0.11	3.29	2.36	-28%	41.5	26.2	25.6	-37%	-38%	-1	initial rise o.k., modelled peak low
Catch. average	21/08/81	16.0	0.33	0.28	2.67	2.26	-15%	23.3	17.8	17.7	-23%	-24%	0	fairly good match
k_c = 16.3	8/09/83	14.6	0.19	0.35	1.36	2.48	82%	19.6	39.7	35.9	103%	84%	1	modelled peak high
	13/09/83	24.7	0.40	0.37	3.16	2.96	-6%	32.0	28.9	41.2	-10%	29%	-5	very good match with storm k_c
	13/05/74	7.9	0.49	0.36	19.50	14.50	-26%	284.8	188.1	133.5	-34%	-53%	-1	multi peaked; poor match
Sevens Creek	15/09/75	15.5	0.51	0.42	13.40	11.40	-15%	335.8	255.4	264.9	-24%	-21%	3	
(405237)	20/07/81	12.9	0.37	0.33	9.82	8.89	-9%	158.6	123.0	114.0	-22%	-28%	-5	
Catch. average	3/10/84	13.7	0.33	0.21	8.47	5.61	-34%	244.7	110.6	105.6	-55%	-57%	-1	modelled peak very low
k_c = 14.9	22/07/86	10.6	0.34	0.36	8.51	8.99	6%	249.1	199.4	146.1	-20%	-41%	1	modelled peak low
	3/10/93	22.0	0.53	0.46	16.70	14.00	-16%	263.2	220.0	254.6	-16%	-3%	-1	reasonably good match
	13/05/74	11.3	0.38	0.49	4.95	6.39	29%	54.3	60.3	56.6	11%	4%	-	double peaked;
Wanalta Creek	3/10/74	13.2	0.30	0.23	1.20	0.91	-25%	21.1	14.9	14.5	-29%	-31%	-7	poor match; timing errors suspect
(405229)	23/10/75	15.4	0.32	0.31	1.91	1.92	1%	15.0	14.2	15.4	-5%	3%	-	modelled hg. rises early
Catch. average	26/08/79	13.3	0.20	0.23	0.81	0.95	18%	15.1	17.7	17.2	17%	14%	-1	modelled hg. rises early
k_c = 13.7	7/09/83	18.1	0.60	0.38	1.42	0.89	-38%	17.6	9.6	12.1	-45%	-31%	-4	modelled peak low
	13/01/84	12.0	0.13	0.16										zero baseflow; not modelled
	3/07/91	12.7	0.28	0.26	1.20	1.10	-8%	21.2	19.4	18.3	-9%	-14%	3	good match sp. with storm k_c

Aire River @ Wyelangta (235219)

For all four events analysed, the peak discharge was underpredicted (by up to about 55%). However, the initial rise and general shape of the modelled hydrograph well match the observed hydrograph for all four events. In general, the event k_c values tend to give a slightly better fit with the observed hydrographs.

Goodman Creek above Lerderderg tunnel (231219)

The modelled runoff volume and peak discharge tend to be underestimated for the majority of events analysed. This is a consequence of the predicted runoff coefficient being too low, in addition to inappropriate distribution of modelled rainfall excess, especially for events having distributed rainfall over a long period (eg. events on 7 Nov. 1971 and 14 Oct. 1976). In these events, the modelled rainfall excesses appeared to be overpredicted towards the end of the storm. This illustrates the difficulty in modelling multi-peaked events or events with distributed rainfall over long periods. The modelled initial rise is generally sluggish indicating excessive losses predicted by the loss model during the initial period of the storm.

Moe River @ Darnum (226209)

For this catchment, the modelled hydrographs appear to match reasonably well with the observed hydrographs for the majority of the events analysed, including a double-peaked event, particularly with event k_c values. The loss model was also shown to predict event runoff coefficients to a significant degree of accuracy for all events but one. In general, the hydrograph rise and shape match with the observed, in particular, for modelling with event k_c values.

Lerderderg River @ Sardine Ck. (231213)

For three out of the four events, the runoff coefficient is predicted by the loss model with sufficient accuracy. As a result, the modelled peak discharges match well with the observed values for those three events. The event k_c values tend to produce better results than with catchment average k_c values. Modelled hydrographs are also well matched in shape with those observed. However, only two events showed a satisfactory match for the initial rise; for the other two events the modelled hydrographs tend to rise too early.

Seven Creeks @ Euroa Township (405237)

The modelled peak discharges are well underestimated, compared with the corresponding underprediction of the runoff coefficient by the loss model. Multi-peaked events in particular, are poorly modelled both in shape and magnitude. There is also a difficulty in modelling sharp spiky peaks of observed hydrographs (eg. events on 15 Sep. 1975, 03 Oct. 1984 and 22 Jul. 1986). Only the event on 03 Oct. 1993 was well modelled. For many events the initial rise tends to start too early.

Wanalta Creek @ Wanalta (405229)

There appears to be a consistent deficiency in the loss model in predicting the initial rise of the hydrograph. The modelled hydrographs rise too early suggesting that the losses accounted by the loss model during the initial storm period are too low. The inadequacy of the fit of the derived loss function ($R^2 = 0.45$) for this catchment could have a significant influence on the results.

6.3 Review of Results from RORB Modelling

Although the peak discharge is not well modelled for many events, in general the results indicate that the proposed loss model can be implemented reasonably well for real-time flood forecasting. This is because the modelling of the initial formation of the hydrograph is generally satisfactory (except for Avon and Wanalta), given that timing errors could exist in the data. The Moe and Lerderderg catchments were found to be modelled particularly well by the adopted procedure.

A successful application of the proposed loss model for real-time flood forecasting would lie primarily in the ability of the loss model to predict volumetric runoff coefficients, with a sufficient degree of accuracy, early in the event. This has a direct relation to the accurate assessment of the runoff volume of the predicted hydrograph and, in turn, provides a firm basis for the accurate prediction of flood peaks, despite the inaccuracies that may be due to deficiencies in the runoff routing model and adopted parameters. It may be worth noting that the runoff coefficients predicted by the loss model for the selected events of some catchments were generally lower than the actual (eg. Aire River, Seven Creeks), resulting in a general underprediction of the modelled peak discharges.

Another aspect which would be worth investigating is whether the flood peaks would be predicted accurately if a volume balance was achieved, ie. runoff coefficients predicted accurately. An overview of the results here indicate that there is a slight tendency to underpredict the peak discharge even if the amount of rainfall excess is predicted accurately. One possibility is that the k_c values being used may be too high for the proposed loss model. This could also be a result due to inappropriately predicted higher rainfall excesses at the latter period of the burst, particularly when modelling multi-peaked events.

The results indicate that there may be difficulties in applying the proposed loss model to storms of a distributed nature or multi-peaked storms. This is because, the curves are mostly based on single bursts of rainfall and the lack of a suitable function in the distribution of losses to account for the depletion of soil moisture during rainless periods within the event.

For practical application of the loss model in real-time flood forecasting, it is required to calculate the loss model parameters (*a*, *b*, *c* and *d*) for the catchment as described in Chapter 3. Knowing the baseflow at the onset of the storm and total rainfall up to the time of forecast, progressive runoff coefficients can be estimated as explained in Section 4.3, which can be applied to a routing model (eg. RORB) to formulate the predicted hydrograph. This may be continued until the rising limb of the hydrograph is formed. Corrective measures may then have to be taken to match the modelled hydrograph with the observed. This may be carried out by adjusting an appropriate parameter of the loss model (*a*, *b*, *c* and *d*), on the assumption that uncertainties inherent in the procedure are solely due to the inaccuracy of the loss model.

7. SUITABILITY OF THE PROPOSED LOSS MODEL FOR DESIGN FLOOD APPLICATION

This chapter describes a preliminary investigation of the applicability of the proposed loss model for design (rather than real-time) purposes. The proposed variable proportional loss (VPL) model can be incorporated in the procedure given in ARR87 to estimate design flood peaks for various recurrence intervals up to 100 years. In applying the loss model, parameters of the loss function (*a*, *b*, *c* and *d*) and a representative value for median pre-storm baseflow need to be estimated. The results obtained from this procedure are compared with those obtained from a flood frequency analysis

7.1 Application of VPL Model for Design Flood Estimation

The basic procedure recommended in the ARR87 for estimation of design flood hydrograph can be summarised as follows :

- Obtain design rainfall intensities for the desired average recurrence interval (ARI) from Chapter 2 of ARR87;
- Apply an areal reduction factor and a temporal pattern appropriate for the region (Chapter 3 of ARR87) to account for the spatial and temporal variation of the design rainfall;
- Apply a suitable loss model (eg. initial loss/continuing loss or initial loss/proportional loss) to obtain the rainfall excess hyetograph; median loss parameters are recommended for application;
- Route the rainfall excess using a runoff routing model (such as RORB) to obtain the design flood hydrograph.

This procedure is repeated for a range of rainfall durations to determine the critical duration that produces the maximum peak flow.

In testing the VPL model for design application, the rainfall excess in the above procedure is estimated by applying the VPL model instead of using a conventional loss model. In order to apply the loss model for design purposes, values for the loss function parameters (*a*, *b*, *c* and *d*) and a design value of pre-storm baseflow representing average (or median) antecedent conditions need to be estimated.

7.2 Determining Pre-storm Baseflow Level for Design

The saturation curves derived for the test catchments show clearly that pre-storm baseflow (as a catchment wetness index) has a dominant effect on the magnitude of surface runoff. It is observed that many severe storms occurring under dry antecedent conditions do not cause significant runoff, whereas moderate storm events under wet antecedent conditions can cause severe floods. The basic question that arises is what pre-storm baseflow level should be used for design together with IFD values given in ARR87.

7.2.1 Seasonal Variation of Pre-storm Baseflow

ARR87 recommends median loss values in flood estimation. Hence, the median value of the pre-storm baseflow for all storm events above a threshold rainfall total (or intensity) could be considered as a suitable criterion for design purposes. It may be noted that, these could also include events with negligible runoff.

Another useful measure of the median value for pre-storm baseflow, determined at a gauged catchment, was based on the continuous baseflow hydrograph over a long period (using HYDSYS). In calculating the median value the time periods for which surface runoff occurs were excluded from the analysis. The baseflow values at discrete time intervals (eg. 6 hour intervals) were ranked and values at 50 percent probability of exceedance was taken as the representative median value. The analysis was initially carried out on monthly basis; as such the discrete values of baseflow for different months were treated separately. This measure is easy to extract and particularly useful in comparing the values for different catchments, as well as visualising the significance of seasonal variation

The monthly median values of 'pre-storm' baseflow for the 20 catchments are plotted in Figure 7.1. The seasonal variation is very high for some catchments; one exception is the La Trobe (226222) for which 'pre-storm' baseflow remains high throughout the year. A marked seasonal variability of the 'pre-storm' baseflow implies that the magnitude of the design floods is sensitive to the month of the year that the design storm is applied.

An average value of 'pre-storm' baseflow for the catchments was estimated by taking the arithmetic average of the monthly median values; the results are shown in Table 7.1.

Table 7.1 indicates that the values derived for median 'pre-storm' baseflow appear to be appreciably lower than the average pre-storm baseflow values of the events used in calibration of saturation curves. This is because the latter tend to be based on flood events, and biased towards wet antecedent conditions. The resultant rainfall excess corresponding to median 'pre-storm' baseflow would be considerably smaller than that corresponding to the mid range baseflows of the calibrated saturation curves.

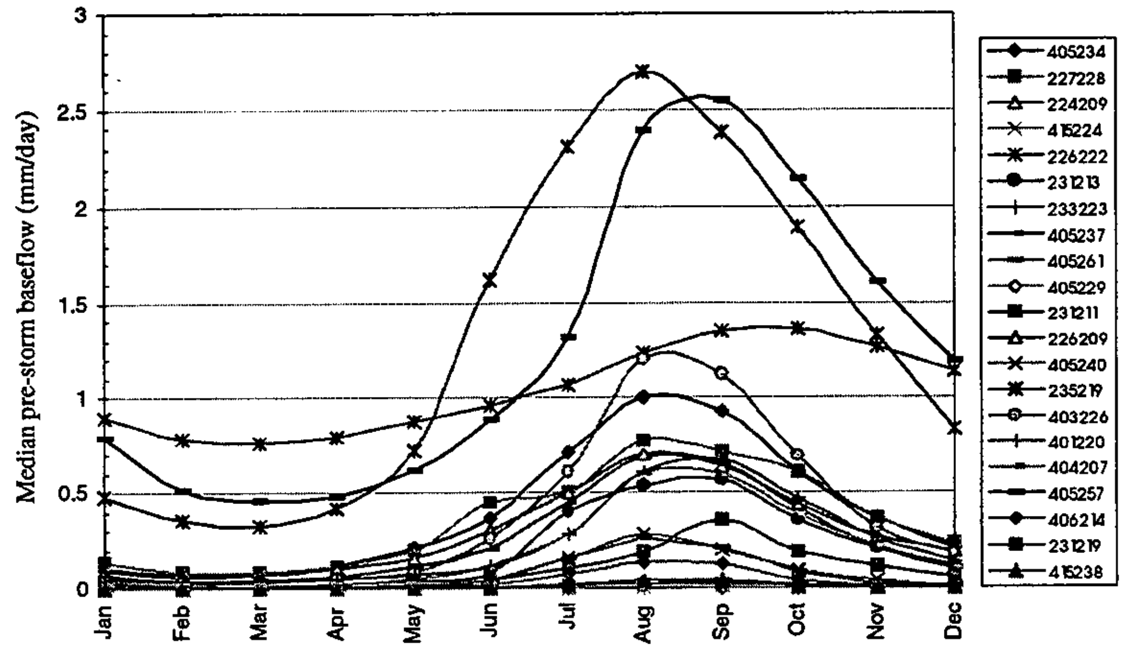


Figure 7.1 : Seasonal variation of median values of pre-storm baseflow

Table 7.1 : Median 'pre-storm' baseflow derived for test catchments

Station	Median 'pre-storm' baseflow		Pre-storm baseflow for saturation curves (mm/day)	
Code	(m^3/sec)	(mm/day)	Range	Mean
224209	0.012	0.010	0.001 - 1.0	0.21
226209	0.73	0.30	0.02 - 3.0	0.59
226222	0.75	1.04	0.50 - 2.0	1.27
227228	0.18	0.35	0.04 - 2.0	0.53
231211	0.24	0.09	0.001 - 2.0	0.36
231213	0.35	0.20	0.002 - 2.0	0.52
231219	0.003	0.008	0.003 - 0.6	0.07
233223	0.002	0.002	0.001 - 0.7	0.09
235219	1.33	1.28	0.20 - 5.0	1.67
401220	1.27	0.24	0.01 - 2.0	0.40
403226	0.48	0.38	0.01 - 4.0	0.93
404207	1.06	0.20	0.002 - 3.0	0.42
405229	0.001	0.001	0.003 - 1.0	0.12
405237	0.97	0.25	0.01 - 1.5	0.37
405240	0.50	0.07	0.001 - 3.0	0.25
405257	0.73	1.25	0.10 - 7.0	1.89
405261	0.05	0.07	0.002 - 2.0	0.30
406214	0.10	0.04	0.001 - 2.0	0.19
415224	0.007	0.002	0.001 - 0.3	0.06
415238	0.017	0.010	0.01 - 0.5	0.09

7.2.2 Prediction Equations for Median 'Pre-storm' Baseflow

Suitable prediction equations for median 'pre-storm' baseflow (expressed as mm/day) were derived as a function of catchment parameters, for application on ungauged catchments. The median 'pre-storm' baseflow values derived for 20 catchments were correlated against catchment parameters in order to select suitable parameters for regional analysis. The results are given in Table 7.2. ANNRAIN, MARUN and BFI were found to be useful indicators with respect to high coefficient of correlation.

Although ANNRAIN and BFI are not considered to be independent, the two parameters in combination produced a very satisfactory relationship for predicting median pre-storm baseflow with a R^2 of 0.99 (Equation 7.1). Alternatively, mean annual rainfall alone can be used to derive a prediction equation for median pre-storm baseflow (Equation 7.2).

$$\mathrm{PRE\_BASE} = 1.78\times10^{-7} \,.\, (\mathrm{ANNRAIN})^{2.17} \,.\, (\mathrm{BFI})^{1.03} - 0.184 \qquad (7.1)$$
$$R^2 = 0.99, \quad \mathrm{SEE} = 0.04$$

$$\mathrm{PRE\_BASE} = 3.88\times10^{-7} \,.\, (\mathrm{ANNRAIN})^{2.02} - 0.184 \qquad (7.2)$$
$$R^2 = 0.94, \quad \mathrm{SEE} = 0.11$$

where, PRE_BASE = median 'pre-storm' baseflow for the catchment (mm/day)
ANNRAIN = mean annual rainfall (mm)
BFI = baseflow index

In applying Equation (7.1) for ungauged catchments, the baseflow index needs to be estimated using a regional prediction equation or from a representative gauging station in a nearby catchment. Equation (7.2) can be directly applied.

Table 7.2 : Correlation of median 'pre-storm' baseflow with individual catchment characteristics

Catchment Characteristic	Coeff. of deter. (R^2)
AREA	0.10
ANNRAIN	0.89
MARUN	0.93
WET	0.49
PET	0.23
BFI	0.65
BVI	0.37
SHAPE1	0.17
SHAPE2	0.10
20I2	0.00
20I48	0.14
IRATIO	0.24
S1085	0.19
FCOV	0.16
FCOVW	0.13

7.3 Application of VPL Model for Design Flood Estimation

Seven test catchments shown in Table 7.3 were used for the estimation of design flood peaks using the VPL model. The table shows parameter values used for this exercise. It should be noted that the *generalised loss function* (Eq. 5.1) with parameter *a* determined from Equation 5.2 was used to estimate rainfall excess. The catchment specific median pre-storm baseflow values were determined as described in Section 7.2.1.

Table 7.3 : Design flood peaks from ARR87 procedure using VPL model

Catchment	Area (km^2)	Parameter *a*	Antecedent baseflow (m^3/s)	FFA* peak flow (m^3/s)	10-yr design flood (VPL) peak flow (m^3/s)	10-yr design flood (VPL) % diff.	10-yr design flood (VPL) crit. dur. (hours)
Goodman (231219)	32	10.6	0.003	69	31	-55%	36
Aire River (235219)	90	229.1	1.330	130	133	2%	48
Wanalta (405229)	108	3.8	0.001	49	15	-69%	30
Lerderderg (231213)	153	98.4	0.351	120	76	-37%	48
Moe River (226209)	214	106.7	0.732	44	96	118%	48
Avon River (415224)	259	4.6	0.007	108	58	-46%	30
Seven Cks (405237)	332	134.1	0.971	257	137	-47%	72

* Flood frequency analysis

Design rainfall excesses for 10-year average recurrence interval (ARI) were determined for the seven test catchments; the excesses were then routed using the RORB model to obtain the design peak flows. In Figure 7.2, these are compared with corresponding estimates from a flood frequency analysis.

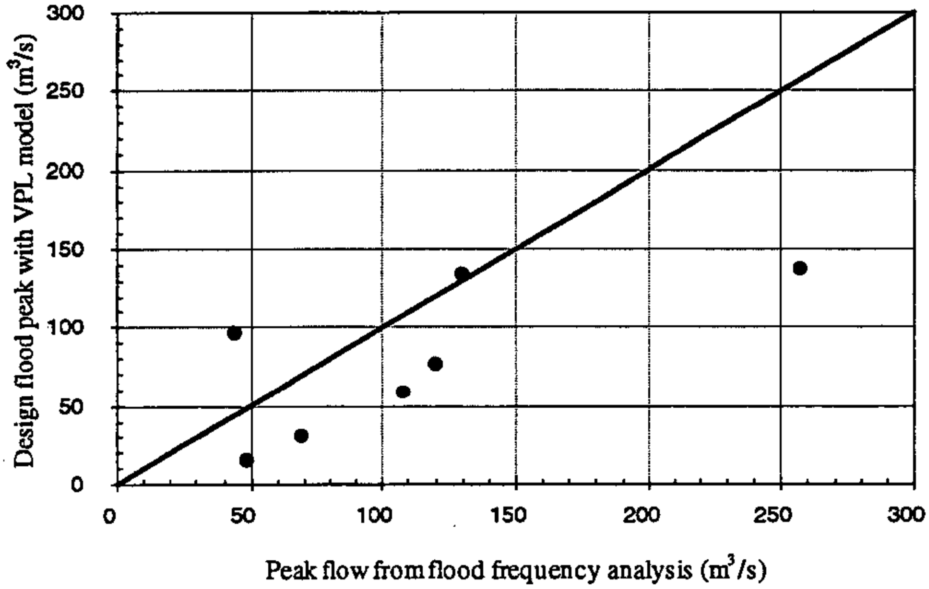


Figure 7.2 : Comparison of design flood peaks using VPL model against peaks from flood frequency analysis for ARI of 10 years

In general, the design flood peaks determined using 'median' pre-storm baseflow values tend to be lower than those derived from the flood frequency analysis.

It should also be noted that the development of the variable proportional loss model is based on the analysis of complete storms. In contrast, the design rainfalls given in Chapter 2 of ARR87 are based on the analysis of bursts embedded in complete storms. This suggests that the losses need to be less than those estimated from a loss function based on analysis of complete storms. If the effect due to this anomaly is allowed for, the design flood peaks determined using 'median' pre-storm baseflow values would be higher and closer to those derived from the flood frequency analysis.

7.4 Conclusion

It needs to be stated that the investigations carried out in this chapter are only preliminary and further studies are recommended to test the VPL model for design applications. In determining a suitable measure for pre-storm baseflow to be used in conjunction with the VPL model, the convenience of application and the accuracy of the estimated flood peak need to be examined. This study also indicates the strong seasonality of average antecedent baseflow values. This may also need to be considered in deriving design flood hydrographs.

8. CONCLUSION

8.1 Summary

This report details the development and application of a variable proportional loss model intended for use in real time flood forecasting and design flood estimation. The method is based on the assumption that the size of the saturation areas of the catchment increases as the rain progresses, resulting in an increased proportion of rainfall contributing to runoff as the storm progresses. This concept is considered to be more representative of the physical processes than those underlying conventional loss models

The development of the VPL model was based on the analysis of 20 Victorian catchments, representing different climatological and topographical regions. Events representing a wide range of antecedent conditions were selected to estimate the runoff coefficient, pre-storm baseflow and storm rainfall. A 4-parameter logistic function was then fitted to each catchment to define volumetric runoff coefficient as a function of pre-storm baseflow and storm rainfall.

The coefficient of determination (R^2) of the fitted relationships varied from 0.05 to 0.91 representing varying levels of success. It can be concluded that satisfactory results have been obtained for a majority of catchments which have a R^2 greater than 0.70 (15 out of 20 catchments). Of these, 8 catchments showed relationships with R^2 greater than 0.85. The hydrologic behaviour of the La Trobe River and Snobs Creek catchments are different from the rest and hence cannot be modelled satisfactorily.

A single parameter loss function was developed to use on a regional basis by assigning three parameters (*b*, *c*, *d*) of the general equation (Equation 3.1) by average values of the catchments analysed. It was shown that the loss of accuracy caused in simplifying the relationship for regional application is not significant. Values for parameter *a* determined for the 20 catchments using this simplified function were regressed against catchment characteristics to obtain a prediction equation for parameter *a*. The relationship for parameter *a* can best be represented by a non-linear function involving the baseflow index (BFI) and mean stream slope (S1085).

The relationship derived either for an individual catchment or on a regional basis allows for determination of 'initial loss' and progressive runoff coefficients knowing the pre-storm baseflow. Progressive runoff coefficients calculated for the catchments analysed were consistent and behaved satisfactorily when extrapolated beyond the range of storm rainfalls used for calibration of the curves. This shows the suitability of the logistic function in modelling losses.

The suitability of the proposed VPL model for real-time flood forecasting was investigated for a number of test catchments. The rainfall excess hyetographs determined from the VPL model were routed using the calibrated RORB model; recorded and predicted hydrographs were then compared.

A preliminary investigation was also carried out to access the suitability of the VPL model for design application.

8.2 Conclusions from the Study

The following conclusions can be drawn from this study.

- The results of this study showed that the pre-storm baseflow is a convenient and robust measure of antecedent wetness and that can be incorporated in a loss model to model the catchment response to rainfall.

- The proposed loss model has the advantage that the separation of initial loss is not required and timing errors in the data are not critical as with the conventional methods. One of the disadvantages of the proposed method is that the relationship only holds when the baseflow is above a measurable quantity. This method is also unable to account for the changes in the catchment wetness during rainless periods within a storm.

- The 'saturation curves' of the type proposed in this study cannot be fitted satisfactorily for the catchments showing strong baseflow conditions (eg. La Trobe River and Snobs Creek). These catchments are likely indicated by a baseflow index (BFI) greater than 0.60, Baseflow variability index (BVI) less then 1.5 or mean annual rainfall greater than 1300 mm.

- The proposed loss model has a direct application in real time flood forecasting as proportional runoff factors can be estimated progressively, knowing the pre-storm baseflow. Testing the loss model using the RORB indicated that the proposed loss model can be adopted satisfactorily in real-time flood forecasting within the context of uncertainties associated with the procedure. The successful application lies primarily in the ability of the loss model to predict runoff coefficients accurately; modelling of the rise of the hydrograph was quite satisfactory for the majority of events tested. However, there may be difficulties in forecasting the catchment response to storms of a distributed nature or multi-peaked storms.

- The variable proportional loss model can also be applied for design purposes if the mean or median value of pre-storm baseflow or any design level of antecedent condition is known. A measure of median pre-storm baseflow was defined on the basis of continuous baseflow hydrographs over a long period. However, design flood peaks estimated using this measure were found to be consistently lower than those derived from the flood frequency analysis. Further research on this area is required before recommending a procedure for design application.

8.3 Recommendations for Future Studies.

1. For modelling purposes, the VPL model needs to be incorporated with a routing model such as RORB. Selection of suitable loss model parameters (*a*, *b*, *c* and *d*) for optimisation together with the routing parameters is an area that requires further study.

2. The study carried out for testing the suitability of the loss model for real-time flood forecasting can further be improved by comparing the results with those obtained using conventional loss models and derived relationships for determining antecedent loss parameters such as a relationship of initial loss and API.

3. In view of the positive results achieved from this study, it is recommended that the adopted procedure be extended over other regions outside Victoria. This would indicate the suitability of the pre-storm baseflow as a measure of antecedent wetness for the adopted modelling procedure for those regions.

4. An area which require particular attention is the use of the proposed loss model in design applications. Further work is required in determining a suitable measure of median antecedent conditions that need to be applied to obtain design losses. This study indicates the strong seasonality of median antecedent baseflow values. The implication of this on the design values may also needs to be considered in determining a suitable measure of antecedent conditions for design applications.

5. The design losses determined from the VPL model are based on the analysis of complete storms, in contrast to the design rainfalls which are based on the analysis of bursts embedded in complete storms. A study towards determining corrective measures for this effect would be useful.

9. REFERENCES

Cordery, I., (1970). Initial Loss for Flood Estimation and Forecasting. J. Hydraul. Div. ASCE., 96(Hy12), pp. 2447-2466.

DCNR (1994), Catchment Characteristics for Selected Victorian Catchments, Department of Conservation and Natural Resources.

Drobot, D. and Iorgulescu, I., (1991). Modele Pluie-ecoulement et Identification de ses Parametres Hydrologiques. UNESCO Programme Hydrologique International, Rencontres Hydrologiques Franco-Roumaines, pp. 159-166. (Abbreviated translation of original paper in French by Weinmann, E.)

Dyer, B.G., Nathan, R.J., McMahon, T.A. and O'Neill, I.C., (1994). Development of Regional Prediction Equations for the RORB Runoff Routing Model. CRC for Catchment Hydrology, Report No: 94/1.

Hill, P., (1994). Catalogue of Hydrologic Data for Selected Victorian Catchments. Working Document No. 94/1, CRC for Catchment Hydrology.

Hill, P., Maheepala, U., Mein, R. and Weinmann, E., (1996a). Empirical Analysis of Data to Derive Losses for Design Flood Estimation in South-Eastern Australia. CRC for Catchment Hydrology, Report No. 96/5.

Hill, P., Mein, R. and Weinmann, E., (1996b). Testing of Improved Inputs for Design Flood Estimation in South-Eastern Australia. CRC for Catchment Hydrology, Report No. 96/6.

Institute of Hydrology, U.K., (1980). Low Flow Studies. Research Report 1, Institute of Hydrology, Wallingford, U.K.

Institution of Engineers, Australia, (1987). Australian Rainfall and Runoff, Volume 1.

Lacey, G.C., (1996). Relating Baseflow to Catchment Properties - A Scale Approach. CRC for Catchment Hydrology, Report No. 96/8.

Laurenson, E.M. and Mein, R.G., (1995). RORB Version 4 Runoff Routing Program, User Manual. Monash University, Department of Civil Engineering.

Linsley, R.K., Kohler, M.A. and Paulhus, J.L., (1982). Hydrology for Engineers. Third edition. (McGraw-Hill Co.:New York.)

Lyne, V. and Hollick, M., (1979). Stochastic Time Variable Rainfall-Runoff Modelling. Hydrol. and Water Resour. Symp., I.E. Nat. Conf. Pub. No. 79/10, IE Aust., pp. 89-93.

Mag, V.S. and Mein, R.G., (1994). A Flood Forecasting Procedure which Combines the RORB and TOPOG Models. Hydrol. and Water Resour. Symp., I.E. Nat. Conf. Pub. No.94/15, pp. 217-222.

Malone, T.A. and Cordery, I., (1989). An Assessment of Network Models in Flood Forecasting. *In: New Directions in Surface Water Modelling*, IAHS Publ. No. 181, pp. 115-124.

Mein, R.G., Nandakumar, N. and Siriwardena, L., (1995). Estimation of Initial Loss from Soil Moisture Indices (Pilot Study). Working Document No. 95/1, CRC for Catchment Hydrology. pp. 59.

Mein, R.G. and O'Loughlin, E.M., (1991). A New Approach for Flood Forecasting. Hydrol. and Water Resour. Symp., I.E. Nat. Conf. Pub. No. 91/12, pp. 219-224.

Morton, F.I., (1983). Operational Estimates of Areal Evapotranspiration and Their Significance to the Science and Practice. Journal of Hydrology, No. 66, pp. 1-76.

Nandakumar, N., Mein R.G. and Siriwardena L., (1994). Loss Modelling for Flood Estimation - A review. Report 94/4, CRC for Catchment Hydrology, pp 43.

Nathan, R.J., Austin, K., Crawford, D. and Jayasuriya, N., (1995). The Estimation of Monthly Yield in Ungauged Catchments Using a Lumped Conceptual Model. Aust. Journal of Water Resour. Vol 1, No. 2, pp. 65-75.

Nathan, R.J. and McMahon, T.A., (1990). Evaluation of Automated Techniques for Baseflow Analysis, Water Resour. Res. Vol. 26(7), pp.1465-1473.

Nathan, R.J. and Pamminger, F.J., (1995). Derivation of Mean Monthly Evaporation Estimates for Victoria, Department of Conservation and Natural Resources.

Nathan, R.J. and Weinmann P.E., (1993). Low Flow Atlas for Victorian Streams, Rural Water Corporation, Melbourne.

Natural Environmental Research Council (NERC), (1975). Flood Studies Report : Volume 1. Hydrological Studies, London, U.K.

Oddie, M.F., Tilleard, J.W. and Cloke, P.S., (1982). Application of Techniques from the UK Flood Studies Report to Modelling of Australian Catchments. Hydrol. and Water Resour. Symp., I.E. Aust. Nat. Conf. Publ. No. 82/3, pp.183-188.

O'Loughlin, E.M., Cheney, N.P. and Burns, J., (1982). The Bushrangers Experiment: Hydrological Response of a Eucalypt Catchment to Fire. *In: First National Symposium on Forest Hydrology*, I.E. Nat. Conf. Pub. No. 82/6, pp.132-138.

Rockwood, D.M., (1968). Application of Streamflow Simulation and Reservoir Regulation Program SSARR on the Lower Mekong River. FASIT Symposium, Tucson, Arizona.

Siriwardena, L. and Mein, R.G., (1995). Development and Testing of a Variable Proportional Loss Model Based on 'Saturation Curves'. Working Document 95/2, CRC for Catchment Hydrology, pp 52.

Siriwardena, L., Hill, P. and Mein R.G., (1997). Development and Testing of a Variable Proportional Loss Model. Working Document 97/1, CRC for Catchment Hydrology.

Siriwardena, L. and Mein R.G., (1996). Development and Testing of a Variable Proportional Loss Model. Hydrol. and Water Resour. Symp., I.E. Aust. Nat. Conf. Publ. No. 96/5, pp.709-710.

Yang, J. and Laurenson, E.M., (1985). Prediction of Loss Parameters in Three Victorian Representative Basins. Report No. 2/85, Department of Civil Engineering, Monash University, 52 pp.

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