An Investigation into Improving the Accuracy of Real-Time Flood Forecasting Techniques for the Onkaparinga River Catchment, South Australia

by

J.C. Pannell
B.E. (Hons), Grad. I.E. Aust., P.Eng.

A Thesis for the Degree of
Master of Engineering Science

Department of Civil and Environmental Engineering
The University of Adelaide
March 1997

Table of Contents

List of Figures

List of Tables

List of Appendices

Abstract

Three aspects of real-time flood forecasting were investigated on the Onkaparinga River catchment in the Mount Lofty Ranges, South Australia, firstly antecedent soil moisture indices, secondly artificial neural networks (ANNs) and finally, the application of the RORB model. The aim was to investigate whether the subjectivity associated with flood forecasting can be eliminated, particularly real-time updating and understanding the hydrologic processes occurring in order to achieve an improvement in forecast accuracy.

Antecedent precipitation index and pre-storm baseflow were used to estimate initial loss, however poor correlations were obtained. Antecedent precipitation index performed marginally better than pre-storm baseflow in estimating initial loss, although the best relationship containing antecedent precipitation index had an R^2 of only 0.68.

A backpropagation artificial neural network was used as a real-time runoff forecasting model. Both 1 and 5 hour runoff forecasts were made with input combinations of previous runoff and rainfall. The ability for the ANN model to forecast in real-time was not as encouraging as first hoped, in fact most forecasts were no better than what a 'trained forecaster' could achieve. Best results were obtained when the training sets contained the least amount of hydrologic variability and the most accurate representation of the storms. It was concluded that perhaps the limiting factor in the development of an ANN model of this nature is the accuracy of the model data itself, particularly the rainfall input.

The RORB model was automated using a PASCAL program and a DOS keystroke faker for 5 hour real-time forecasts. Forecasts were performed with different rainfall scenarios, continuing loss values and model parameters k_c and m. In one case, the model parameter k_c was adjusted in real-time. Best estimates were made using an accurate continuing loss value and the exact time distribution of rainfall. Again, the forecasts were probably no improvement to what could be achieved by a 'trained forecaster'. Altering the continuing loss as the storm proceeds to achieve a more accurate forecast, is probably more desirable than adjusting k_c alone.

The main factor that prevented a reduction in the subjectivity and an associated improvement in the accuracy of the real-time flood forecasts for the Onkaparinga River catchment, was due to the availability of only a small historical data set. This data set contained floods with vastly different characteristics, combined with an inadequate spatial representation of rainfall throughout the catchment which meant that relationships were unable to be successfully developed.

Statement of Originality

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution, and to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

I give consent to this copy of my thesis, when deposited in the University Library, being available for loan and photocopy.

SIGNED: DATE: 14/3/97

Acknowledgments

The author firstly wishes to thank his supervisors Trevor Daniell and David Walker in their tremendous assistance and guidance throughout the duration of this study. During difficult times it was Trevor's cynical comments and remarks that kept the thoughts flowing and the mind sane. At the other end of the scale was David's great optimism and encouragement in knowing that everything would turn out well eventually.

Other support staff within the department must also be credited including Byron Riessen and Stephen Carr for providing computer assistance throughout this study.

Acknowledgment must also go to fellow postgraduate students for providing times of laughter, jokes and discussion.

The author wishes to thank certain people from outside departments and organisations who had input into this research.

Chris Wright from the Hydrology Section of the Bureau of Meteorology, Adelaide for initiating this project and providing hydrologic data and discussion, even though the initial envisaged catchment was unfortunately not studied in the detail that Chris perhaps would have liked.

Errol Bamford of the Geography Department, at the University of Adelaide for teaching the author how to operate ARC-INFO and digitise some of the maps.

A number of local councils must also be thanked including Mitcham, Unley, Adelaide, Burnside and West Torrens City Councils for providing the most up to date stormwater drainage maps of the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment.

Graham Bennett and Dan Barker for proof reading the thesis and providing valuable comments and discussion.

Chapter 1

Introduction

1.1 Background

Flooding is a natural way of dispersing excess rainfall and is among the most destructive acts of nature. In recent years, human activities in the flood plains of rivers have made us vulnerable to damage when flooding occurs. With ever increasing development, pressure on flat and low lying land causes the potential for disaster to increase every year. World-wide the cost of flood damage to industry, agriculture, homes and public works amounts to billions of dollars annually. In addition, many lives are lost from flood disasters resulting from dam breaks, and other flash flood type phenomena in urban areas (United Nations, 1990). In most cases the potential for flood damage remains high even though billions of dollars are spent every year on flood mitigation. Where flood risk is high, and the potential for flood damage is great, significant benefits can be obtained by providing a flood warning system.

The purpose of a flood warning system is to enable and persuade people and organisations to take action before the flood overwhelms them, therefore increasing safety and reducing the economic and social costs of flooding (Soste et al., 1994). Yevjevich (1994) described the two main aims of flood warning as firstly, providing more time for evacuation, and secondly, defence. Evacuation usually consists of the physical removal of people from the affected flood plain, and defence is provided generally by erecting physical barriers, levees and walls so that flood waters do not innundate valuable property. The relocation of objects above the proposed level of flooding is another strategy used to reduce flood damage.

Real-time flood forecasting is a technique used to improve the effectiveness of flood warnings using the most recently known hydrological states to predict future hydrologic parameters within the catchment, so that an adequate flood warning is achieved.

Recently, the effectiveness of real-time flood forecasting has improved through using a number of technological advancements including computer technology, and the ability to communicate quickly and efficiently between the forecasting authorities and the community threatened by the flood (Hudlow, 1988).

Improved data collection and processing techniques such as the ALERT (Burnash, 1984) and PROPHET (Carroll, 1993) systems have been developed for efficient access to hydrologic information during a flood event. A major challenge with such systems is being able to interact them with the various flood forecasting models and the operating systems from which these models run.

The performance of a flood forecasting model is very much catchment dependent. The success of a model is a function of the model complexity, catchment response and the reliability of the input and output data. It is debatable whether newer, more sophisticated modelling techniques will produce better accuracy than simpler, more traditional modelling techniques, such as unit hydrograph methods and rainfall-runoff modelling, such as RORB and RAFTS. However, sophistication in rainfall-runoff modelling can never be a substitute for good quality rainfall data, which is properly representative of the storm over the entire catchment.

In Australia there has perhaps been a lack of collaboration between the different flood forecasting authorities, resulting in some uncertainty as to which of the current forecasting methods are best suited to different situations, which was evident in the review of real-time forecasting methods by Srikanthan et al. (1994).

Fundamentally, all flood forecasting relies heavily on precedent. With good reliable historical data, forecasting can become relatively easy, however in most cases, and certainly for extreme events, the flood history is inadequately known. In Australia, most forecasting techniques are manual and subjective, requiring the forecaster's experience to evaluate 'what to do next' based on relationships and parameters, in many cases derived from an inadequate number of historical events. Many overseas authorities have not only longer historical flood records, but also use complex, objective techniques to evaluate the accuracy of a forecast, therefore relying less on historical catchment response and the parameters derived from previous events. This makes the job of the forecaster easier because less judgement and input is required. Infact, Georgakakos and Hudlow (1984) stated that the 'human-machine' approach to hydrological and weather forecasting has been used for many years and will continue for many years to come, which is perhaps applicable to the future direction of Australian flood forecasting environments. To overcome this, the subjectivity associated with flood forecasting in this country caused by short historical records must be reduced.

How much improvement can be made to the accuracy of a flood forecast by removing the subjectivity and user input was unknown, and is therefore the primary focus of this thesis. The balance required between the experience and judgement of the forecaster, and to those of sophisticated and technological developments is an aspect which is unclear and needs to be established.

1.2 Research Objectives

This research was initiated by the Hydrology Section, Bureau of Meteorology (Adelaide Office). It was initially proposed to develop an operational, flood forecasting methodology for the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment; a predominantly urban catchment in the south-eastern suburbs of Adelaide, South Australia.

This catchment can be categorised as a high risk flash flood catchment (WBCM Consultants, 1984; Maguire, 1986) and was seen by Wright (1994, pers. comm.) as a catchment which required urgent forecasting development. Since this catchment is part of the Patawalonga catchment, which has recently been the centre of much attention regarding catchment management plans in terms of water quality and quantity issues (MFP Australia, 1995), it was seen as an ideal catchment to study.

In the late 1980s, the Bureau of Meteorology began radio telemetary catchment monitoring using an ALERT system throughout the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment. The ALERT system comprises a network of pluviographs and streamflow measurement stations linked by UHF radio to a central base station.

Brownhill Creek drains a rural portion of the Adelaide Hills, approximately 20 percent of the total area of the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment. For this study initially, only the rural portion of Brownhill Creek was investigated in an attempt to establish the rainfall to flood hydrograph relationship at the Scotch College ALERT station. No headwater flow gauging stations were available at this location. It was then envisaged to use the remaining downstream ALERT stations, to improve the accuracy of a flood forecast in Keswick Creek at Adelaide Airport. By doing so, it was hoped to develop a combined rainfall and flow 'driven' forecasting model.

As the ALERT stations had been operational for only five years, only six small flood events had occurred. A detailed study on this catchment was therefore not be possible because any parameters derived using these storms would not be applicable to more extreme events. Appendix A contains details of these small flood events and some preliminary analysis of the available data from the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment.

It was therefore decided to investigate an alternative catchment to carry out the study. The catchment selected was the Onkaparinga River catchment which contained a longer historical data set, but did not at that stage have the advantage of an ALERT system, nor was there as much urgency for developing a forecasting methodology for this catchment. The Onkaparinga River catchment is larger, and therefore results in a longer rainfall-runoff response time than the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment. Runoff forecasts for the Onkaparinga River catchment were made at Houlgraves Weir, upstream of the Mt. Bold Reservoir. At this location, it was possible to use upstream flow stations to assist the downstream forecasts. To correspond to the situation in the rural part of Brownhill Creek down to the Scotch College ALERT station, only the single downstream gauging station was used for the analysis.

The analysis of this research was performed on a single PC with no connection to other real-time database systems located at the Bureau of Meteorology.

In order to determine what modelling procedures should be examined, a review of the available real-time flood forecasting techniques was needed, concentrating on those models most applicable to operational situations in Australia. Based on this review, modelling techniques were chosen and researched in more detail, concentrating on those related to flash flood type situations. Both simple, traditional forecasting techniques and complex, unconventional modelling procedures were considered, particularly those that showed potential for reducing the subjectivity associated with real-time flood forecasting, and therefore improve the accuracy of the flood forecast.

It should also be pointed out that throughout this research, rainfall forecasting, although an extremely important aspect of any flood forecast, was not studied in any great detail.

1.3 Thesis Layout

This thesis details the research undertaken into the investigation of the accuracy of certain real-time flood forecasting techniques on the Onkaparinga River catchment. Chapter 2 describes the nature of flooding, the way in which people have coped with flooding in the past, and the importance of flood forecasting procedures in ensuring flood damage mitigation. The flooding problem within South Australia is briefly discussed, including its causes and the current flood warning measures used to minimise its damaging effects.

Chapter 3 describes the differences between design flood forecasting methods and real-time flood forecasts. The techniques and models used in real-time flood forecasting throughout the world are reviewed. Following the review in Chapter 3, three separate methods for real-time flood forecasting were selected for further investigation and reviewed in more detail as they were thought to be methods which may lead to improvement in the accuracy of a flood forecast by removing user subjectivity. These three methods are antecedent catchment moisture index methods, artificial neural networks and the RORB runoff-routing model combined with an automatic updating algorithm.

Antecedent catchment moisture index methods are not an actual modelling procedure, but merely a simple method to assist the forecaster in determining the future catchment response. Artificial neural networks were seen as a complex, unconventional, yet encouraging method for real-time flood forecasting. Finally, the RORB model was viewed as a more traditional rainfall-runoff model, commonly used throughout Australia that has in the past, perhaps lacked suitable development to real-time forecasting situations.

A detailed summary of the current usage of antecedent catchment moisture indices for flood forecasting is made in Chapter 4. The main emphasis of this chapter is to review the estimation of initial losses from soil moisture indices.

Artificial neural networks were seen as ideal for flood forecasting because of their success in forecasting complex relationships in other applications. Chapter 5 reviews in detail how artificial neural networks operate, concentrating essentially on backpropagation networks. A comprehensive review of how artificial neural networks have been applied to flood forecasting is also described.

Chapter 6 describes the Onkaparinga River catchment, essentially outlining the catchment instrumentation available, and the historical events available for examination.

In Chapter 7 the use of two soil moisture indices; antecedent precipitation index (API) and pre-storm baseflow (BF), to real-time flood forecasting are examined specifically with reference to developing exponential relationships for the estimation of initial loss through regression analysis.

Chapters 8 and 9 apply artificial neural networks to runoff forecasting on the Onkaparinga River catchment. Chapter 8 involves complete simulation of the hydrograph, similar to a design situation. The sensitivity of the model was investigated by altering the input data, and the way in which the network was trained. Antecedent precipitation index was also used during training to observe whether the artificial neural network could establish a relationship between antecedent precipitation index and rainfall-runoff response. Chapter 9 provides a description and the results of real-time forecasting based on a rainfall-driven model. Again, the amount of input data was varied and the information used for training was altered. To explain some of the results, sensitivity analysis of the model inputs was undertaken.

In Chapter 10, the application of the RORB runoff-routing model to a real-time forecasting situation is described. Automation of RORB was achieved on a PC, combined with a specifically written PASCAL program which contained an updating algorithm. The model parameters k_c and m were updated, combined with different forecasted rainfall scenarios.

Chapter 11 presents a summary of the research and how the findings can be used in the future, not only for the Onkaparinga River catchment, but to other catchments as well.

Chapter 2

Flood Management

2.1 Introduction

Australia receives less rainfall than all other continents, except for Antarctica. Once rainfall has reached the ground, only 12 percent is converted into runoff after evapotranspiration and other loss processes have occurred. Consequently, it might seem that Australia has very little potential for flooding. However, in economic terms, floods are Australia's biggest natural disaster, ahead of drought and cyclonic wind disasters (CRC, 1994).

Major flooding has occurred in large sections of Australia in 1863, 1890, 1910, 1921, 1925, late 1940s, 1955-56, 1973-74, 1990 and more recently in 1996. It is estimated that on average, flood damage costs the Australian community about $300 million per annum (CRC, 1994). Of this value, over half reportedly occurs in urban centres from both mainstream and stormwater flooding, the remainder occurs in rural areas. In early 1974, the floods in Brisbane caused $200 million of damage and 30 percent of N.S.W. was inundated. In fact, in any non drought year a major flood is experienced somewhere in Australia.

The Australian rural flood problem is physically larger than the urban problem, and serious implications to the Australian economy can occur as a direct result of damage to stock, crops and transport disruptions. The majority of Australia's flooding occurs on the most productive agricultural land because these areas are commonly flood plains and therefore usually have major watercourses situated nearby. Flooding occurring in urban areas is a significant problem due to the high population density and a potentially greater risk to human life, and the greater economic risk to commercial, industrial and urban infrastructure.

Approximately 70 percent of Australians live in the 8 capital cities. All except Canberra, lie on the coast, and are subject to either riverine flooding, or the storms associated with tropical cyclones. A number of major non-capital urban centres have previously been, and are subject to, potential flood damage. These include Newcastle, Wollongong and Townsville on the east coast, Alice Springs in central Australia and Launceston in Tasmania. Emphasising the urban flooding problem, Smith and Handmer (1986) reported that in 300 urban communities in Australia, approximately 100,000 buildings lie within the 1 in 100[1] year flood plain.

Despite the statistics concerning urban flooding, only in recent years has an effort been made to reduce the impacts of such damage. Pilgrim (1990) stated that stormwater flooding from surcharge of urban drainage systems has received little co-ordinated attention, even though damages from this source are probably at least as great as those from mainstream flooding.

Perhaps the greatest threat in terms of flood damage and loss of life, is caused by dam failure. Floods associated with dam failure have occurred with devastating consequences throughout the world with little or no prior warning. The problem with this form of flooding, is that the water volumes, velocities and heights are much greater than even the most extreme natural flood events. These occurrences have led to an increased awareness and attention to flood prevention, and particularly to flood warnings.

2.2 Flood Prevention

Despite the alarming statistics in Section 2.1, damage due to flooding in terms of property and human lives lost is perhaps the most avoidable major natural disaster (CRC, 1994). Over the years, four methods have been used to deal with floods namely: (Yevjevich, 1994)

- Do nothing;
- Structural mitigation;
- Non-structural mitigation; and
- Combination of structural and non-structural mitigation.

On many catchments, nothing is done to reduce the impact of flood damage. This is due to a lack of funding, poor regulations and more commonly, no awareness of potential

[1] 1 in 100 year flood plain is defined as the flood plain expected to occur on average, once every 100 years

problems. Quite often nothing is done until after a flood event, even if the potential exists for property damage and loss of life.

Previously, flood mitigation through large scale hydraulic structures including levees, dams and diversion channels was the sole method for flood protection, commonly described as a 'hard' or structural approach.

Historically, 'soft' or non-structural measures have comprised mainly of land use zoning along riverine areas, building regulations, insurance and defence. Non-structural mechanisms do not change the physical characteristics of floods, but are simply intended to reduce the impacts and consequences without changing the physical nature of the problem.

A combination of both 'soft' and 'hard' strategies are described by Evans (1994) primarily to physically change the river regimes. Since flooding is likely to be more catastrophic due to 'concrete walls' and other man made structures preventing high flows from dissipating, authorities in Britain on the River Thames, Dutch authorities in the Rhine Delta and the U.S. Army Corps of Engineers in Florida have converted land back to its old state, including natural flood plains, therefore dissipating more energy and allowing more infiltration.

The major rivers of the world have had flood hazard reduction schemes in place for years. For example the Danube River, Europe; Mississippi River, North America; Yellow and Yangtse Rivers, China; have extensive levee systems. Due to their size and large investments within the flood plain, forecasting and warning arrangements, evacuation of people, animals and movable objects have had to be comprehensive and well organised. For these particular rivers if a flood threatens to overtop levees, prior planning usually means that the water can be diverted to other parts of the flood plain into flood release basins, but in some unfortunate situations, water is diverted straight through settlements.

In recent times, the combination of high costs, environmental and social considerations and inadequate land acquisition, have meant that structural mechanisms have become less favourable and the non-structural measures have become the more desirable option (Yevjevich, 1994).

The recent push to 'defend' against flooding rather than to alter the physical process was highlighted by Yevjevich (1994) who stated that, *"....it may be easier to fight consequences of natural disasters than to fight for a change in the severity of these disasters."* (p 37) and that the, *"....21st century may witness a rebirth in sophistication and attractiveness of the non-structural measures for coping with floods."* (p 40).

More recently, non-structural defence has consisted of flood warning, and in the last 10 years, the importance of improved flood warnings has increased. Damage to property and loss of life will continue to increase as urban development in flood plains becomes more intense, therefore flood warning, as a cost effective non-structural flood mitigation measure, is receiving increased attention in the development of strategies for reducing the cost of flooding (AWRC, 1992). As urbanisation increases, the main problem for the 21st century will be the defence from floods in the smaller river basins. The smaller the river, the faster the flooding, therefore the flood defence must become more improvised (Yevjevich, 1994).

A report by the Co-operative Research Centre for Catchment Hydrology, Melbourne (CRC, 1994) highlighted that more accurate and detailed flood warnings have perhaps the greatest potential for reducing the costs caused by flooding.

2.3 Flood Warning

A flood warning can be defined as, (Penning-Rowsell, 1986, p 19)

> *".....the complete process from the collection of hydrometeorological information, the 'forecast', to the dissemination of warning messages and the response from all sectors of the community....".*

The components of a flood warning system include:

- Observation of flood producing phenomena;
- Communication to the analysis centre;
- Analysis : threat recognition and forecast;
- Communication to the warning system;
- Warning; and
- Action : deployment of emergency crews, evacuations and other emergency operations.

A simplified flood warning can be divided into three time periods as shown in Figure 2.1.

The flood warning system is initialised through the observation of a flood producing phenomena (eg. rain event) through a data collection and data transmission network. Analysis of this data is carried out to recognise the potential threat. A flood forecast is made and possibly a flood warning is issued. The time taken to do this is called the forecast time.

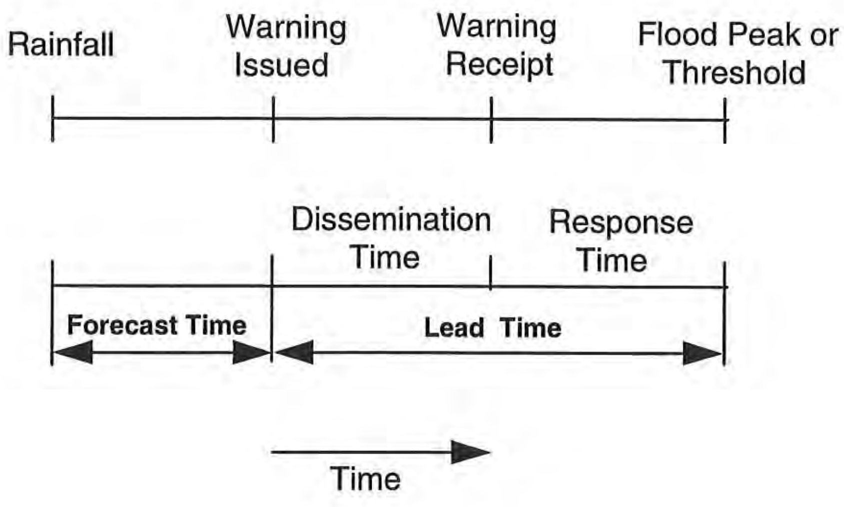


Figure 2.1 Simplified flood warning structure (Source: Penning-Rowsell, 1986)

The dissemination time is the period when communication occurs between the relevant monitoring authorities and the people affected, warning them of the onset of a potential flood event. The response time is the time which people and organisations have before the flood peak or threshold occurs, in which to take action by moving, removing and protecting valuable possessions, setting up flood protection works (i.e. sand bagging) or deploying emergency crews.

Perhaps the most important component of flood warning is the lead time. This can be described as the time between when a flood forecast is made by the authorities to when the flood peak or threshold occurs. A longer lead time is possible when forecasting is made for the downstream end of a large contributing drainage area. For real-time forecasts of dam failure, flood warnings must be even more computationally efficient (WMO, 1994).

The overall aim of flood warning is to maximise the response time by reducing the forecast and dissemination time, however this is not an easy task. A complex integration exists between all parts of the flood warning system. If there is one weak link (generally the dissemination time), no matter how advanced the technology used to make the forecast, the overall system becomes inefficient.

Peart and Jayawardena (1993), encountered a limitation with current forecasting methodology for a small (11 km^2), highly urbanised catchment in Hong Kong subject to a 'classic' flash flood situation. For this catchment, the current warning time is about 2 hours. It was shown that through current telemetric monitoring of rainfall, not enough warning time is provided. Due to the small size and rapid response (approximately 3 hours), monitoring of upstream water levels, also does not provide enough warning. Apart from more advanced rainfall forecasting, such as radar, the only way of reducing the warning time, is to improve communication methods and dissemination of the warning to the people.

Soste et al. (1994) reported that the failing of present warning systems was due to the tendency of these components to be treated separately rather than together. It was reported that the effectiveness of user response is the ultimate measure of the quality of the flood warning system. Without adequate response, technical improvements will be of limited value. For example, an accurate forecast that is too late, is of little or no use, especially in flash flood situations because the event is over very quickly.

A guide to the Australian perspective on flood warning has recently been published by AEMI (1995).

2.4 Flash Flood Warning

Flash flooding develops very quickly and therefore requires a different forecasting and warning methodology to longer response time floods. The defining factor is basin response time, therefore speed is of the essence for flash flood warning. There is no exact definition of a flash flood because it varies between regions and authorities throughout the world.

Milne (1986, p 77) qualitatively described that a flash flood may occur when, *".....an unexpected and torrential downpour falls on an impervious surface."*.

WMO (1981, p 1) describe flash flooding as, *".....a flood of short duration with a relatively high peak discharge."*.

Slightly more specific to response times is the definition of the National Weather Service (NWS) of the U.S. cited in Georgakakos and Hudlow (1987, p 1233) as, *"....any flood that occurs at a certain location within a few hours after the causative event (e.g. rainfall, dam break...."*.

Flash flooding is generally conceived as flooding that occurs within 6 hours of the causative event (WMO, 1981). As a result, in Australia the Bureau of Meteorology have described flash flooding to have occurred when the, *"rain-to-flood time is 6 hours or less"* (Srikanthan et al., 1994, p 74).

The key words however, from the above expressions, are 'short', 'few hours' and 'unexpected'.

The effects of flash flooding are likely to be most severe in areas which are not accustomed to severe rain events, since those affected by the floods have little or no experience on which to base an appropriate response, nor is there likely to be any monitoring equipment prior to the flash flood event (Wright, 1994a). For example, the worst flash flood in recent history reportedly killed 2000 religious pilgrims gathering near Teheran, Iran in a normally arid desert valley (Milne, 1986).

Damage and death rates from flash flooding can be extensive. WMO (1981) highlighted that since the 1940s the death rate in U.S. from flash flooding has tripled (most likely due to increased urbanisation), and property damage is estimated at $1 billion annually.

WMO (1981) highlighted the annual death rate from flash flooding in the U.S. to be roughly 0.0001 % of the population. Given that the forecasting techniques in the U.S. are the best in the world, it is suggested that developing countries with poor infrastructure in terms of forecasting and communication facilities, may face annual death rates several times that of the U.S.

The causative factors of flash flooding are: (Georgakakos, 1987)

1. Heavy localised rainfall (generally of convective origin);
2. Storm Movement;
   - Speed
   - Direction
3. Slope of Land;
4. Degree of urbanisation; and
5. Sudden release of water from impounded water (dam and levee failure).

Perhaps the biggest underlying problem with flash flooding, is that opportunities to practise procedures for dealing with them, occur too infrequently for forecasters to develop experience with them, meaning the forecaster *".....has to get it right the first time."* (Doswell et al., 1995, p 4).

2.5 Historical Development of Flood Prevention in Australia

The Meteorology Act of 1906 established the office of the Commonwealth Meteorologist with the responsibility for, *".....the display of ..... flood signals."* (BoM, 1983, p 1). In 1908, flood warning gauges began operation in Queensland and New South Wales by the state meteorological services. In the same year the Commonwealth Bureau of Meteorology began generalised flood warning services. In April 1957, following the 1955-56 floods, the Federal Government established a hydrometeorological service within the Commonwealth Bureau of Meteorology.

The duties of this service were to:

- Act as the national authority in development of water resources and mitigation of floods;
- Carry out research and investigations into hydrological and meteorological problems and to advise authorities (governments and municipal authorities) on these problems; and
- Provide flood forecasts.

The Federal and State Governments initiated programs to reduce the impact of flood damage through extensive structural mitigation. During the late 1950s and 1960s, there was a tremendous push towards structural flood mitigation schemes. The N.S.W. government established programs for the construction of flood mitigation works which included levees, floodways, river channel clearing and post-flood drainage. In 1963, flood mitigation works became a national program. These mitigation works were aimed at mainstream flooding from rivers and creeks, generally in inland rural areas on flat land, with little emphasis on the urban areas.

In 1962, the first flood forecasting service to provide an accurate prediction of expected flood height was introduced to the Macleay River, N.S.W. (BoM, 1963a). However, little attention was given to flood warning schemes until the early 1970s. The lack of attention was a result of the uncertainty about who was responsible for funding and providing such schemes. During this period, the provision of such schemes was generally initiated after an event had occurred. In 1976, a Federal Committee of Inquiry into the Bureau of Meteorology was undertaken and recommended that responsibilities be passed onto the individual states. Between 1976 and the mid 1980s, limited technological developments in flood warning occurred in Australia compared with other industrialised nations. This was a direct consequence of uncertainties and problems remaining unsolved regarding funding and provisions of such schemes, even at state levels. However, compared with other overseas countries, the proportion of Australian buildings liable to flooding is small. For example, it is estimated that in the U.S., 10 percent of the population live in the "1 in 100 year" flood plain compared to about 2 percent in Australia (Smith and Handmer, 1986).

A Flood Warning Consultative Committee (FWCC) currently operates in each state to oversee the development of flood warning services. The Bureau of Meteorology along with some local authorities have the responsibility for predicting, warning and co-ordinating the response to flooding in Australia.

2.6 Flood Warning in South Australia

It is difficult to categorise the different types of flooding that occur in South Australia due to the large hydrologic variability in this state. Maguire (1986) categorised flood warnings in South Australia into three distinct groups based on the response time of the river, these being:

- Long response times;
- Short-medium response times; and
- Short response times.

Some overlap exists between the three different categories.

2.6.1 Long Response Times

Flooding of this nature is characterised by response times of many weeks or even months. The principal watercourse in this category is the River Murray. In South Australia, flooding associated with the River Murray poses the greatest threat in terms of damage and disruption to the public, and has provided the main focus for flood warning in South Australia for many years.

Flooding of the River Murray can be a result of either:

- High snow melts in the Australian Alps; or
- Heavy rains from monsoonal low pressure cells over the north eastern/eastern part of the continent, essentially over the Darling River system in southern Queensland and northern New South Wales.

Heavy monsoonal rain often results in extensive flooding of the interior watercourses, including the Coopers Creek, Diamantina/Warburton Rivers and eventually Lake Eyre. This flooding poses little more than a disruption to inland transport routes and pastoralists, and is seen as being environmentally and economically desirable to the rural sector in terms of agricultural productivity.

These catchments contain areas of up to thousands of square kilometres which result in long warning times, therefore alleviating the need for intensive and expensive flood warning systems. Currently, S.A. Water Corporation (formerly the E&WS department) operates flood forecasting and warning procedures for the River Murray. The Bureau of Meteorology is not required to provide any forecasting service for the River Murray in South Australia.

2.6.2 Short-Medium Response Times

Flooding of these river systems is associated with response times of a number of hours, and has been the highlight of media attention in recent years. The main rivers of concern are located in the Mount Lofty Ranges namely the Gawler, Torrens and Onkaparinga Rivers. These catchment areas are up to hundreds of square kilometres and predominantly rural in their upper reaches. The lower reaches of these catchments occur in the flatter, more densely populated Adelaide Plains. Flooding within these catchments is usually a result of either: (Maguire, 1986)

- Localised intense convective storms; or
- Interaction of southerly frontal troughs and moist tropical northerly air streams combined with the orographic effect caused by uplifting and therefore cooling of air over the Mt Lofty Ranges.

Historical accounts of flooding are well documented for many of these catchments. For example, Daniell and Hill (1993) made a detailed documentation of the historical flooding that has occurred in the Onkaparinga River catchment.

In recent years, these catchments have been the focus of much hydrological attention. Gauging stations and data collection programs have been in existence for a number of years and were particularly intensive during the 1970s and 1980s by the E&WS department. Large water control structures (including reservoirs and levees) have been constructed and have therefore reduced flooding downstream. The Bureau of Meteorology currently operates flood forecasting and warning procedures for each of these catchments.

2.6.3 Short Response Times

Short response time flooding poses the most significant problem within the developed areas of metropolitan Adelaide, and the upper catchments of the rivers which run through the city, particularly the smaller tributaries of the Gawler, Torrens and Onkaparinga River. The type of flooding associated within these catchments is flash flooding. The potential problems have been highlighted by Maguire (1986) who suggested that the danger to life and property from short flashy floods in the urban areas puts them second in priority to the River Murray.

Appendix B shows flooding that has occurred in the metropolitan area of Adelaide and adjacent catchments in the Adelaide Hills in the past few decades. A recent example of the danger of such flooding would be the drowning of two people on 30/8/92 at Cudlee Creek in the upper Torrens River catchment in the Mount Lofty Ranges. Appendix B illustrates an example of such flooding that occurred during this study in the Adelaide Hills.

Other short response time watercourses within Adelaide include:

- Dry Creek, North of Adelaide;
- First to Fifth Creek, Mt Lofty Ranges;
- South eastern suburbs drainage system comprising Brownhill, Glen Osmond, Keswick and Parklands Creeks; and
- Sturt River.

These catchment areas are small (up to 100 square kilometres) but combine rural and urban land use. Little historical hydrological data is available for these catchments, and almost no data regarding any major flood events that have occurred within metropolitan Adelaide. Increased urbanisation has altered the hydrologic response of these catchments. If similar storms which had occurred in the past were to occur today, the extent and intensity of flooding would be much greater.

Following the 1983 Ash Wednesday bushfires in the Mt. Lofty Ranges, flooding in the eastern suburbs of Adelaide close to the foothills was a result of the altered land characteristics through the reduction in vegetation.

Due to the short time between the commencement of a storm event and peak runoff, conventional flood forecasting is not a practical damage mitigation option for these catchments.

Flood forecasting and warning procedures are not clearly defined, nor have they been implemented for a major event on such catchments. Defence measures within these catchments are more often improvisations, or fast *ad hoc* reactions rather than well planned and implemented actions. However since 1988, data collection development has improved within some of these catchments and the systems developed are believed to be unique in Australia (Wright, 1994a).

Appendix C documents how the effects of catastrophic flooding in the urban areas of Adelaide have been changed over the past few decades, and how the authorities are dealing with such problems.

2.7 Summary

This chapter has provided information about the nature of flood phenomena and the methods used to suppress its damaging effects, from both a structural and non-structural aspect. The type of flooding that can be expected in South Australia, particularly within the Adelaide region, has been described.

A detailed look at the concept of flood warning was outlined with particular reference to quick response (or flash flood warning). The problems associated with forecasting flash floods have been highlighted together with reasons why early notification of such occurrences is often difficult.

This chapter has therefore provided the reader with a necessary background of information to proceed to the concepts and requirements of a real-time flood forecasting model, which are discussed in the following chapter.

Chapter 3

Real-Time Flood Forecasting

3.1 Introduction

Flood forecasting dates back to Ancient Egyptian times when floods on the River Nile were forecasted by sending rowers up to the headwaters to investigate the amount of snow and rises in lakes. When the rowers returned from the headwaters, they were able to tell the people whether there was a chance of flooding or if it would be a good season for farming or not. During these times the flood forecaster was considered the 'high priest' (Biswas, 1970).

More recently, successful flood forecasts have been dependent on simple empirically derived relationships based on visual observations including manually read staff gauges, flood debris marks and rainfall gauges. In the past few decades, the physical understanding of the hydrologic and hydraulic processes have improved. In addition, the growth in computer and information technology has led procedures become more automated. Improvements have also been made to data measurement including stage height and rainfall recording.

Flood analysis usually involves the investigation of practical problems, either design of engineering structures such as levees, culverts and reservoirs, or forecast models for flood warning. In order to perform this analysis, one must look at the theoretical hydrologic processes that create a flood phenomenon through rainfall and runoff processes.

Floods can be evaluated through a combination of peak flow and/or hydrograph computations. In some cases the peak flow alone is not sufficient, therefore the time distribution of runoff is required, and a knowledge of the entire hydrograph is necessary. This is not only important for flood warning procedures, but also for the design and operation of certain structures (i.e. reservoir operation).

In the 18th century and the first half of the 19th century, the only flood analysis method was regular visual observations of upstream rainfall and river stage to calculate the downstream river stage. This was the first form of hydraulic routing. In 1851 the 'rational method' was developed to compute peak discharge caused by a given rainfall intensity. This is still the most widespread design method for urban drainage (Pilgrim, 1986).

The late 19th century saw the development of the concept of isocrones (lines of equal travel time) which introduced the time distribution effect of runoff. This, and the availability of accurate streamflow and rainfall measurements over a catchment, led to the development of rainfall-runoff modelling. The development of the unit hydrograph theory by Sherman (1932) was the first of such models. Limitations with this method led to the development of 'conceptual models' which are rainfall-runoff models composed of simulated components such as linear reservoirs, linear channels or time-area diagrams. The first successful 'conceptual models' (cited in Rossi, 1994) were those of Nash (1957) and Dooge (1959).

During the 1970s the interest in rainfall-runoff models intensified, especially those of 'conceptual models', as the need for real-time forecasting tools for flood warning systems increased (Williams and Field, 1985). In the last decade, applications using weather radar systems, satellite technology and Geographic Information Systems (GIS) have improved flood forecasting (Kouwen and Soulis, 1993). These areas provide the focus for current research into real-time flood forecasting. New, alternative ways of flood forecasting are now being tested including fuzzy theory, artificial neural networks and chaos theory, which have been successfully used in other forecasting applications.

This chapter aims to provide a summary of the real-time flood forecasting techniques that are currently used throughout the world, concentrating mainly on rainfall-runoff modelling. The main components of a real-time flood forecasting model are discussed. One of the purposes of this chapter is to observe the relative differences in technological input required for different modelling techniques currently being used, with particular emphasis on the requirements of Australian forecasting situations. Some suggestions as to how the accuracy of these forecasting procedures can be improved are also made. Once established, these suggestions will be investigated further with particular reference to the Onkaparinga River.

3.2 Real-Time Flood Forecasting Versus Design Flood Forecasting

Real-time forecasting has been used in a variety of applications related to water-resources management including flooding, low-flow situations (including groundwater and aquifers) and in water-quality. However, the most common use for real-time forecasting is flood forecasting, especially for forecast periods of less than twenty-four hours (WMO, 1992).

Real-time flood forecasting is different to conventional design flood estimation and modelling. Generally, the type of forecasting models used are the same in both situations. The difference is the way in which they are used. Real-time forecasting has the ability to respond to the feedback of new information and improve its forecasting ability as the current system information is received at each time step.

A design flood estimation uses hypothetical or median data. For example, hypothetical rainfall data can be determined at some design annual exceedance probability (AEP) and a median loss rate may be used. For real-time flood forecasting, real (current) rainfall and actual losses must be adopted.

Figure 3.1 compares a generalised real-time forecasting model to a design (simulation) forecasting model. The design forecasting model consists of a 'process model' only, whereas the real-time model incorporates an 'updating' component as well. The 'process model' consists of numerical equations which contain state variables and model parameters. Measured input parameters are also included which may be precipitation, air temperature, evaporation, snow melt and other factors. The difference between model parameters and state variables is that model parameters generally remain fixed, whilst the state variables change in time. A state variable may be a baseflow indicator, or in the case of conceptual models, an amount of water in the conceptual reservoirs. The output of the 'process model' is usually either discharge or stage height.

An example of a complex 'process model' is the Sacramento Model which is a complex conceptual soil moisture accounting model (Georgakakos, 1986a). The output of the Sacramento Model contains various components of flow including direct runoff and baseflow. The inputs to the model are evapotranspiration and precipitation. There are six state variables which are associated with the soil moisture content of different zones in the soil, including the upper zone tension water content and lower zone secondary free water content, to name just two. In addition, there are seventeen model parameters excluding the ones in the routing component. A schematic description of the Sacramento Model is shown in Figure 3.2. The Sacramento Model has been used for real-time flood forecasting on the River Nile, Egypt (Grijsen et. al, 1993) and by the Queensland Department of Primary Industries for real-time flood forecasting on the Brisbane and Pine River catchments (Loy et al., 1996). Details of less complex 'process models' relevant to operational forecasting will be discussed in Section 3.3 including the RORB, RAFTS and WBNM rainfall-runoff models.

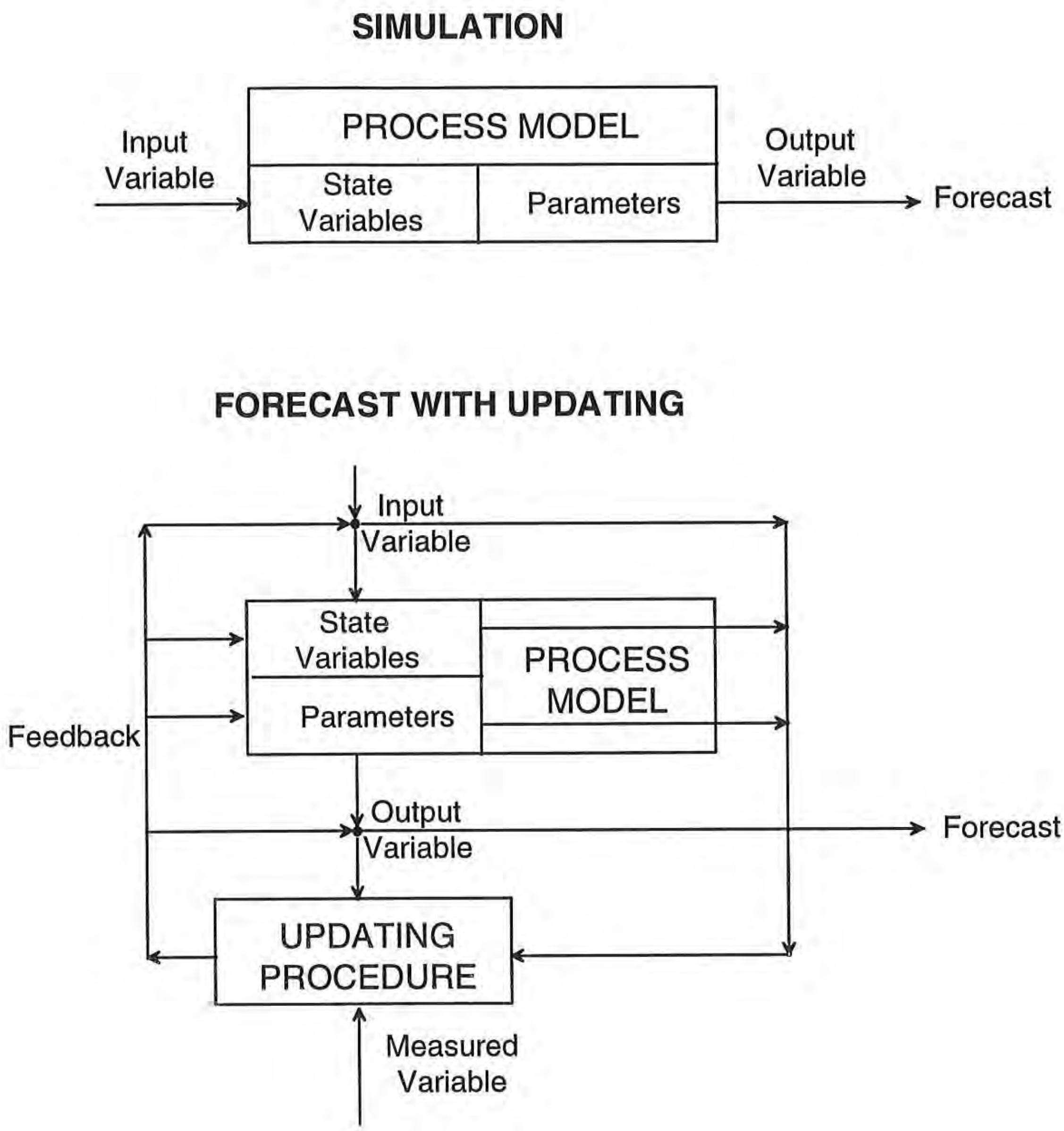


Figure 3.1 Comparison of a real-time flood forecasting model to a design (simulation) forecasting model
(Source: WMO, 1992)

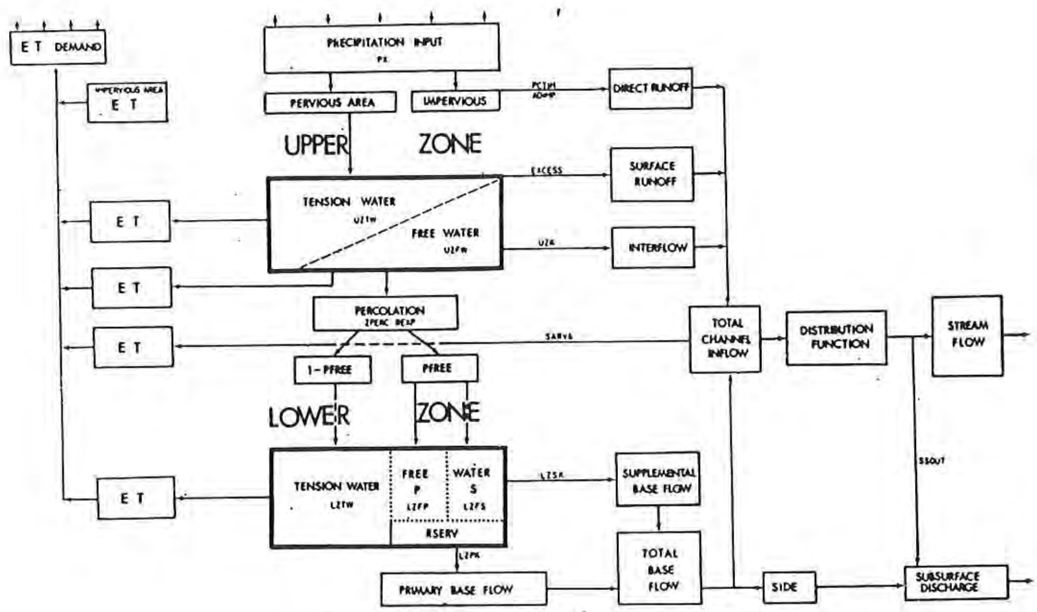


Figure 3.2 An example of a 'processing model' : the Sacramento Soil Moisture Accounting Model (Source: Kitanidis and Bras, 1980a)

It is important in real-time flood forecasting to realise that model parameters and state variables must be correctly initialised at the time the forecast is made, otherwise differences will occur between the actual and predicted runoff. This leads into perhaps the most important component of the real-time flood forecast; the updating procedure, which considers the model output when a forecast is made. The overall aim of the updating procedure is to consider the relative errors between the computed and measured output in order to modify the forecast, and improve the model's performance by bringing the observed and simulated output closer together.

Real-time flood forecasting can be described as the, *".....execution of the forecasting procedures on the basis of currently available data."* or *".....a model which takes information on the past and current states of the river basin, and inputs to it, and predicts discharge rates for a certain period into the future."* (WMO, 1992, p 6).

Peddie and Ball (1993, p 406) described real-time flood forecasting as, *"....having the ability to monitor a flood event .... and to forecast future runoff rates."*.

In each of these statements there is no discussion of forecasting based on future input states. For example through estimation of future model inputs, namely rainfall, a more accurate forecast with a larger lead time can be achieved.

3.3 Flood Forecasting Models

There are many models available to forecast discharge and stage height. No one model is suitable for all situations, the choice of model depends on many factors. Quite often it is worthwhile to have a number of suitable methods and then choose the one which is most applicable for the catchment at a particular time. One method might perform well on one catchment, but may be unsatisfactory on another catchment nearby, possibly due to an incomplete understanding of the hydrologic conditions or because too many local empirical factors are present.

Srikanthan et al. (1994) carried out a detailed review of the currently used real-time flood forecasting models. A less detailed summary is given in this chapter, and highlights the main models used, emphasising those models used in Australia. Some of the models have been developed for real-time forecasting situations but have been used only as a research tool, and never used operationally.

Nemec (1986) classified flood forecasting models into deterministic and stochastic models. Deterministic models are those that simulate the complex physical relationships occurring in a catchment during the rainfall-runoff phase of a hydrological event. Stochastic models use statistical and probabilistic techniques to evaluate a forecast based on previous historical data. Deterministic models are divided into two distinct groups:

- Flood Routing Models-Hydrometric models that use stream flow only; and
- Rainfall-Runoff Models-Hydrometeorological and hydrometric models that use stream flow and the conversion of rainfall to runoff.

It is these two groups that have provided the main focus for flood forecasting, not only in Australia but throughout the world.

Feldman (1994) described the different components and complexities of typical flood forecasting systems using deterministic models which are summarised in Table 3.1. The type of forecast system that is used is a function of :

- Hydrologic responsiveness of catchment; and
- Technological, financial and size of resources in the organisation making the forecast.

Table 3.1 shows that although an increased amount of information gives an improvement in lead time, the potential uncertainty of the forecast increases. As pointed out by Feldman (1994), the major current challenge is to provide a balance between these two aspects.

Table 3.1 Components and complexities of typical flood forecasting systems of deterministic models (Source: Feldman, 1994)

Model	Inputs	Forecast Lead Time	Sophistication of Forecast Procedures	Expense	Potential Uncertainty
Flood Routing	Stream Flow	Shortest	Shortest	Least	Least
Flood Routing	Stream Flow and Rainfall	Short	Simple	Little	Little
Rainfall-Runoff	Stream Flow and Rainfall	Long	More Complex to Very Complex	More to Very	More
Rainfall-Runoff and Meteorological Model	Stream Flow and Rainfall	Longer	Very Complex	Very	More
Rainfall-Runoff, Meteorological Model and Rainfall Forecasts	Stream Flow and Rainfall	Longest	Most Complex	Most	More

Rainfall-runoff modelling is generally more complex but often results in less accuracy than the hydraulic flood routing of a hydrograph from an upstream gauging station. In most real-time flood forecasting situations, especially small catchments subject to flash flooding, upstream gauging stations do not exist, nor would there be adequate warning time even if hydraulic routing was used.

Hydraulic flood routing is more successful for large basins with long, slow moving river systems. The travel time of flood peaks from upstream to downstream stations must be long enough to allow for adequate lead time, therefore, hydraulic routing is more applicable to slower moving rivers than rainfall-runoff modelling and so in this review, hydraulic routing is only briefly discussed.

Fuyi (1993) found that a rainfall-runoff model combined with a forecasting method based on corresponding water levels of hydrological stations in upper and lower reaches greatly improved the accuracy of flood forecasting.

Stochastic models have been used considerably less than deterministic models for operational real-time flood forecasting. They are more often used to forecast daily, monthly and yearly flow values. These types of models include:

- Autoregressive (AR) models (Masahiko et al., 1989);
- Moving average (MA) models;
- ARMA models (Singh and Mandakinee, 1994);
- Non-linear (threshold) time series models; and
- Adaptive algorithm models.

In some cases, stochastic models have been combined with deterministic models (Chow et al., 1983; Georgakakos, 1986a; Georgakakos, 1986b). A discussion of stochastic modelling is not covered in this study, however a brief review was made by Srikanthan et al. (1994).

For completeness, Srikanthan et al. (1994) also briefly discussed spatially distributed models. To date these tools have been mainly used for research. These models include the:

- *SIMPLE Model*;
- *TOPOG Model*;
- *TOPMODEL*; and
- *SHE MODEL.*

3.3.1 Hydraulic Routing Models

Empirical relationships are among the simplest to use, and easiest to derive methods for flood forecasting, and usually consist of historical data plotted in graphical form. Visual observations of stage are easy to make, which is the reason why peak-stage relationships were the first method of forecasting floods. Even today, they remain an important tool for flood warning (Malone, 1994b). Such methods have been in operation around the world for about 100 years and often provide accurate flood forecasts.

Peak-stage relationships may use an automatic recorder at an upstream location, the approximate peak magnitude and timing is predicted by factoring and lagging the upstream hydrograph. Alternatively, the upstream stage can be correlated with the downstream stage, with a lead time equal to the travel time of the flood wave. The travel time can be calculated through flood wave equations but is usually calculated using data from previous floods. The latter is only appropriate however for larger rivers with stages that do not change rapidly. Therefore they are not very suitable to flash flood type situations.

More rigorous flood routing techniques have been used; namely dynamic routing. This is often referred to as hydraulic routing. This involves numerical solutions of the generalised one-dimensional St. Venant equation which describes continuity and momentum of unsteady fluid motion with a free surface. The solution to such an equation is complicated which makes the use of such techniques inappropriate to operational flood forecasting. However in recent years, because of advancements in computer technology, its use has increased. Approximations of the full St. Venant equation have been made, and the kinematic and wave routing methods have been developed, which have simplified the full momentum equation as discussed by Srikanthan et al. (1994).

The least complicated methods have been defined as hydrologic routing methods and involve only the continuity equation and a storage-discharge relationship. These include the Muskingum and Muskingum-Cunge methods, to mention only two.

Statistical routing methods have also been developed, and are summarised by Srikanthan et al. (1994).

3.3.2 Rainfall-Runoff Models

3.3.2.1 Empirical Relationships

Approximate correlations between the flood volume and/or peak flow rate can be made with physical catchment variables and parameters (BoM, 1963a; BoM, 1963b; Giesemann, 1986). The most commonly used variables and parameters used to establish these correlations are gross rainfall, rainfall intensity and catchment storage deficit at the commencement of the rainfall. In doing so, measurement of soil moisture indices such as antecedent precipitation index (API) becomes an important part of such relationships.

3.3.2.2 The Unit Hydrograph Method

This is a very commonly used technique in Australia. It is simple, effective and quick to operate and for this reason is particularly useful in flash flood situations. It is based on a concept that if the runoff hydrograph is calculated using one unit of rainfall, with the addition of more units, an estimate of a flood can be obtained. It is essentially a rainfall routing model which involves two steps.

Firstly, the conversion of total rainfall to effective rainfall by subtracting losses. A number of loss models have been developed for different situations. In Australia, perhaps the most widely used loss model for this purpose involves an antecedent precipitation model; combined with either initial loss-continuing loss or proportional loss. Secondly, through a linear relationship, transformation of effective rainfall into surface runoff and the addition of base flow is used to obtain the total flood hydrograph.

The unit hydrograph method has been used on its own, and has been combined with other techniques into larger packages. For example, the HEC1F model operates in two phases; the first phase utilises the unit hydrograph concept and the second phase performs runoff and routing computations and other operations throughout the basin (Mimikou et al., 1993).

Chander and Shanker (1984) studied a procedure for making on-line estimates of the ϕ-index and rainfall excess, and used the unit hydrograph to formulate a real-time flow forecasting technique for two Indian catchments. Forecasts of up to 3 hours were found to be accurate.

Srikanthan et al. (1994) illustrated the heavy dependence in Australia, on the unit hydrograph as a forecasting model.

3.3.2.3 Non-Linear Routing Models

A number of non-linear routing models have been developed in Australia, for Australian conditions, primarily for design flood estimation. These models have, over the years, been modified and adapted for real-time flood forecasting. Without doubt, the three most commonly used non-linear rainfall-runoff models in Australia are RORB, WBNM and RAFTS. The main feature of all of these models is the division of the catchment into sub-catchments and the representation of the catchment storage effects by non-linear reservoirs. Each sub-catchment has independent rainfall inputs allowing for spatial and temporal variation of rainfall over the catchment. Rainfall excess is calculated and the associated runoff hydrograph from each sub-catchment is routed and combined at the basin outlet.

Perhaps the most important aspect in making these models suitable for real-time flood forecasting is linking them to the appropriate data management software and the operating systems used by the models. Difficulties have occurred in adapting these design oriented models to adaptive forecasting tools. This led to the development of the URBS model in Queensland which is described later in this section.

RORB is probably the most widely used rainfall-runoff model for design flood estimation, however its use as a real-time forecasting tool has been somewhat limited. The loss routines are either initial loss-continuing loss or initial loss-proportional loss.

RORB is most readily available and used on a DOS based operating system. This creates difficulties in interfacing the PC version of RORB with real-time data bases. RORB as a real-time forecasting tool has been used primarily in Melbourne by Melbourne Water (Giesemann, 1986; Crapper, 1989) and by the New South Wales Public Works Department on the Tweed River (Avery, 1989). Recently a real-time version of RORB was developed by Melbourne Water for the Watts River, Upper Yarra Dam and Diamond Creek Catchments in Victoria (cited in Srikanthan et al., 1994).

A Windows version of RORB is in its Beta test stage which has a more friendly 'front end' than the current PC version, and will perhaps be more suited to real-time interaction (Dyer, pers. comm., 1994).

The Watershed Bounded Network Model (WBNM) is structurally similar to RORB, except WBNM has two types of storages for two types of sub-catchments. Different storages are given to the sub-catchments based on geomorphologic relations. Both linear and non-linear versions of the model are available. The use of WBNM as a real-time forecasting tool has not yet been investigated in detail, however a more comprehensive description of the model structure can be found in Srikanthan et al. (1994) and Boyd et al. (1989).

RAFTS has a slightly different conceptual storage model to RORB and WBNM. RAFTS models both the impervious and pervious portions of each sub-catchment and routes the excess rainfall separately, combining the two at the sub-catchment outlet. RAFTS incorporates a choice of more sophisticated loss models based on algorithms of the Australian Representative Basins Model. A Muskingum-Cunge procedure is used to route the hydrograph to the catchment outlet. RAFTS is currently used as a flood forecasting tool in the A.C.T by the Electricity and Water Authority (Knee and Falkland, 1989). The potential for using RAFTS on the Upper Parramatta River, N.S.W, was also investigated by Peddie and Ball (1993).

The Hydro-Electric Commission in Tasmania has developed a flexible real-time modelling system called HYDROL which can be adapted to different water management systems, in particular for use in the hydro-power generation scheme (cited in Srikanthan et al., 1994).

The URBS model was developed by the Brisbane City Council specifically for real-time use and has since been used by the Queensland Bureau of Meteorology (Carroll, 1994; Malone, 1994a; Malone, 1994b). It is a RORB compatible flood routing model however, it can accommodate both channel and runoff routing. The runoff routing component is essentially the same as RORB except a number of important advantages exist over the other conventional models of RORB, RAFTS and WBNM because:

- It can be operated on a number of operating systems including DOS, Windows, XENIX, HPUX and QNX. Operating systems at the Bureau of Meteorology and Brisbane City Council have used URBS on both QNX and DOS operating systems respectively;
- The model can calculate both flood heights and discharges using built in rating curves;
- The model can be run interactively or in batch mode;
- Comprehensive plotting and textual output is incorporated which can be placed into an easy to read spreadsheet format;
- Forecast rainfall can be easily added to the model; and
- It is capable of being dynamically linked to real-time monitoring systems.

3.3.3 Flood Forecasting Models used in South Australia

Flood forecasting in South Australia is not as sophisticated as in other parts of the world, including the rest of Australia. The E&WS department prior to 1988 was responsible for flood forecasting throughout South Australia. Since then, the Bureau of Meteorology has been responsible for flood forecasting in all areas except the Murray River.

The first formal flood warning system developed in South Australia was based on a RORB model developed by B.C. Tonkin & Associates for the South Para Reservoir in 1986/87 (Wright, 1994b). Three pluviometers were used, however it was never used in full operation. Prior to this (in the 1970s and early 1980s) informal procedures were used by the E&WS to help forecast floods on the Onkaparinga, Torrens, North and South Para Rivers using the RORB model. These used limited rainfall stations with data manually fed into the models. These RORB models were developed primarily for flood mitigation studies to predict the areal extent of flooding in conjunction with HEC-2 analysis, and to predict reservoir yields.

More recently, peak height relationships have been developed for predicting flood flows at Turretfield on the North Gawler River. Hydrographs from locations on the South Para and North Para Rivers are added together and lagged by three hours to predict the flows at Gawler. The floods of 1992 were successfully predicted in this manner and the timing and magnitude of peak flows have been predicted fairly accurately.

Currently, unit hydrograph techniques are available for the other flood prone catchments. The unit hydrograph models are DOS based and computed on PCs. The biggest problem with using DOS based models is that data collection and storage is performed on a QNX system located at the Bureau of Meteorology, Kent Town, meaning important data is transferred manually, therefore slowly and awkwardly from one system to the other. Work is currently being undertaken to adapt unit hydrograph software in QNX.

Previously, the biggest problem was that not enough data had been collected to establish reliable hydrological relationships. Better monitoring systems including new radio telemetry ALERT stations, have been installed at many locations since the 1992 floods, and will help support the development of modelling techniques similar to those on the eastern coast of Australia (Wright, 1994b).

3.4 Rainfall Forecasting

3.4.1 Introduction

Rainfall forecasting is important if improvements in forecast lead times are to be made. Due to the short lead times associated with flash flooding, short-term rainfall prediction is an important aspect of flood forecasting (Seo and Smith, 1992). Once the lead time is increased, then the warning time can be increased (Burlando et al., 1993). Bertoni et al. (1992), stated that to achieve increased warning times, a more realistic hypothesis must be established rather than assume zero future rainfall, which is often the case.

Figure 3.3 shows the potential lead times that can be achieved through using different amounts of monitoring, and highlights the importance of the rainfall forecast. Simple hydraulic flood routing based on observation of flow only, produces the least warning time. A hydraulic flood routing forecast can be improved by combining it with a rainfall-runoff model that also monitors flow. However, in order to substantially increase the lead time of a forecast, quantitative rainfall forecasting is needed. The effect on forecast accuracy with the introduction of rainfall monitoring and forecasting combined with modelling is shown.

Rainfall forecasting becomes even more important as the characteristics of the catchment change. For example, it is very important for smaller catchments with a high degree of urbanisation and quick response times.

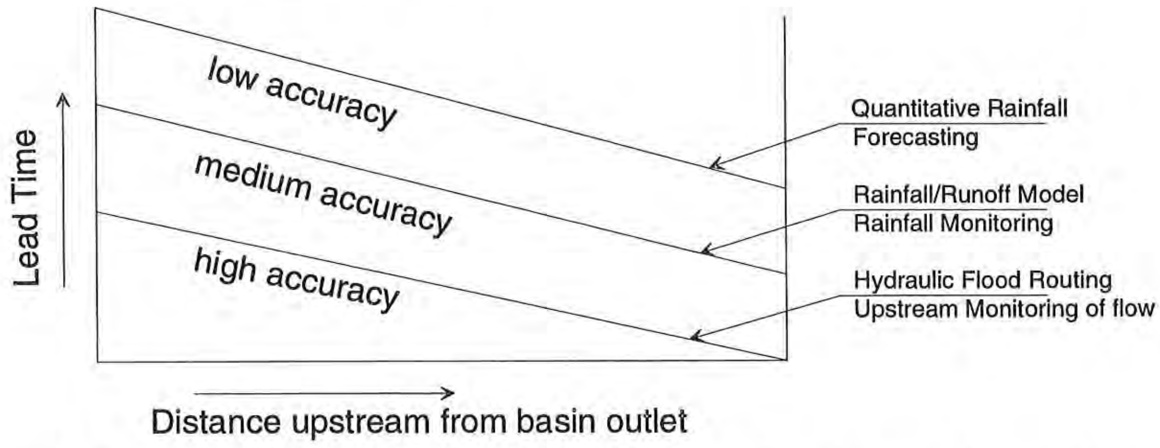


Figure 3.3 Potential lead times achieved through different degrees of monitoring (Source: Grijsen et al., 1993)

Georgakakos and Hudlow (1984) described the rainfall forecast as perhaps the most important hydrological parameter. Infact the forecast should contain the areal distribution and amount of precipitation expected to occur over a given area over a given time (Smith and Handmer, 1986). However it was stated by Georgakakos and Hudlow, 1984 that rainfall forecasts are often the most elusive of all estimates because of its great variability in both space and time.

The current limitations of rainfall forecasting were that they generally do not provide sufficiently accurate values (at least for forecast periods exceeding 30-60 minutes) for direct input to hydrologic models (Georgakakos and Hudlow, 1984).

Wright (1994b) pointed out that with radar and satellite use in the future it may be possible to predict a flood before the rain has even landed. However, recent studies on rainfall properties based on fractal and deterministic chaos have raised doubts about the predictability of rainfall using mathematical modelling techniques for long lead times (Zawadzki, 1987). Zawadzki suggested that the limit on the lead time that rainfall may be forecasted is perhaps about 15 minutes.

3.4.2 Methods of Forecasting Rainfall

Rainfall forecasts have been attempted using a number of approaches. The type of forecast depends on the size of the catchment, availability of hydrometeorological stations, and more recently, on the availability of remote sensing instrumentation.

The biggest problem with using ground observation stations to monitor rainfall is the high density of the network required to achieve adequate network performance. Michaud and Sorooshian (1994) compared the rainfall fields based on a very dense rain gauge network to rainfall fields based on only a subset of the maximum number of gauges. By using a subset of the maximum number of rain gauges, errors in simulated peak flows were about 58 percent of the observed peak flow.

3.4.2.1 Remote Sensing

Remote sensing probably offers the biggest potential for major improvements to flood forecasting accuracy (Hall and Elliot, 1986; Collier, 1985). Rainfall forecasting using remote sensing is of particular interest in catchments where upstream gauging stations do not exist (Lardet and Obled, 1994).

Two approaches are possible; weather radar and satellite imagery. Using radar, the rainfall rate is directly related to the raindrop size spectrum based on reflectivity. Satellite imagery estimates rainfall amounts based on physical interpretations of the convective clouds which includes rate of cloud growth, cloud top temperatures and other factors. A discussion of the meteorological dynamics associated with the development of rainfall can be found in French et. al (1994) and French and Krajewski (1994).

Weather radar measurements can be achieved with high resolution in space (down to 1km ×1km). Difficulties are associated with calibrating the system to transform the electromagnetic radar echo into a rainfall rate. Radar is good for short range forecasts for lead times up to about 6 hours (Georgakakos and Hudlow, 1984).

The United Kingdom and Japan have the most extensive radar systems in the world. The Dee Weather Radar and Real-Time Hydrological Project is an example of the extensive work carried out in the United Kingdom (DWRP, 1977). Recent research findings by Japanese hydrologists are summarised by Yoshino et al. (1993), Takasao et al. (1994) and Moriyama and Hirano (1990).

Satellite data provides the 'bridge' from forecasting lead times of several hours ahead, to warning times of only a few minutes. GEOS, Meteosat, GMS and NOAA are examples of satellites used primarily for meteorological purposes. 'Cloud indexing' and 'live-history' are common techniques which rely on infra red (IR) and/or visible image data. They show the earth's cloud cover using visible frequencies during the day and IR frequencies during night time.

A combination of data from weather radar and satellite imagery (Meteosat) is used in the FRONTIERS system (Forecasting Rainy Optimised using New Techniques of Interactively Enhanced Radar and Satellite data) in Britain.

Moore (1995) discussed the HYRAD system which uses combinations of radar and ground rainfall measurements, as this was found to work better than radar alone. One advantage of this method is to have the ability to use one or the other of the data inputs if one becomes inoperational during a flood.

The WATFLOOD system, as described by Kouwen and Soulis (1993), converts radar Constant Altitude Precipitation Index maps (CAPPIs) into rainfall maps, then calibrates it with ground rainfall stations for flash flood forecasting. WATFLOOD can also use combinations of radar and ground rainfall measurements if one or the other of the input systems becomes inoperational.

3.4.2.2 Quantitative Precipitation Forecasting (QPF)

Quantitative Precipitation Forecasting (QPF) provides numerically a distribution and an amount of rainfall expected over a catchment (Hall and Elliot, 1986). Most QPFs are not solely driven by computer modelling. Meteorologists also apply their own hydrometeorological skills and local knowledge in association with the models output to derive the best QPF. Three conventional approaches have been used; empirical, statistical and physical methods.

Empirical methods generally use an extrapolation of the existing precipitation areas and movements. They use past and/or current conditions to determine the trend for the future and are generally used to provide short period forecasts. A linear extrapolation forecast can predict a few hours ahead by observing the detailed distribution and movement of the associated weather patterns, and assuming that the weather pattern will continue without change (nowcasting). This can be useful for a frontal type system with a relatively high amount of uniformity (Browning et al., 1982). For example, Schultz and Klatt (1980) assumed the rainfall in the next 2 hours to be the same as that which fell in the past two hours.

Statistical regression techniques use correlation between the rainfall at a point (or on an areal basis) with some other parameter usually either hydrometeorologically, climatologically or orographically. The problem with such methods is that a large amount of historical data is needed. Burlando et al. (1993) developed an autoregressive moving average (ARMA) process for short-term rainfall forecasts of 1 and 2 hours.

Recently, there has been increasing interest in rainfall simulators that use large amounts of historical data to generate future events. Klatt and Schultz (1983) using rainfall observed up to the time of forecast, forecasted the rainfall for the immediate future based on a probabilistic model using 192 historical flood producing rainfall events.

Lardet and Obled (1994) also developed a stochastic rainfall generator with a 4 hour lead time. Each storm was defined by 6 hydrologic characteristics, assuming each storm had a triangular shape. The cumulative density function of each of the 6 characteristics was determined using a log-normal distribution. A confidence limit was defined and a storm was generated.

Deterministic models use physical equations to explain the dynamics of the atmosphere. These models range in size from the LAM model (limited area fine mesh) which covers the entire United States with grid mesh size of 150 km, to 1 dimensional small scale microphysical cloud physics models.

Georgakakos and Bras (1982) developed a physically based non linear precipitation model compatible with hydrologic catchment models. Meteorological input variables include temperature, pressure and dew point temperature. The state variable is the liquid water content of the clouds. Simplified cloud microphysics produces expressions for the mean areal precipitation rate in terms of the input variables, the model state and storm invariant parameters.

3.4.3 Rainfall Forecasting in Australia

In Australia the use of radar has been somewhat limited, mainly because of cost. Radar, using 5 cm wavelength's are used in most forecasting centres, however for more accurate results, 10 cm wavelength radars are required. As yet, only a limited number of these have been used for operational forecasting.

Radar for meteorological systems in Australia have a resolution of 1 km and a range of 128 km. Up to 16 reflectivity levels are used to approximate the various rainfall rates, and new pictures are available every 5-10 minutes. In the near future in Australia, it appears that a combination of high resolution 10 cm radar and ground based measurements are most likely to give the most accurate method of estimating catchment rainfall (Wright, 1994a).

Rainfall estimates from satellite data imagery have been limited to only studying selective events, and have not been used for operational forecasting. For most Australian flood forecasting situations, rainfall is forecasted with the objective to gain a lower and upper limit of possible discharges by using a number of 'what if scenarios' starting at some point during the storm. The lower limit is achieved by assuming zero future rainfall. In many situations a constant rainfall intensity has been assumed over the forecast period. Different rainfall intensity scenarios are often used. The intensity for the forecast period may be made equal to or some percentage of the previous hour(s) (North, 1986).

Avery (1989) did not use future rainfall when using the RORB model for flood forecasting, which accounted for the inaccurate timing of peak magnitudes. Carroll (1993) in outlining the PROPHET system, described two methods of assigning rainfall forecasts. Firstly, assume that say 100 mm falls over the next 2 hours, and secondly, assume that it will rain as hard over the next 2 hours as it did for the past 4 hours. Peddie and Ball (1993) in using the RAFTS model also used a 'no more' rainfall case which caused the predicted surface runoff hydrograph to fall quickly. Malone (1994b) for forecasting the Mary River to Gympie, used three predefined rainfall scenarios and tested the sensitivity of each. Large differences in their accuracy were observed.

Srikanthan et al. (1994) concluded that a reliable QPF is not yet available. Currently most work around the world is focused on radar, satellite and LAM development, whilst in Australia, meteorologists from the local Bureau of Meteorology issue the hydrologist with an estimate based on numerically generated models. These models have large resolutions of up to 150 km, therefore are not accurate for smaller catchments subject to flash flooding (Wright, 1995, pers. comm.).

Objective techniques using extrapolation of data from radar and satellite imagery are yet to be developed in Australia. Interfacing radar data with hydrologic forecasting models is seen as a high priority for future research (Srikanthan et al., 1994).

3.5 Real-Time Updating

Predicted hydrographs are always different to the actual hydrograph in real-time hydrologic modelling. There are a number of reasons why the computed and actual hydrographs differ. The main factors are:

- Model uncertainty;
- Input uncertainty;
- Parameter uncertainty;
- Initial state of the system; and
- Output uncertainty.

A detailed report of real-time updating procedures was carried out by Serban and Askew (1991) and has been summarised by Srikanthan et al. (1994).

Simplifications to the rainfall-runoff process are always made during the development of rainfall-runoff models. For example, the overall hydrologic process is a spatially distributed system, but for convenience the different elements are often lumped together. The components of the hydrologic system are all interrelated and dependent on each other. The relationships between these components are almost always simplified.

Model inputs are usually measured, or forecast. For example, precipitation is measured from ground stations, but can be estimated using QPFs or radar.

Model parameters are selected either because they represent physical characteristics of the basin, or because they simply give a good reproduction of the behaviour of the system (and may have no physical meaning).

A poorly initialised model for a particular event can create errors which may be due to poor initial selection of model parameters, or the actual model itself. This can also be a function of the time, since physical changes may have occurred within the catchment to make the current model formulation obsolete (due to construction, land clearing etc.).

To remove these errors, it is useful to compare the predicted system output with the observed system output (discharge) to update the system and correct the errors. A number of updating procedures have been developed to take these errors into account. These generally assume that the observed system output is correct, however in most cases, output uncertainty exists as well.

Moore (1995) suggested that any updating technique is only as good as the output accuracy. It was suggested that in flood forecasting systems with only limited historical hydrological data, perhaps the largest source of error results from stage-discharge relationships established from only a small data base. Srikanthan et al. (1994) also identified poor rating curves as one restriction to accurate modelling and emphasised that operational data collection is the key to improving the accuracy of rating tables.

Bae et al. (1995), suggested that updating is a very important component of operational flow predictions, especially during the initial period after field implementation, when historical parameter estimates are relatively unknown.

3.5.1 Updating Procedures

Four different approaches have been used for real-time updating: (Srikanthan et al., 1994)

- Updating model input variables;
- Updating state variables;
- Updating model output variables; and
- Updating model parameters.

A combination of these methods may work better in some situations. The method used is dependent on local conditions. Updating both rainfall and outflow will often produce the most accurate discharge forecast (Bae et al., 1995).

Updating can be achieved using either automatic or a manual-interactive procedures. Some models have used both techniques. For example, after applying the automatic procedure, the forecaster may review the system and compare it with the actual data over the basin. If any unanticipated error or unusual circumstance arises, the user is then able to manually change the variables subjectively and re-run the model again.

3.5.1.1 Updating Model Input Variables

The most commonly updated model input variable is forecasted rainfall. The error between the predicted and actual hydrograph is compared with some pre-determined acceptable error level. If the error is greater than this pre-determined value, a trial-and-error approach is undertaken. The input variable (forecasted rainfall) is iteratively adjusted, and the model re-run until an acceptable error is achieved.

This process is easy to program and combine with most rainfall-runoff models, and generally takes only a small time to run. It has been found to be equally successful for both the rising and falling limb of the hydrograph (Serban and Askew, 1991).

3.5.1.2 Updating State Variables

This technique has been used throughout the world for updating conceptual rainfall-runoff models, especially in cases where snow melt is an important part of the model. This has been adapted as the updating procedure for real-time forecasting on the River Nile, Egypt using the Sacramento Model (Grijsen et al., 1993).

Updating is usually achieved through a Kalman filter (Kitanidis and Bras, 1980a; Kitanidis and Bras, 1980b) for linear models, and an extended Kalman filter for non-linear models (Georgakakos, 1986a; Puente and Bras, 1987). Kalman filtering involves a set of mathematical procedures that can be used to process numerical data to make accurate statements and predictions of parameters and data variables that have unknown future values. This process is based on filtering theory derived from communication engineering and is discussed in great detail by Ahsan and O'Connor (1994), who recently critically reviewed the applications of the Kalman filtering techniques in river flow forecasting.

Kalman filters have been more successful for linear models, the biggest problems are that programming is difficult and computation times are often large. Kalman filters are therefore generally limited to shorter lead time forecasts.

3.5.1.3 Updating Output Variables

The output variable is updated for river routing type models where the output variable (usually discharge) is updated based on either differences between the observed and computed hydrograph, or by predicting future errors based on an autoregressive (AR) model.

The first approach is often called 'blending' and is briefly described by Srikanthan et al. (1994). The computed hydrograph is 'blended' with the observed hydrograph and the consequent blended hydrograph is used for later routing procedures.

Updating the output variables is easy to program and requires little computation time. The accuracy of such methods is dependent on the degree of error between observed and computed hydrographs. The desired error needs to be smallest near the hydrograph peak and oscillations in the autoregressive model may occur. Alternatively, if a timing error occurs, then the autoregressive model will result in large errors. As with Kalman filters, the efficiency of using autoregressive models for updating when phase and shape errors are present is questionable (Serban and Askew, 1991).

3.5.1.4 Updating Model Parameters

Despite many reported problems, updating the model parameters is still quite a popular technique used throughout the world (WMO, 1992).

Bertoni et al. (1992), outlined three methods used to update the estimates of conceptual model parameters:

- Adoption of model to 'state-space' (Kitanides and Bras, 1978);
- Iterative optimisation techniques (Tucci and Clarke, 1993); and
- Minimisation of objective function explicit in the estimated parameters (Chander and Shanker, 1984).

The first technique is very complex and the third is very simple, limited to simple models only. The iterative optimisation technique also has some problems. Serban and Askew (1991) recommend that optimising model parameters should be avoided because often the model parameters are dependent, therefore modification of one parameter would require modification of the other parameter(s). Johnstone and Pilgrim (1976), Nash and Sutcliffe (1970) and Mandeville et al. (1970) explain in detail the difficulties encountered with these optimisation techniques.

Optimising an objective function (either maximising or minimising), searches for a set of parameters by inspection of the objective function's response surface. In many models, especially those with large numbers of model parameters (in excess of 20 parameters), the response surface may not be convex (or concave), and many local optima may be found. Model parameter updating is therefore rather slow compared with more efficient techniques such as Kalman filtering. The correct choice of objective function is also important and affects the speed and efficiency of the optimisation procedure (Brath and Rosso, 1993).

3.6 Evaluating the Accuracy of Real-Time Forecasting Models

A number of factors can be used as a means of assessing the performance of real-time forecasting models. From a practical aspect, the following parameters are widely considered as being most important to real-time flood forecasting:

- Time of peak;
- Peak discharge (or height);
- Flood volume; and
- Threshold levels, such as minor, moderate and major floods based on critical levels.

These parameters are distinct and independent of each other, therefore in calibrating a particular flood forecasting model, the use of different criteria will lead to different derived parameters. In order to gain an appreciation of the overall performance of the predicted hydrograph, an objective function that statistically compares the predicted hydrograph with the observed hydrograph is required to 'combine' the above parameters into a single expression. For real-time forecasting an objective function that is repeatable, and minimises subjective judgement, is most desirable. Srikanthan et al. (1994) and WMO (1992) discuss in detail various model evaluation techniques suitable for real-time flood forecasting.

For this study, two objective functions were considered in the analysis:

- Root Mean Square Error (RMSE)
- Coefficient of Determination (CD)

The RMSE is defined as: (WMO, 1992)

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[Q_{est}(i) - Q_{obs}(i)]^2}{n}} \tag{3.1}$$

and the coefficient of determination (CD) is defined as: (Srikanthan et al., 1994)

$$\mathrm{CD} = 1 - \frac{\sum_{i=1}^{n}[Q_{obs}(i) - Q_{est}(i)]^2}{\sum_{i=1}^{n}[Q_{obs}(i) - \overline{Q}_{obs}]^2} \tag{3.2}$$

where:

$Q_{est}(i)$ = Estimated flow values
$Q_{obs}(i)$ = Observed flow values
$\overline{Q}_{obs}$ = Mean of the observed flows
n = Number of points in the hydrograph

WMO (1992) selected the RMSE as the statistic to summarise forecast results because of its common use and simplicity. Its only problem is its sensitivity to a few isolated errors in the sample. The larger the difference between the estimated and observed values, the larger the RMSE.

The coefficient of determination is a measure of the association between the observed and forecasted discharges (Aitken, 1973). The closer the value is to unity, the better the association. A value of unity implies a perfect association between the predicted and observed discharges. Its only weakness is that the coefficient of determination does not reveal systematic errors. However it has been successfully applied by Wang and Ikebuchi (1994), Kitanidis and Bras (1980a) and Kitanidis and Bras (1980b) for measuring the performance of predicted discharges.

3.7 Summary

In this chapter, the three main components of a real-time flood forecasting model relevant to rainfall-runoff modelling have been discussed, namely the 'process model', the rainfall forecast and the real-time updating procedure. Not only are rainfall-runoff models the most convenient forecasting technique for the Onkaparinga River catchment, but they are also the most commonly used method in Australia. Some of the more unconventional forecasting methods which are operational in other countries were also highlighted. Non-linear rainfall-runoff techniques are the most commonly used, but difficulties exist in interacting them into real-time modes because they were developed primarily for design simulations. This is seen as perhaps the biggest limitation with these models at present.

The RORB runoff-routing model will be used later in this study for use on the Onkaparinga River catchment with the aim of adapting it to an automative, objective real-time mode. The RORB model has been extensively used on the Onkaparinga River catchment for other flood studies, therefore further developments to the model will be relatively simple.

The two areas of a real-time flood forecast which perhaps restrict the accuracy of a flood forecast, are the rainfall forecast technique and the real-time updating technique (procedure defining 'what to do next').

To obtain longer lead times and increased precision in the forecast, an accurate estimation of the future spatial distribution of rainfall in a catchment is required. This is perhaps the biggest barrier preventing the development of more accurate flood forecasts (Fuyi, 1993). The lack of accuracy of such techniques in Australia generally limits the performance of many of the models used. Rainfall forecasting and the estimation of the spatial distribution of rainfall were not explored further in any detail, nevertheless they are considered to be areas that require extensive research in themselves.

One of the biggest problems discussed in Section 3.5 was poor initial selection of model parameters which affects the future performance of a real-time model. These parameters are often derived based on previous events relating to various criteria including antecedent catchment characteristics, storm movement, meteorological conditions and other factors. One method to reduce the subjectivity of not only the initial selection/setting of model parameters, but also the continued adjustment of such parameters, is soil moisture levels. Although not an actual modelling technique, it was decided to investigate soil moisture levels further as a means of removing some of the subjectivity associated with real-time flood forecasting, and therefore improving the accuracy of the forecast. Antecedent catchment moisture conditions, although simple and relatively easy to calculate, are often neglected, therefore their value as a tool to improve the speed and efficiency of flood forecasting, is somewhat unknown. This will be discussed in more detail in Chapter 4.

Other tools have been used only to a minor degree for flood forecasting and have therefore not been addressed in any detail here. Some however, have considerable potential for improving the accuracy of real-time flood forecasting. For example, artificial intelligence (AI) has only recently been used for flood forecasting, especially the use of fuzzy reasoning and artificial neural networks (Zhu et al., 1993; Shiiba et al., 1993). Artificial neural networks offer a new approach to flood forecasting, which have not yet been fully investigated in Australia, nor overseas. The advantage of using artificial neural networks, is that they are closely related to stochastic models, in that they find relationships between historical data sets, rather than directly understanding the complete physical processes. Therefore artificial neural networks are seen as an attractive alternative to flood forecasting because they are indirectly an objective modelling procedure, potentially relying less on the forecaster's experience, judgement and understanding of the catchment processes. Srikanthan et al. (1994) highlighted artificial neural networks as one of five research areas that needs investigation in Australia, and will therefore be addressed later in this thesis.

Chapter 4

A Review of Antecedent Catchment Moisture Conditions and its Application to Flood Forecasting

4.1 Introduction

For many years, antecedent catchment conditions have been used as indicators for determining future hydrologic states within a catchment. Once antecedent catchment indicators have been determined, an attempt can be made to establish relationships between important parameters needed in producing an effective flood warning, in particular the warning time and reliability of flood forecasts (Dotson and Peters, 1990). Until recently, the importance of antecedent catchment indicators to flood forecasting at the commencement of a storm, particularly in Australia, appears to have been neglected, and is one of the main limitations to current Australian flood forecasting (Mein and O'Loughlin, 1991).

The Great Flood of 1993 in the Upper Mississippi Basin is an example that shows the importance of the estimation of antecedent catchment conditions, as this phenomena was due in part to an extended wet period in Autumn 1992 which saturated soils and raised stream levels to bankfull or flood levels. These exceptionally wet antecedent conditions combined with 8 weeks of excessive unseasonable rain in Summer 1993, caused massive flooding which became the largest floods ever seen in the United States (Hudlow, 1994).

The surface runoff potential observed from the extended rain period, assisted forecasters in predicting the extent of flooding before the peak flows occurred. Without this prior knowledge of catchment conditions, more property damage would have occurred, and more lives would have been lost.

In Australia, antecedent catchment conditions have not only been used to establish loss models, but have also been used to create empirical correlations for forecasting parameters such as peak river levels and peak travel times, from currently available and predicted rainfall (Giesemann, 1986; BoM, 1963b).

This chapter reviews the use of antecedent catchment moisture conditions for flood forecasting, with particular reference to soil moisture indices that can be easily calculated and applied to operational forecasting.

4.2 The Importance of Antecedent Catchment Moisture Conditions

Laurenson and Pilgrim (1963) stated that antecedent catchment wetness was perhaps the most important antecedent condition that affected storm loss rate, and speculated that a relationship probably exists between loss rate and antecedent wetness. Later, BoM (1963a), Cordery (1970a) and Yang and Laurenson (1985) again suggested the prior moisture condition of the catchment was a major influence in the degree of loss in a storm, and hence the magnitude of a flood event.

For dry catchments, most rainfall is lost as interception, initial infiltration, depression storage and evaporation. In wetter catchments, most of these capacities are satisfied and hence the losses from the gross rainfall are smaller. For a given rainfall amount, more surface runoff (hence a larger flood) would be expected from a 'wetter' catchment than from a 'drier' catchment. This is why determining the moisture condition throughout the whole catchment at the commencement of the storm is of such great importance. Catchment moisture assessment is therefore a fundamental requirement for efficient and speedy estimation of initial losses, and hence an indicator of the surface runoff potential of the catchment.

4.3 Measurement of Antecedent Catchment Moisture Conditions

For real-time flood forecasting, measurement of antecedent catchment moisture conditions can be divided into direct and non direct methods. Evapotranspiration is the most difficult and impractical antecedent catchment moisture parameter to measure. Direct measurements can be performed through actual soil moisture measurements and in theory provide accurate indications of moisture conditions. Probe measurements can be performed using an automated system, but considerable time, effort and money is generally required (BoM, 1963a). Not only do considerable problems result from instrumentation errors and measurement processing, but the vast spatial problem of providing measurements at multiple locations in a catchment and the consequent high cost means that such methods are impractical for real-time flood forecasting.

Indirect measurements have been successfully used by many researchers. A number of complicated and theoretical methods can be applied to measure soil moisture conditions including soil moisture budgeting methods based on infiltration, evaporation and evapotranspiration. Studies have shown that simpler soil moisture indices can be defined to indicate the catchment moisture conditions and perform equally well, if not better (Saxton and Lenz, 1967).

Perhaps the most comprehensive study into the use of soil moisture indices for flood forecasting in Australian conditions, was performed recently by Mein et al. (1995). This study compared the results of using four simple soil moisture indices for the estimation of initial loss. The following indices were used:

- Antecedent precipitation index (API);
- Pre-storm baseflow discharge (BF);
- Antecedent retention index (ARI), based on the same concept as the API except the runoff (mm) is subtracted from the precipitation; and
- Soil moisture deficit (SMD) at the start of the storm which uses a basic soil moisture accounting model and takes into account evaporation and other factors.

Loy et al. (1996) investigated three methods for estimating rainfall losses for use in real-time flood forecasting for catchments in South East Queensland. The three methods examined were; a conceptual soil moisture store relationship based on the Sacramento Model, antecedent precipitation index and antecedent mean daily flow.

BoM (1963a) also discussed the possibilities of using groundwater levels as a measurement of antecedent catchment moisture condition.

Although the relationships derived by Mein et al. (1995) only used between 8-12 storms, it was concluded that both the antecedent precipitation index and pre-storm baseflow discharge gave the most encouraging results. As a result these two indices were investigated in this study.

4.4 Antecedent Precipitation Index (API)

Antecedent precipitation index has been a primary tool for operational forecasting in many countries (WMO, 1994). Antecedent precipitation index is now the most frequently encountered soil moisture index (SMI) and was described by Nemec (1986) as the simplest soil moisture index to calculate.

Antecedent precipitation index is a measure of the soil moisture in the upper levels of the soil stratum. Its most obvious weakness is its inability to account for infiltration capacities of different soil types, and transpiration and interception of various vegetal covers (B.C. Tonkins & Associates, 1977).

The rate at which moisture is depleted from the soil stratum is assumed to occur logarithmically with time when no precipitation occurs (Linsley et al., 1949). The antecedent precipitation index t days after precipitation last occurred (API_t) is given by Equation 4.1.

$$API_t = API_0 . K^t \qquad (4.1)$$

where:

API_t = Reduced soil moisture value t days later (assumed at the end of the day);
API_0 = Assumed initial value for the antecedent precipitation index;
K = Recession factor;
t = Number of days since rainfall last occurred.

The recession factor (K) has a range normally between 0.85-0.95. Its value depends on the precipitation carry over effect and on how fast the soil moisture changes, which depends greatly on the season and on unusual climatic conditions. Its value however, is usually taken as 0.90 (United Nations, 1990).

For continuous antecedent precipitation index forecasting, the antecedent precipitation index is usually calculated on a daily basis (t=1), whereby Equation 4.1 is reduced to the following form:

$$API_1 = API_0 . K \qquad (4.2)$$

This means that the antecedent precipitation index for any day is equal to the previous day antecedent precipitation index multiplied by the recession factor (K). If rain occurs during a day, this value is added to the index value calculated from Equation 4.2 to compute the overall antecedent precipitation index value at the end of each day.

The antecedent precipitation index for a particular storm is generally taken at the beginning of the first day of rain (or the end of the day prior to the storm commencement). An example of an antecedent precipitation index recession curve is shown in Figure 4.1.

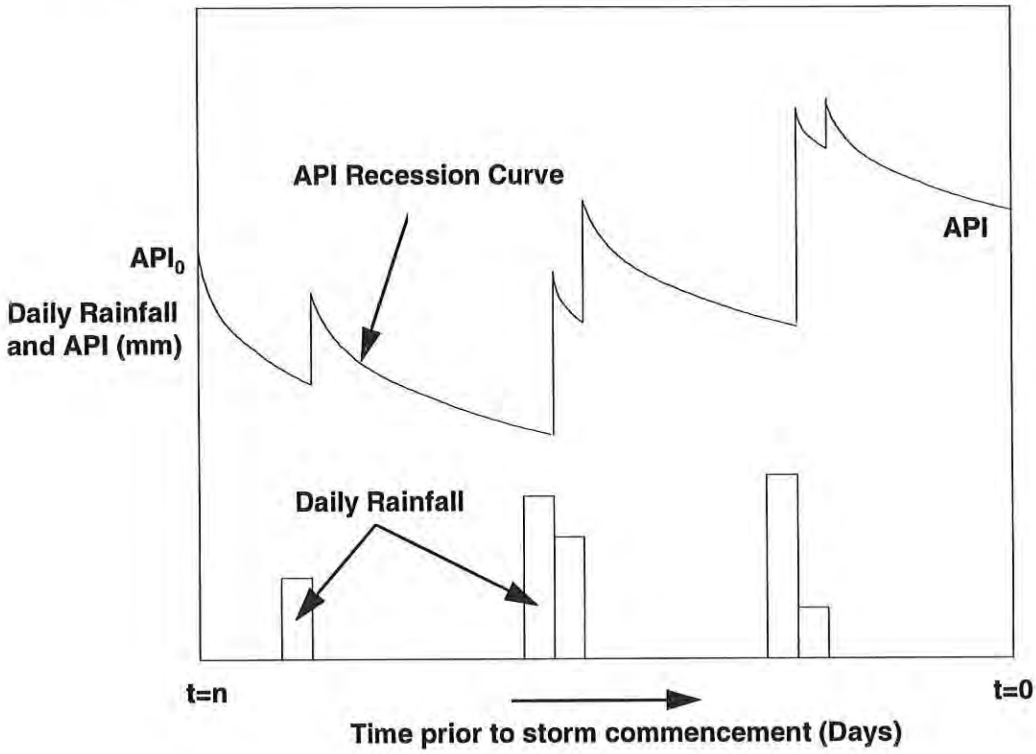


Figure 4.1 A hypothetical example of an antecedent precipitation index recession curve

Using Equations 4.1 and 4.2, antecedent precipitation index can be calculated at the commencement of a storm as a function of the antecedent n day rainfall (n days prior). Equation 4.3 calculates the antecedent precipitation index at the commencement of a storm by accumulating the chronological effects of past rainfall so that more weight is given to the most recent rainfall.

$$API = API_0 K^n + P_1 K^1 + P_2 K^2 + \ldots\ldots. + P_n K^n \quad (4.3)$$

where:

API	=	Antecedent precipitation index at the commencement of a storm
API_0	=	Initial assumed antecedent catchment index
P_i	=	Daily rainfall i days antecedent to event
n	=	Number of days prior to event

Although the API depends theoretically on an infinite antecedent length, a reasonable value can be obtained using an antecedent length of only a few weeks (Linsley et al., 1949).

Saxton and Lenz (1967) concluded that calculating the antecedent precipitation index (API) using less than about 1 month of rainfall data, was quite dependent on the initial antecedent precipitation index (API_0). For calculations using 2 or 3 months of rainfall data, the importance of API_0 was insignificant. Saxton and Lenz also observed that by calculating the antecedent precipitation index using precipitation from only the previous week, there was little correlation with soil moisture.

4.5 Pre-Storm Baseflow Discharge (BF)

Pre-storm baseflow discharge is the stream flow at the commencement of surface runoff, which is often a difficult part of the hydrograph to estimate (Laurenson and Pilgrim, 1963). At this point, surface runoff is assumed zero, which therefore reflects the moisture condition of the sub-surface, rather than the catchment wetness. B.C. Tonkin and Associates (1977) also defined the residual flow in a stream as a measure of water table depletion.

Cordery (1970a, p 2449) defined two criteria to separate initial loss from storm rainfall. One of which states that the, "*....initial loss must have been satisfied before surface runoff commenced.*".

Other problems also exist when estimating pre-storm baseflow. For example, Mein and O'Loughlin (1991) stated that in the middle of a rainy period, it may be difficult to accurately evaluate a 'correct' pre-storm baseflow. In many cases, stage height readings and hence stream flows are not accurately recorded until the rise of the river is quite well advanced, due to poor accuracy of the recording instruments at low flows (BoM, 1963a). For perennial streams, pre-storm baseflow has been shown to be a good index to the initial moisture conditions (Mein et al., 1995). For many studies, the commencement of the rising limb of the stream flow hydrograph has been a practical indicator for use in real-time flood forecasting (Chander and Shanker, 1984; Peddie and Ball, 1993) and was adopted throughout this study.

4.6 Estimation of Initial Loss

The next two sub-sections review some of the work carried out by other researchers into initial loss estimation using the two soil moisture indices that were to be investigated in this study.

4.6.1 Estimation of Initial Loss from Antecedent Precipitation Index

The Bureau of Meteorology (BoM, 1963a) reported on the development of a flood forecasting system for the Lower Macleay River, N.S.W and used API as an indicator for catchment storage deficit. Antecedent precipitation index was calculated based on the rainfall occurring in the 30 days prior to the event. The recession factor (K) used, was 0.9. The response of thirteen floods was estimated by the Unitgraph method. A linear relationship between antecedent precipitation index and initial loss was developed as shown in Figure 4.2. From Figure 4.2, four of the thirteen floods were neglected in deriving the relationship. The Bureau of Meteorology concluded that the reasons for these four points being inconsistent with the linear relationship, was because of an inaccurate rainfall representation. It was suggested that a large volume of surface runoff may result from certain parts of a catchment before the rainfall over the whole catchment exceeded the estimated initial loss.

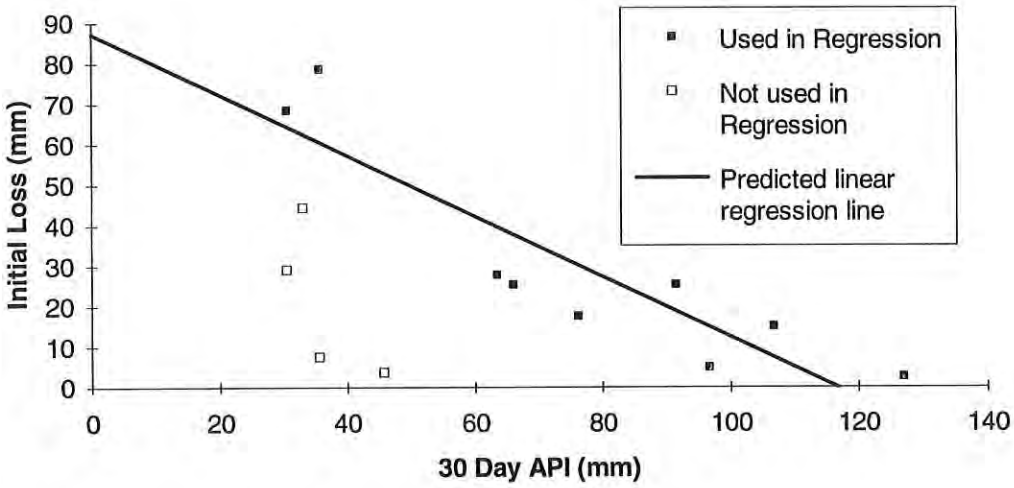


Figure 4.2 Initial loss versus 30 day API assuming linear relationship displaying points removed for regression (Source: BoM, 1963a)

A significant suggestion was made by Cordery (1970a) commenting on the work done by the Bureau of Meteorology (BoM, 1963a). It was suggested that if an exponential relationship was considered in Figure 4.2, then a straight line plot would be obtainable using all data points. Cordery (1970a and 1970b) provided a more thorough discussion of antecedent precipitation index. Exponential relationships were developed between the initial loss and antecedent precipitation index for 14 catchments of varying physical characteristics in N.S.W. Relationships were log-linear as shown in Equation 4.4.

$$IL = IL_{max} N^{API} \tag{4.4}$$

where:

IL	=	Estimated design initial loss (mm)
IL_{max}	=	Maximum initial loss value associated with that particular catchment (mm)
N	=	Constant, less than but approaching unity
API	=	Antecedent precipitation index

The main parameter to affect antecedent precipitation index was the recession factor (K), which was related to monthly evaporation, monthly temperature and to a sine curve function. The relationships between antecedent precipitation index and initial loss (using a constant K value) for these three adjustments were compared. As expected, the relationships were all slightly different. The K values were varied between 0.85 and 0.96. Correlation coefficients varied from 0.77 to 0.93. It was found that there was equally good correlation between initial loss and antecedent precipitation index when monthly evaporation or monthly temperature was used, however the sine curve did not perform as well. It was suggested that monthly evaporation would be the most logical indicator as it could be more adaptable elsewhere in other situations, however temperature would probably give adequate results if evaporation data was not available. An upper limit was observed for the initial loss for each catchment. For flood forecasting on N.S.W catchments it was recommended that a mean annual value of 0.92 be used for K. This meant that for these catchments, 0.98 should be adopted for winter months and 0.86 for summer months.

Cordery (1970a) also estimated the initial loss for ungauged catchments for a given K value, based on catchment area, mean annual rainfall and daily rainfall records.

B.C. Tonkin & Associates (1977) attempted to calculate an IL-API relationship based on 10 events for the Torrens River catchment upstream of the Gorge Weir. Only storms with an API greater than 18 mm were analysed. The curve of best fit was an exponential type relationship with an R^2 value of 0.31 indicating poor correlation.

Giesemann (1986) discussed the use of antecedent precipitation index for Melbourne's flood warning system. Polynomial relationships between antecedent precipitation index, mean catchment rainfall loss rate and duration were calculated at critical locations.

Bertoni et al. (1992) used a conceptual rainfall-runoff model (IPH-II) for real-time flood forecasting and a stochastic model to evaluate quantitative rainfall-runoff forecasts. Updating was performed using an optimisation technique of the time-area histogram (TAH) and an infiltration parameter. The model used seven parameters, six of which were fixed and one was optimised based on an objective function. The optimised value was maximum soil infiltration capacity (I_0). A relationship between antecedent precipitation index and I_0 was developed, and the initial value, I_0 was chosen based on the antecedent precipitation index.

Mein et al. (1995), in estimating initial losses from antecedent precipitation index, found that the most significant factor that affects the accuracy of initial loss estimation was probably caused by seasonal variations of the recession parameter K.

4.6.2 Estimation of Initial Loss from Pre-Storm Baseflow

BoM (1963a) used an area index method, which meant that once the stream flow volume had increased by 5000 cubic metres or more in 3 hours, it was assumed then that surface runoff had commenced, thus the rainfall up to that time was considered as initial loss. This was used as a more practical criterion for checking the estimated initial loss derived from the API methodology.

Mein et al. (1995) identified that pre-storm baseflow performed slightly better for predicting the initial loss than the antecedent precipitation index, having a superior correlation coefficient (R^2), which ranged from 0.55 to 0.90. The study identified the existence of seasonality between the relationship between sub-surface moisture and upper soil moisture store. In some catchments, no correlation could be observed between baseflow and initial loss, which was probably due to some unique geological condition of the catchment such as porous soil formations. Initial loss predictions for ephemeral catchments with 'cease to flow' characteristics were difficult to estimate.

4.6.3 Derivation of Empirical Relationships for Initial Loss Estimation

As mentioned in Section 4.6.1, Cordery (1970a and 1970b) established the relationships between initial loss and API to be of an exponential type. Mein et al. (1995) also described the relationships between initial loss and the other four soil moisture indices described in Section 4.3, to best fit an exponential relationship. However based on work by the Brisbane Bureau of Meteorology, Loy et al. (1996) successfully developed linear relationships between the initial loss and 30 day API, whereas the relationship with antecedent mean daily flow was deemed exponential. These differences create confusion as to the best relationship to adopt. Despite these discrepancies, it was the exponential relationship that was concentrated on throughout this study. The equations used to describe an exponential fit can be expressed as either:

$$IL = a_1 10^{(b_1 SMI)} \tag{4.5}$$

or

$$IL = a_2 (\log_{10} SMI) + b_2 \tag{4.6}$$

where:

SMI = Soil Moisture Index (either BF or API)
a_1, a_2, b_1, b_2 = Coefficients determined by regression analysis

Equation 4.5 represents a straight line relationship when plotting log IL against SMI, whereas Equation 4.6, represents a straight line relationship when IL is plotted against log SMI.

Exponential regression analysis was used to determine these straight line relationships, and for each relationship the corresponding coefficient of determination (R^2) was calculated. The coefficient of determination is a measure of how well the actual data points fit the calculated regression line and is computed by the following:

$$R^2 = \frac{\sum (Y_{est} - Y_{av})^2}{\sum (Y - Y_{av})^2} \tag{4.7}$$

where:

Y_{est}	=	Estimated value from regression
Y_{av}	=	Average of actual values
Y	=	Actual value

4.7 Other Empirical Relationships derived from Soil Moisture Indices

Many other relationships have been developed, apart from initial loss estimation for flood forecasting, that rely on soil moisture indices as a means of correlation for flood forecasting. Soil moisture indices may be used alone, or combined with other hydrologic variables. This section provides an overview of some of these relationships.

A coaxial correlation technique was developed by Linsley et al. (1949) and is still one of the best examples of forecasting flood volumes. However in its 'raw' form it is unable to incrementally calculate the hydrograph of a flood as it progresses. Coaxial correlation methods have been used in the U.S. to determine peak stage heights from rainfall in the catchment (Anderson, 1993). Typically, the API value at the start of the storm is related to the season, rainfall duration and rainfall depth. The storm rainfall is forecasted and then used to predict the peak stage height of an event.

BoM (1963a) established a predicted catchment rainfall-API-peak stage relationship for the Macleay River at Kempsey for 27 floods as shown in Figure 4.3. It was recommended that for future research, flood runoff volumes could be established in this manner. The limitation with these simple correlation techniques, is they do not predict the time of occurrence of the peak flow.

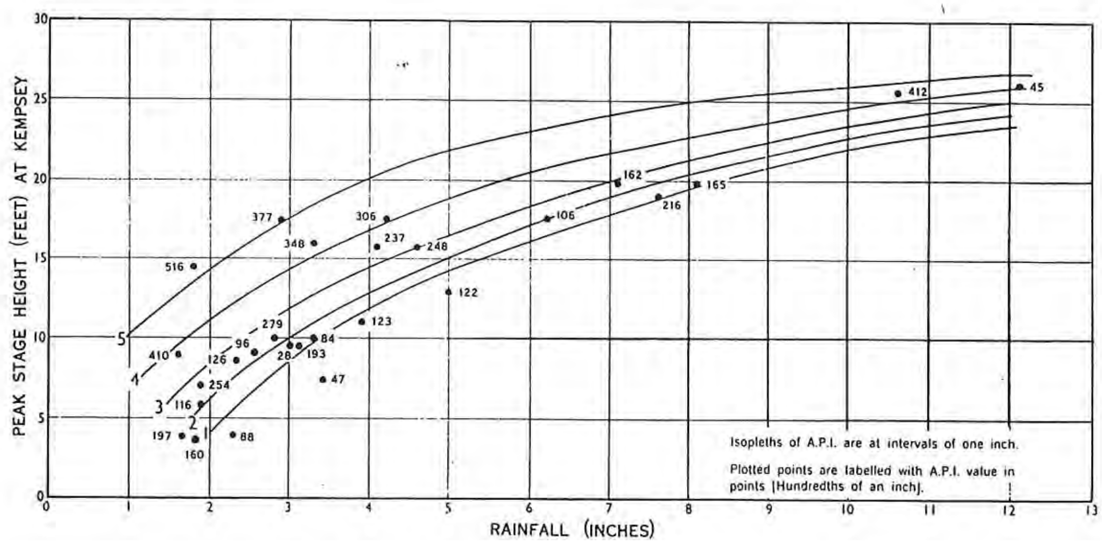


Figure 4.3 Catchment rainfall - API - peak stage relationship for the Macleay River at Kempsey (Source: BoM, 1963a)

A continuous API based hydrologic model was developed by Sittner et al. (1969). The model consists of four parts; a relationship for computing groundwater recession, a method to compute groundwater flow hydrograph as a function of the direct runoff hydrograph, an API type relationship which uses retention index (RI) and the unit hydrograph method. Groundwater and direct runoff are computed for 6 hour periods.

B.C. Tonkin & Associates (1977) correlated the average storm loss rate (ϕ-index) with the API using 17 events at Gorge Weir on the Torrens River. A good correlation was achieved yielding an R^2 of 0.90.

Giesemann (1986) established correlations between the mean catchment rainfall intensity, storm duration and peak discharge using API at various locations within the Melbourne metropolitan area. Again, no relationship was established to predict the timing of peak flows.

O'Loughlin (1986) linked the pre-storm baseflow with the proportion of storm runoff from a catchment. This finding was extended to flood forecasting by Mein and O'Loughlin (1991), and more recently by Mag and Mein (1994) who outlined an approach to predict the size and location of runoff producing areas of a catchment, as a function of the pre-storm baseflow using the TOPOG model. The volumetric runoff coefficient (percentage of the catchment area considered saturated) was plotted against pre-storm baseflow and lines of rainfall depth drawn through the data points. In this way, by using the cumulative rainfall that had occurred so far during a storm, and the pre-storm baseflow, the percentage of the catchment area saturated was estimated. This is unique, in that previously, forecasted rainfall was used in such relationships, whereas here the rainfall that had fallen up to the forecast time was used.

Crapper (1989) developed a loss model which related initial loss to the mean daily flow, 7 days antecedent to a storm event for a real-time reservoir routing procedure used in flood warning near Jackson Creek, Gisborne. A 7 day antecedent period was arbitrarily chosen. It was found that for mean daily flows greater than 9 ML/day, the initial loss was constant at about 20 mm.

Loy et al. (1996) recently attempted to estimate the continuing loss of a storm based on two methods primarily related to the contents of conceptual stores of the Sacramento Model for real-time forecasting for catchments in South East Queensland as discussed in Section 3.2. The two methods were; upper zone free water deficit relationships (UZFW) and upper zone tension water excess relationships (UZTW). The UZTW excess method performed marginally better, but despite both methods performing well in the majority of storms tested, a number of limitations were noted. In particular both methods were dependent on the accuracy of forecasted rainfall.

4.8 Summary

From the review presented in this chapter, it is evident that antecedent catchment moisture indicators have a wide application to flood forecasting. Antecedent catchment indicators have been calculated and used to establish empirical relationships between other important hydrologic parameters in order to improve the effectiveness of a flood forecast. Antecedent indicators have the ability to measure the 'wetness' of the catchment and the potential for runoff, and are therefore a critical factor in producing an accurate flood forecast.

The two soil moisture indices reviewed in this chapter namely antecedent precipitation index and pre-storm baseflow, are easy to calculate and do not require a large amount of information. Soil moisture indices such as antecedent precipitation index and pre-storm baseflow, have been widely used to estimate the initial loss at the commencement of a storm. They are now seen as having the potential to remove a great deal of the subjectivity associated with flood forecasting, but how much improvement from a quantitative point of view, is unknown. This is one aspect that needs further research and will be addressed in the remainder of this thesis with reference to the Onkaparinga River catchment.

The estimation of initial loss from soil moisture indices will be extensively addressed in Chapter 7. The soil moisture indices calculated and relationships developed to estimate initial loss will then be applied to improve forecasting techniques associated with artificial neural networks and the RORB rainfall-runoff model in later chapters.

Chapter 5

A Review of Artificial Neural Networks and their Application to Flood Forecasting

5.1 Introduction

Artificial neural networks (ANNs) are a computational tool modelled on the human brain and nervous system. The human neural system is a natural neural network (NNN) of which the cerebral cortex within the brain is one example.

The human brain receives and processes new information in what is called a learning process. This is important, because once the brain has learnt something new, it stores it, and can retrieve this information when it is required. As it receives more information, the brain continually learns, and as a consequence has the ability to retrieve more information. As more information is received, the learning process continues and can become more complex with the ability to process and retrieve learned materials. It is this learning process that makes the brain so powerful, and is what neural computing has been based on. The exact mechanisms by which the brain learns and retains information is extremely complex, even more so than that modelled by ANNs, meaning a description of this process is well beyond the scope of this study.

The attractive advantage of using artificial neural networks is that they have the potential to find complex mathematical relationships between many parameters. For example, the relationship between rainfall and runoff is non-linear and very complex to model, even with the 'best' conventional techniques, since it is dependent on many hydrological factors. It is for this reason that artificial neural networks are an encouraging alternative to rainfall-runoff modelling.

As a predictive tool, artificial neural networks have been used for many different situations in both non-engineering and engineering fields. Their use in forecasting economic trends, especially in the stock exchange, has been well documented. Appendix D details just one example that shows the consideration and publicity that ANNs have received lately. In addition a discussion of the applications of neural networks to civil engineering, has been made by Flood and Kartam (1994a and 1994b).

Daniell (1991) suggested that artificial neural networks should be used as an alternative model for water engineering related topics, in particular hydrological and environmental applications. More recently, artificial neural networks have been considered for such purposes (Daniell and Wundke, 1993; Fleming, 1994; Maier and Dandy, 1993; Maier and Dandy, 1995a; Maier and Dandy, 1996).

This chapter reviews firstly how ANNs operate and secondly how they have been used in flood prediction over the years. The aim of this chapter is not to present a definitive detailed review of ANNs, but rather to provide adequate information for an appreciation of their applicability in this study.

Three different uses of ANNs related to flood forecasting are described. Firstly, runoff prediction which describes the prediction of the whole storm runoff hydrograph at one time given the complete storm hyetograph, similar to a design situation. Secondly for flow prediction, which uses upstream flow only, similar to flood routing, to determine the downstream flood hydrograph and finally, using ANNs for real-time runoff prediction. An example of rainfall forecasting using ANNs is also presented.

5.2 Description of Natural Neural Networks

An example of a natural neural network is the human brain. The human brain consists of small units called neurons, of which there are billions. A neuron may be connected to thousands of other neurons. These neurons are linked by electrochemical pathways which link and transmit the information. A neuron receives output from the other neurons through an input path called a dendrite. If this signal is strong enough, the neuron produces an output which is transmitted through the output path, called axons.

The connection between an output path of one neuron and an input path of another neuron is called a synapse. The strength of this connection is adjusted as the brain learns new information. The memory mechanism of the brain is a combined result of the information processing in the neuron and the action of the synapses. The structure of a typical natural neural network is shown in Figure 5.1.

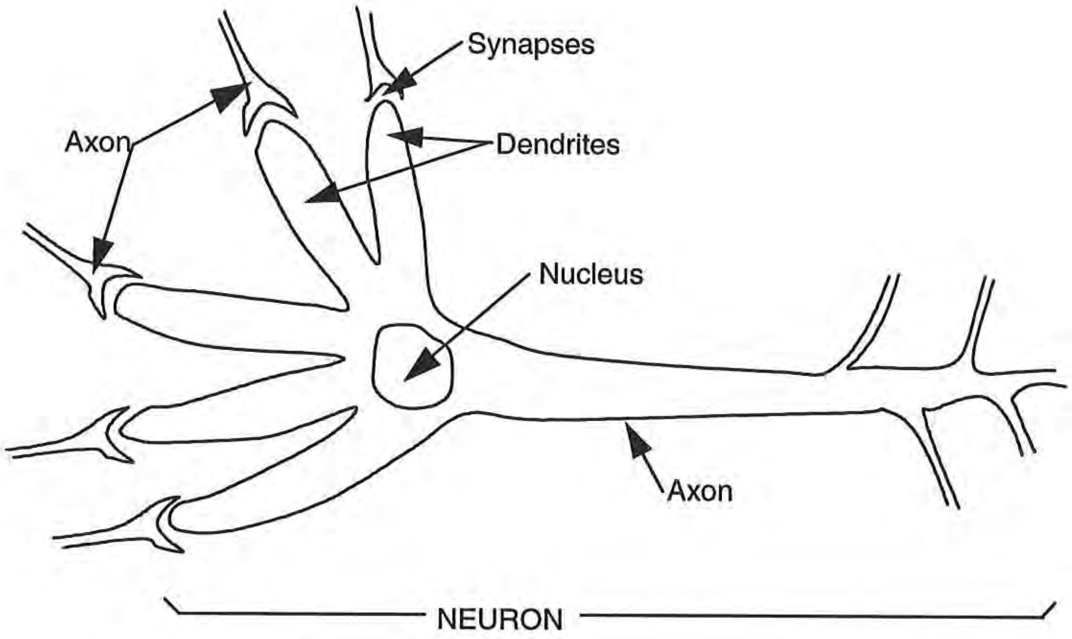


Figure 5.1 Typical structure of a neuron (Source: NeuralWare, Inc., 1991)

5.3 Description of Artificial Neural Networks

Artificial neural networks are similar in structure to natural neural networks but their computational capabilities are considerably less. The fundamental element of artificial neural networks is a processing element which performs in the same manner as the neuron. The processing element consists of input paths, output paths and weights. The main difference between the processing element and the neuron is that the processing element can only receive local information, meaning the input to a processing element is directly affected only by another processing element connected to its input path.

Each processing element is arranged in layers containing input, hidden and output layers. Information is presented to the network through the input layer and the response to this input is issued at the output layer. Between these layers are hidden layer(s) which allow for non-linearity in the presented information. Layers may be fully or partially interconnected with adjacent layers. The structure of a typical fully connected ANN is shown in Figure 5.2.

The input layer is where information is received and then transmitted to the output layer if the 'signal' is strong enough. The weights are analogous to the synapses of the brain and is how information is transferred between processing elements.

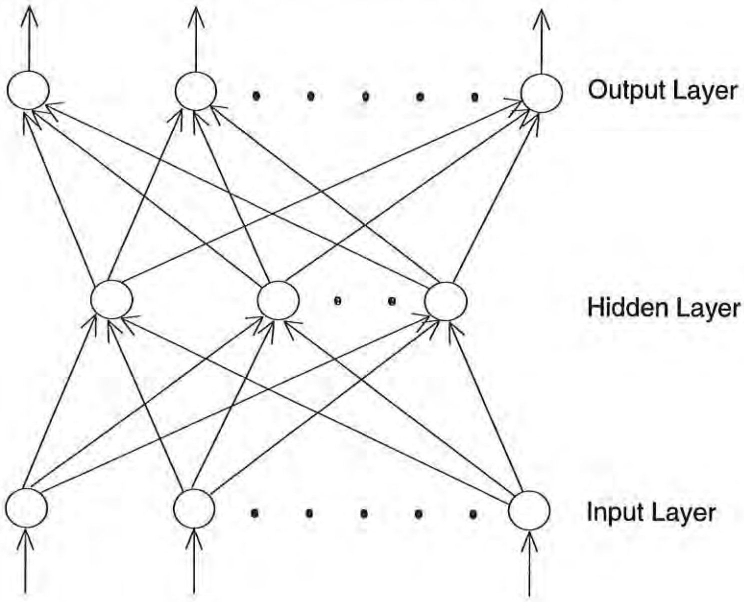
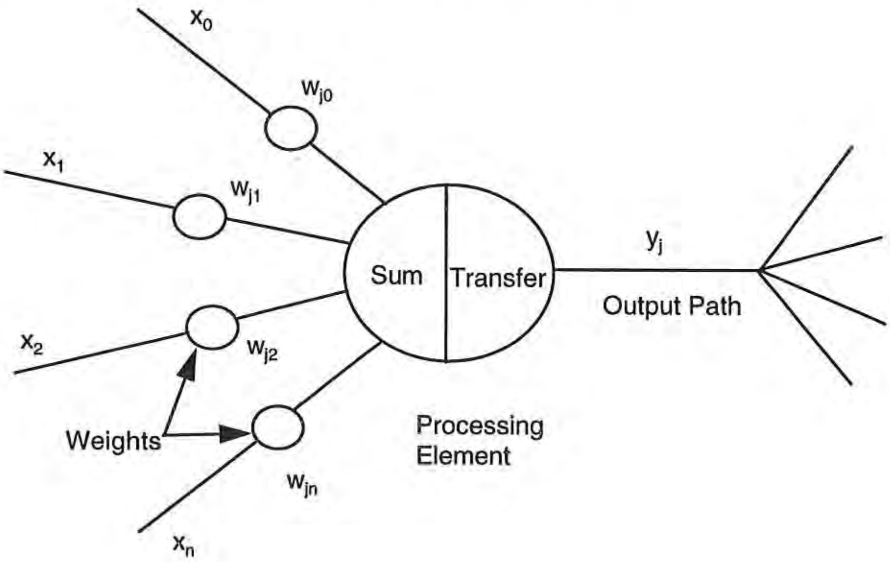


Figure 5.2 A typical fully connected ANN structure (Source: NeuralWare, Inc., 1991)

This process is shown for a particular node 'j' in Figure 5.3.



where:

n	= Number of nodes in previous layer
x_i	= Input from node i (i = 0, 1,...., n)
w_{ji}	= Connective weight between nodes i and j
I_j	= Activation level of node j
$f(\,)$	= Transfer function
y_j	= Output of node j
θ_j	= Threshold for node j

Figure 5.3 Illustration of a processing element (Source: NeuralWare, Inc., 1991)

The sum and transfer functions determine whether the signal is 'strong' enough, and what the output will be. The summation function is the sum of all inputs from previous nodes, multiplied by their connective weights, plus an additional threshold value for that particular node as shown in Equation 5.1.

$$I_j = \sum_i w_{ji} x_i + \theta_i \tag{5.1}$$

Threshold (θ) is similar to a processing element of constant output, and is used to scale the input into a node. It simply adds a value to the already summed input into a processing element.

The transfer function is the factor which determines how much, if any, of this signal is transmitted to the output path, as shown by Equation 5.2. Many transfer functions can be used including threshold and continuous functions (sigmoid and hyperbolic tangent).

$$y_j = f(I_j) \tag{5.2}$$

At each node, processing is performed independently to processing at other nodes, however the output from each node affects the remainder of the network because the output of each node becomes the input to the other nodes.

The connection strengths between nodes are adjusted by the connective weights so that the artificial neural network continually learns new information. The weights modify the input signal by amplifying, attenuating or changing the sign of the input signal. They represent the strength of the internodal connections and are localised to each node and stored in memory. When the learning phase is complete, the network is ready to test data.

5.3.1 Learning Procedures

Learning is the mechanism by which the weights are modified in a response to the training data presented at the input path, and is dependent on the learning rule defined at the output path. Numerous learning rules are available including the generalised delta rule and delta rule. These learning rules will be briefly discussed in this section but are described in more detail by Maier (1995).

Supervised learning is when the outputs and inputs are fed into the network. The network compares the predicted output with the desired output. Unsupervised learning is when no output is fed into the network and therefore no comparisons are made during the learning process. The delta rule is a supervised learning procedure for networks without hidden nodes and the generalised delta rule is used for adjusting weights in multi-layer networks.

The aim of learning is to establish a combined set of weights which minimises the global mean square error between the actual output and the corresponding desired output. The mean square error function at a time t, E(t) can be given by Equation 5.3.

$$E(t) = \frac{1}{2}\sum (y_j(t) - d_j(t))^2 \tag{5.3}$$

where:

$y_j(t)$ = Actual output at time t
$d_j(t)$ = Desired output at time t

A different error is calculated for different weight combinations, producing a typical mean square error surface as shown in Figure 5.4.

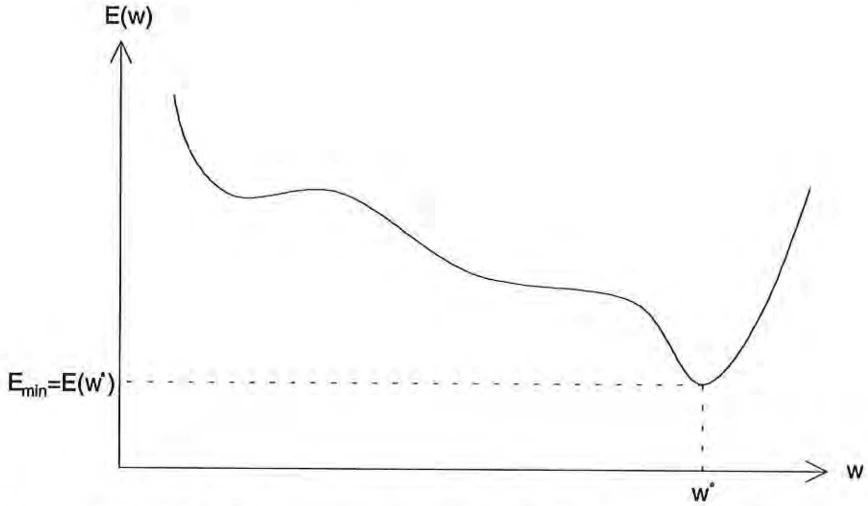


Figure 5.4 A typical global error surface for different weight combinations during the training of an artificial neural network

Having initially assigned arbitrary weight values, the weights become updated after each input-output pair is presented to the network. The standard backpropagation updating equation is shown in Equation 5.4.

$$w_{ji}(t+1) = w_{ji}(t) + \Delta w_{ji} \tag{5.4}$$

where:

$w_{ji}(t+1)$ = Updated weight at time (t+1)
$w_{ji}(t)$ = Weight at time t
Δw_{ji} = Weight increment (change)

Maier (1995) explains a variety of methods for calculating the weight increment Δw_{ji}. Gradient descent learning is the most commonly used method and causes the weights to be altered in the direction of the steepest descent down the error surface until the minimum mean square error is found (E_{min}). The weight change (Δw_{ji}) is given as:

$$\Delta w_{ji} = \eta \frac{\partial E}{\partial w} \tag{5.5}$$

where:

η = Learning rate, which determines the step size down the surface

$\frac{\partial E}{\partial w}$ = Gradient of error surface

The standard learning rule is often referred to as the delta rule (or generalised delta rule). Using the cumulative delta rule, the weights are accumulated over several training presentations and the weights are updated at once. Compared with the delta rule, the cumulative delta rule is less sensitive to the order of the training set, however many more computations may need to be performed before a minimum global mean square error occurs.

During learning the error function will never reduce to exactly zero because exact input-output 'mappings' are not possible, therefore a convergence limit can be set to stop learning once a certain criteria is met. Commonly, the root mean square error (RMSE) between the predicted and actual outputs is used to determine the stopping point during training.

5.3.2 Network Architecture

The design of a neural network is commonly referred to as its architecture and is dependent on many different criteria. Maier (1995) discussed the main factors that distinguish between different network architecture's, and include:

- Number of layers;
- Number of processing elements (nodes) per layer;
- Type of connection between processing elements:
  - Feed forward connections;
  - Feedback connections;
  - Lateral connections; and
- Degree of connectivity between processing elements.

Maier (1995) described six structurally related groups which have been developed to classify neural networks. The most commonly used network type is a multi-layer feed forward network. Feed forward networks use supervised learning and consist of data flow from the input layer to the output layer only. No information is allowed to be sent backwards. There are many different types of multi-layer feed forward networks, and are differentiated by the way that they learn. The backpropagation network is the most widely used network.

5.4 Developing a Back-Propagation Neural Network Model

5.4.1 Introduction

Backpropagation networks are the most widely used network today (Maier, 1995). They consist of at least three layers; an input layer, hidden layer and an output layer. Each layer is usually fully connected to the succeeding layer (NeuralWare, Inc., 1991).

During training, the data is backpropagated through the network. Once testing is performed, the weights are frozen and the network becomes feed forward only.

Backpropagation networks use continuous transfer functions to produce continuous output at each processing element as a function of the total input. The most commonly used transfer function is the sigmoid function. The sigmoid function is an asymptotic function for infinitely large and small activation levels. A more detailed discussion of the sigmoid function can be found in Maier (1995).

5.4.2 Inputs and Outputs

This is perhaps the most important part of neural network modelling (Maier, 1995). The ability of a neural network to predict is related to the quality and quantity of the training data that it is given.

A network must be given sufficient training data in which to find relationships between the input and output variables. Artificial neural networks perform better as an interpolation tool than an extrapolation tool (Zhu et al., 1994), meaning that if a test set falls outside the training set, performance can be poor. Ideally the training set should contain input and output examples from the whole spectrum of possibilities. However, the size of the network should also be kept to a minimum to decrease processing time. This is a particularly important aspect when used as a flood forecasting tool.

Given a large sample of training data, optimisation can be carried out to determine the best set of input parameters for the desired output. Sensitivity of the input data can be carried out to determine these optimum parameters (Maier and Dandy, 1995a).

5.4.3 Network Performance Enhancement

Two factors should be addressed to assess the performance of the neural network; learning speed and generalisation ability (Maier, 1995). Both of these factors are inter-related. Generalisation is the network's ability to map the inputs with the associated outputs, which is directly related to the amount of data needed to train the network. It is widely agreed that the more information used in training, the better the results, however in many cases this may cause an increase in the training time.

In order to improve network performance, a number of factors need to be optimised. Apart from the actual input and output parameters, overall network design is also important. This involves optimisation of:

- Network geometry;
- Initial weight distribution; and
- Learning rate.

Maier (1995) outlines guidelines for network geometry relating to the number of hidden layers and processing elements within each layer. However, Maier and Dandy (1995b) found that in some cases, the number of hidden layer nodes had little influence on the overall network performance.

Adjustment of other network parameters can also be used to increase network performance including momentum and epoch size. Maier and Dandy (1995b) have recently found that changing the network parameters affects the training speed, but has little effect on the performance of the model.

5.5 Rainfall Prediction

5.5.1 French et al. (1992)

French et al. (1992) used ANNs to produce 1 hour lead time rainfall forecasts using a simulated rainfall event generator. The simulator generated 75 independent events, 50 were used for training and the remaining 25 were used for testing.

Events were 6 hours long with 15 minute resolution, creating 24 data fields per storm. Five different hidden node configurations were used. The training sets consisted of rainfall fields where the input was the current time step rainfall field, and the output was the 1 hour ahead rainfall field. Each rainfall field consisted of 625 points (i.e. 625 input nodes and 625 output nodes).

The performance of the network was compared with both persistence and nowcasting. The accuracy was comparable or slightly better than these methods. Persistence uses the current time intensity field as the 1 hour ahead forecast (assumes constant intensity). Nowcasting uses the two latest fields to determine the velocity of the event and extrapolates in time to produce the field intensity 1 hour ahead.

It was found that the network performed equally well on all of the 5 hidden node configurations, given enough training iterations were provided. It was suggested that a balance must be achieved between short training time, and the performance gained from the increased complexity associated with more hidden nodes.

Finally, it was mentioned that more studies are needed using simulated rainfall and real rainfall data before conclusive results can be made.

5.6 Runoff Prediction

5.6.1 Hjelmfelt and Wang (1993a); Hjelmfelt and Wang (1993b)

Hjelmfelt and Wang (1993a) and Hjelmfelt and Wang (1993b) developed a simple interconnected artificial neural network to represent the structure of the unit hydrograph. The weights for the connections to the output layer of the network were considered equivalent to the ordinates of the unit hydrograph. Training and testing was performed on a small catchment in Missouri, U.S.A. The storm database contained 24 storms of which 8 were used for training, leaving 16 for testing. A single rainfall station was used as input. The average RMSE for the computed hydrographs was 57.7 and a comparison between the observed and computed peak discharges produced an R^2 of 0.97. It was concluded that there is a basis in hydrologic fundamentals for the application of artificial neural networks to the rainfall-runoff process.

5.6.2 Foley and Brown (1993)

Foley and Brown (1993) used a fully connected backpropagation ANN for rainfall-runoff modelling on a small rural catchment in the Mt Lofty Ranges, east of Adelaide. Fifty-two events were used for training, however all were small with little hydrologic variation. Rainfall was used as input and the resultant outflow of the event was predicted. Extra input parameters were also included such as the time of the year in which the event occurred and the amount of rain that had fallen in that month, and showed encouraging results. When a rainfall-runoff time lag was included, the results however were not as encouraging.

5.7 Flow Prediction

5.7.1 Lachtermacher and Fuller (1994)

Lachtermacher and Fuller (1994) used ANNs for univariate flow predictions for the Gota River, Canada. Two types of predictions were performed, the one step ahead and iterated multi-step ahead. The neural network models gave better overall performance than other traditional time series models, including ARMA and Markov models, however the differences in performance were very small.

Some important observations were made regarding the performance of the neural network models. In particular, it was concluded that the correct setting of the number of input and hidden nodes were important to the model's performance. For the one step ahead predictions, performance was dependent on the correct number of input nodes rather than the number of hidden nodes. For the multi step ahead predictions, performance was improved by increasing the number of hidden and input nodes. Lachtermacher and Fuller, also discussed multi-step ahead prediction techniques using several nodes in the output layer, with each node representing a step to be forecasted. It was mentioned however, that generalisation problems may occur because the network may have difficulties in mapping the inputs to the output nodes.

5.7.2 Karunanithi et al. (1994)

Karunanithi et al. (1994) used neural networks for flow prediction at an ungauged location on the Huron River, Michigan using flow values from one upstream, one downstream and one tributary. Both daily and five-day averages were predicted. The neural network model was compared with a two-station power model. The neural network model was more accurate and less susceptible to noisy data. It was concluded that neural networks are more flexible, and require less understanding of the flow process than conventional modelling procedures. It was also concluded that neural network modelling for this application needs further research.

5.8 Real-Time Runoff Prediction

5.8.1 Halff and Halff (1993)

Halff and Halff (1993) developed a backpropagation neural network to predict a normalised storm hydrograph given only the storm hyetographs as input. A single pluviograph was used to predict the outflow of the basin. Their study achieved RMSEs of 0.36 cubic feet per second and less.

The network architecture is shown in Figure 5.5. To predict the normalised flow Q(t) at time t, 25 rainfall inputs were used comprising $\chi(t)$, $\chi(t-\tau)$, $\chi(t-2\tau)$.......$\chi(t-24\tau)$ where τ was set to 5 minutes. This resulted in the previous 120 minutes (2 hours) of rainfall being used to generate the hydrograph. The network was fully connected with 5 hidden nodes in a single hidden layer.

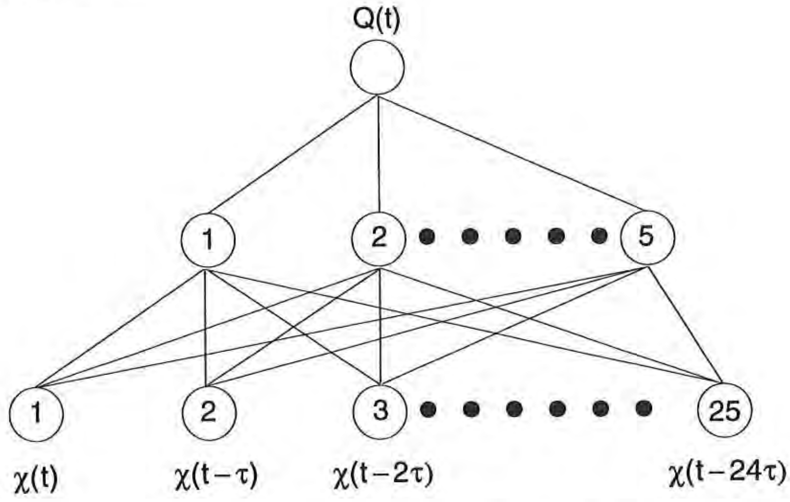


Figure 5.5 Network structure adopted by Halff and Halff (1993) for single outflow prediction Q(t)

Five storms were used for analysis. Each of the 5 storms were tested in turn using a training set consisting of the other 4 storms.

Halff and Halff (1993) concluded that this method of runoff prediction had potential. For future studies they recommended :

- Better normalisation techniques to take into account of the many zeros in the hyetograph;
- An improved time-delay model for rainfall into runoff; and
- Use the previous runoff as a measure to predict future runoff.

5.8.2 Fujita and Zhu (1992)

Fujita and Zhu (1992) began the development of perhaps the most extensive ANN model for real-time flood forecasting to date. The main aim of this research was initially to compare the results with fuzzy inference methods developed by the same authors. Since then, developments have continually been made by the same authors, and the results are well documented by Zhu and Fujita (1993) and Zhu et al. (1994).

Predictions 1, 2 and 3 hours ahead were made at Butternut Creek, New York. Predictions used the currently available runoff data.

Five flood events were used in the analysis. Two storms were used solely for training and the three remaining storms were tested in turn. All of the storms had similar hydrologic characteristics and it was shown that ANNs did not perform well during extrapolation.

The runoff system adopted is expressed in Equation 5.6 with the hourly incremental change in the hydrograph being forecasted. The future basin outflow Q(t) was expressed as a function of the previous outflow and previous rainfall inputs.

$$\Delta Q(t) = f\{R(t-1),\ldots,R(t-m),\Delta Q(t-1),\ldots.,\Delta Q(t-n)\} \tag{5.6}$$

where:

$\Delta Q(t) = Q(t) - Q(t-1)$
m, n = lag parameters dependent on the hydrological characteristics of the basin.

For Butternut Creek the chosen system equation was:

$$\Delta Q(t) = f\{R(t-3),R(t-4),\Delta Q(t-1)\} \tag{5.7}$$

The neural network structure was partially interconnected because the rainfall and runoff components of the input were considered distinct. The primary component of the neural network was its ability to 'map' the rainfall (input) to the basin outflow (output). The network structure is shown in Figure 5.6.

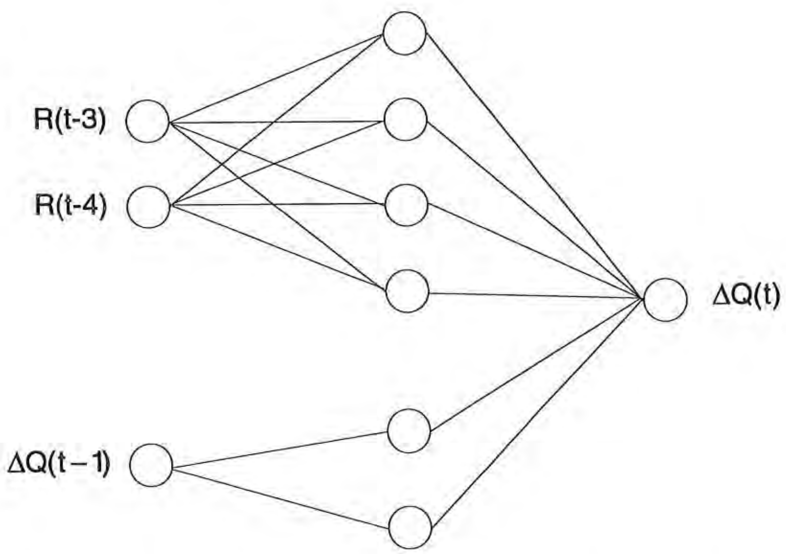


Figure 5.6 Partially interconnected network adopted by Fujita and Zhu (1992)

The secondary component (but still a very important aspect) was to use the change in the most recent flow as input. The purpose of using previous flow change as a model input, was to 'update' the forecasted hydrograph in real-time. This presented to the model what had just occurred on the actual hydrograph to assist in providing a better indication of the next hydrograph increment. To help explain this, an example is shown in Figure 5.7 for a 5 hour forecast on the rising limb for a typical hydrograph, for two scenarios both with and without correction based on the previously known part of the hydrograph.

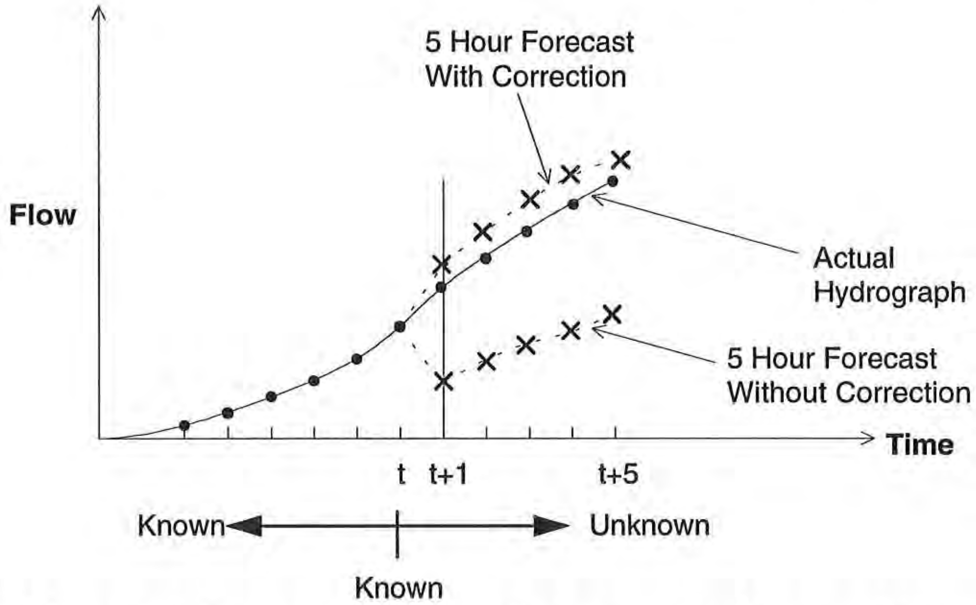


Figure 5.7 Typical representation of how the 'previous flow' inputs assist in updating the hydrograph at each forecast time step

The forecast with correction shows the next forecasted value Q(t+1) with the same increasing trend as the previously known portion of the hydrograph. Without this correction, the next forecasted value Q(t+1) does not follow the same increasing trend as the recently known portion of the hydrograph.

This procedure can be explained using the following notation where " ' " is the value being 'forecasted' and values without notation are known.

The network used a single output node in the output layer. An iterated multi-step ahead prediction was used in a real-time mode for predictions 1, 2 and 3 hours in advance.

At time t, Q(t) was assumed unknown whilst Q(t-1) was known. At each time t, the next incremental change of the hydrograph ΔQ'(t+1) was forecasted, and whilst still at time t, the next 2 values of the hydrograph were predicted {ΔQ'(t+2), ΔQ'(t+3)}. Therefore, the next forecast was dependent on the last forecast made.

When all the values are known, the system equation at time (t+1) is shown in Equation 5.8.

$$\Delta Q'(t+1) = f\{R(t-2), R(t-3), \Delta Q'(t)\} \quad (5.8)$$

and similarly at times (t+2), (t+3) and (t+4) respectively;

$$\Delta Q'(t+2) = f\{R(t-1), R(t-2), \Delta Q'(t+1)\} \quad (5.9)$$

$$\Delta Q'(t+3) = f\{R(t), R(t-1), \Delta Q'(t+2)\} \quad (5.10)$$

$$\Delta Q'(t+4) = f\{R(t+1), R(t), \Delta Q'(t+3)\} \quad (5.11)$$

Table 5.1 summarises this process and shows which of the input variables are known and which used forecasted values at each forecast time. From Table 5.1, a 4 hour lead time as shown in Equation 5.11 could not be performed because there was no means of computing the future rainfall component R(t+1). Due to the relationship developed which linked previous flows and rainfall to future flows, the model was unable to forecast in excess of 3 hours. The R(t+1) term can be calculated only if rainfall is forecasted. This is perhaps the biggest weakness with this technique. In order to achieve longer lead-times, future rainfall must be provided. Zhu and Fujita (1994a) have recently attempted to utilise QPF for longer lead time runoff forecasts with some success.

Table 5.1 Summary of forecast process at time t, developed by Fujita and Zhu (1992)

Output	Lead Time	Input		
		1	2	3
$\Delta Q'(t+1)$ Unknown	1 hour	R(t-2) Known	R(t-3) Known	$\Delta Q'(t)$ Known
$\Delta Q'(t+2)$ Unknown	2 hour	R(t-1) Known	R(t-2) Known	$\Delta Q'(t+1)$ Forecasted
$\Delta Q'(t+3)$ Unknown	3 hour	R(t) Known	R(t-1) Known	$\Delta Q'(t+2)$ Forecasted
$\Delta Q'(t+4)$ Unknown	4 hour	R(t+1) Unknown	R(t) Known	$\Delta Q'(t+3)$ Forecasted

In general, the results of this study were encouraging. However as the lead time increased, the peak was overestimated. When $\Delta Q(t)$ was positive it was unlikely (assuming the neural network 'thinks' the same way as the human brain) that $\Delta' Q(t+1)$ would be 'negative enough' to go from a positive increment to a negative increment, hence there is a general tendency for positive changes as against negative changes.

Zhu and Fujita (1994b) also used a model that included the currently available hourly information of the test storm during training, as well as information from the same hydrographs of two other training events as done by Fujita and Zhu (1992). This was an adaptive forecasting environment where the internal parameters of the ANN were updated each time new flood information was received. In theory, the inclusion of the currently available storm data, should have provided superior results to that of Fujita and Zhu (1992), however the opposite result was observed, with two reasons being suggested by the authors. Firstly, by using the currently available storm data, the amount of training data increased, therefore to save calculation time, the number of training iterations was decreased. This may suggest that the training period was not long enough. Secondly, it was also suggested that the training data set was somehow biased using information from the present event. If the current test event was in an increasing stage of the hydrograph, then the forecast may be biased towards this part of the hydrograph.

5.8.3 Shitawara (1992)

Shitawara (1992) as cited by Shiiba et al. (1993), used two different neural network models for the rainfall-runoff process each consisting of 3 layers: 1 input, 1 hidden and 1 output. Rainfall and outflow up to, and including that at time t, was assumed known. The network was fully connected and is shown in Figure 5.8.

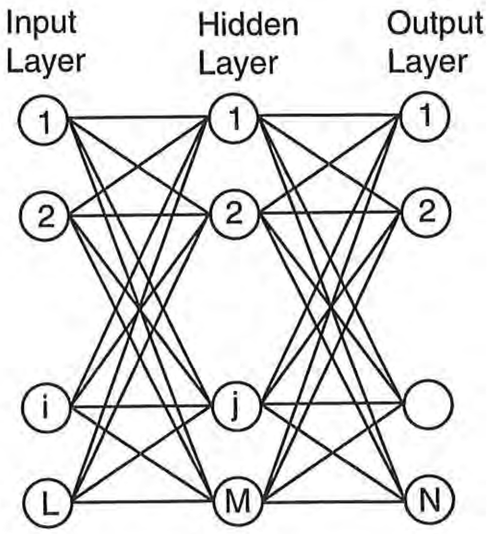


Figure 5.8 ANN model adopted by Shitawara (1992) where L, M and N are the number of nodes in the input, hidden and output layer respectively

Two models were considered:

Model 1 : (L, M, N) = (24,12,1); and
Model 2 : (L, M, N) = (30,15,1).

The details of the input and hidden layers are:

Model 1 : $\{r_i(t), \sum_{j=0}^{1} r_i(t-j), \sum_{j=0}^{2} r_i(t-j), \ldots, \sum_{j=0}^{5} r_i(t-j)\}$

where:

i=1, 2, 3, 4 (i.e. 4 rain gauges in the catchment); and

Model 2: Model 1 + $\{Q(t), Q(t-1), \ldots Q(t-5)\}$

Model 1 had 6 rainfall inputs from 4 stations within each training set. The rainfall inputs are cumulative previous rainfalls from the preceding 6 hours, giving a total of 24 inputs. Model 2 had the same general structure but included the previous 6 known outputs as model inputs for the next forecast. Both models had similar forecasting ability.

5.8.4 Won et al. (1993)

A less intensive study was carried out by Won et al. (1993) who applied artificial neural networks to forecasting daily and hourly stream flows in Pyung Chang River, Korea using one step ahead predictions with rainfall as input. A fully connected backpropagation network was successfully developed using the generalised delta rule and a sigmoid transfer function. However it was concluded that further work was need to establish a more efficient approach to hydrologic runoff forecasting.

5.9 Summary

The main aim of this chapter was to focus firstly on the powerful computational nature of artificial neural networks and how they operate. The second objective was to investigate their application to flood forecasting, in particular to real-time flood forecasting, highlighting their potential for removing some of the subjectivity associated with flood forecasting, therefore improving the accuracy of the forecast. A number of significant findings and consequent solutions have been established which require more analysis. The findings and results from the literature will be used to determine how such models should be set up for flood forecasting on the Onkaparinga River in Chapters 8 and 9.

The research by Halff and Halff (1993), Fujita and Zhu (1992) and Shitawara (1992) were all slightly different in terms of what they were trying to achieve in real-time flood forecasting. They used different input variables, network parameters, network architecture and output and most importantly, all concluded that more research is needed. Fully and partially interconnected networks have been used to link the input and hidden layers. Both Fujita and Zhu, and Shitawara used previous flow and rainfall as input to their models, but used partial and fully connected networks respectively. Despite the vast differences between these two models, both achieved good results. It was encouraging to observe that the artificial neural networks all performed well, considering that in many of the cases, only a limited amount of data was used. This would therefore substantiate the idea that ANNs do not require a full understanding and knowledge of the complete hydrologic process in a catchment.

So far, all researchers have analysed different input and output variables. This may lead to confusion as to which variables are best suited to real-time forecasting. Why some of the input variables were chosen, and why other combinations were ignored (if in fact they were actually ignored) did not appear to be all that logical. Fujita and Zhu (1992) used changes in flows $\Delta Q(t)$ and total rain fallen per hour, whereas Shitawara (1992) used actual flows $Q(t)$ and cumulative rain fallen per hour. Halff and Halff (1993) used actual flows and total rainfall/hour.

All models have used a single pluviograph to represent the catchment rainfall. Only Shitawara (1992) attempted to include spatial effects by using a summation of four pluviographs. A weighted catchment representation would appear in theory to give better results than using only a single pluviograph. An operational Theissen-type method would use multiple rainfall stations, therefore if one or more of the stations became in-operational during an event, the procedure could still operate, however when only a single pluviograph is used, the forecasting system becomes obsolete. This is an aspect which needs to be researched further and will be addressed in later chapters.

Two types of predictions were performed; one step ahead and a multi-step ahead predictions, however the forecast lead time was essentially limited to 1 hour. The only weakness with this is that most trained forecasters would be capable of predicting the next hour of the hydrograph knowing the previous portion of the hydrograph, with some degree of accuracy. The one-step ahead forecast predicts the next value in the hydrograph, such that each new forecasted value was independent and uncorrelated from the previous forecasted value(s). The multi-step ahead prediction adopted by Fujita and Zhu (1992) was an iterated type with each forecast dependent on the previous predictions. No researchers have tried using a neural network to forecast a number of hours at the one time with a number of nodes in the output layer. This will therefore be a main focus in using artificial neural networks for real-time forecasting in the remainder of this thesis.

No studies have investigated the sensitivity of the performance of the ANN to variations in the quantity and quality of the training storms. Fujita and Zhu (1992) used only a few storms for training, which had very similar hydrological characteristics. It is perhaps this reason why such encouraging results were achieved, however had extreme events with considerable variation been used, much different results may have been achieved. This factor will be examined at a later opportunity in this study. Ideally, a test storm should be trained on other storms with similar hydrological characteristics. However, in a real situation at the commencement of a storm, catchment response is difficult to predict and knowledge of the resultant hydrograph characteristics are unknown. No studies are known to have used antecedent catchment conditions such as antecedent precipitation index, to assist in forecasting using artificial neural networks and for selecting storms suitable for the training procedure. The addition of antecedent precipitation index to the artificial neural network model is also included in the analysis for flood forecasting in the preceding chapters.

Chapter 8 will analyse the simulation of the complete hydrograph using an artificial neural network similar to a design situation. The results of Chapter 8 will then be used to help set up the real-time forecasting model, which will be considered in detail in Chapter 9.

Chapter 6

Hydrometeorology of the Onkaparinga River Catchment

6.1 Catchment Description

The Onkaparinga River commences about 30 km east of Adelaide in the Mount Lofty Ranges near Mount Torrens as shown in Figure 6.1. It enters the sea at Port Noarlunga after meandering through the southern suburbs of Adelaide in a south-westerly direction.

The total area of the Onkaparinga River catchment is 557 km^2. The catchment contains two man-made storages; the larger one being the Mount Bold Reservoir which is used to supply water to the Adelaide region, and the smaller one being the Clarendon Weir which is diverted to Happy Valley Reservoir. The catchment area to Mount Bold Reservoir is 388 km^2. For this study only the catchment upstream of the Mount Bold Reservoir was considered and is shown in Figure 6.2.

Within this part of the catchment, lie a number of urbanised areas including Stirling, Bridgewater, Aldgate and Hahndorf, essentially in the Aldgate Creek catchment. Despite these small urbanised locations, the catchment is essentially rural. The most dominant form of agriculture would be livestock grazing, however horticulture also plays an important role. A large portion of native vegetation still remains within the catchment, essentially on steep, mostly inaccessible regions, especially around the Mount Bold Reservoir. Due to the high degree of land use, many farm dams have been constructed. Although small in size, the vast number of farm dams appear to have altered the hydrological characteristics of the catchment and may account for large initial losses (Hill, 1993).

Flooding in the Onkaparinga River catchment has occurred frequently over the years, however the construction of the Mount Bold Reservoir has reduced the severity of damage in the downstream regions. Recently, the worst flooding has occurred upstream of the Mount Bold Reservoir in the smaller tributaries of the Onkaparinga River, an example being the extreme event occurring on the 30/8/92.

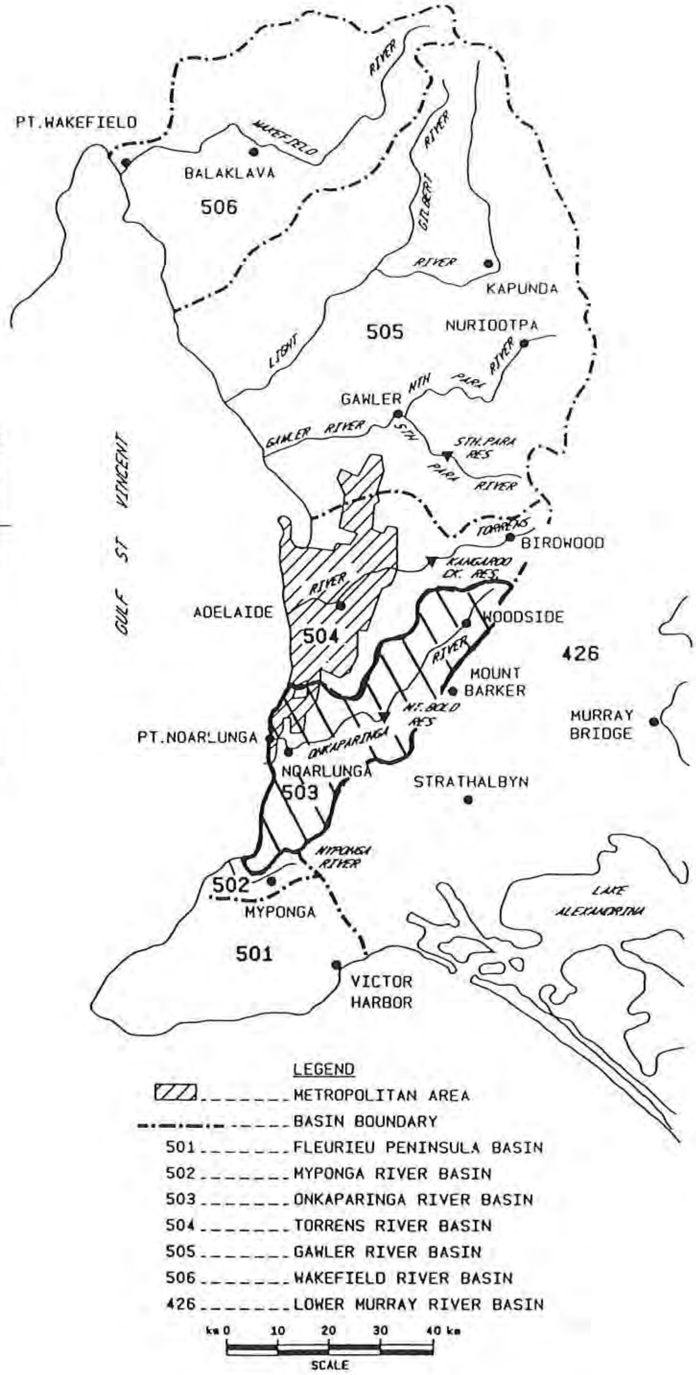


Figure 6.1 Location of the Onkaparinga River catchment (Source: Maguire, 1986)

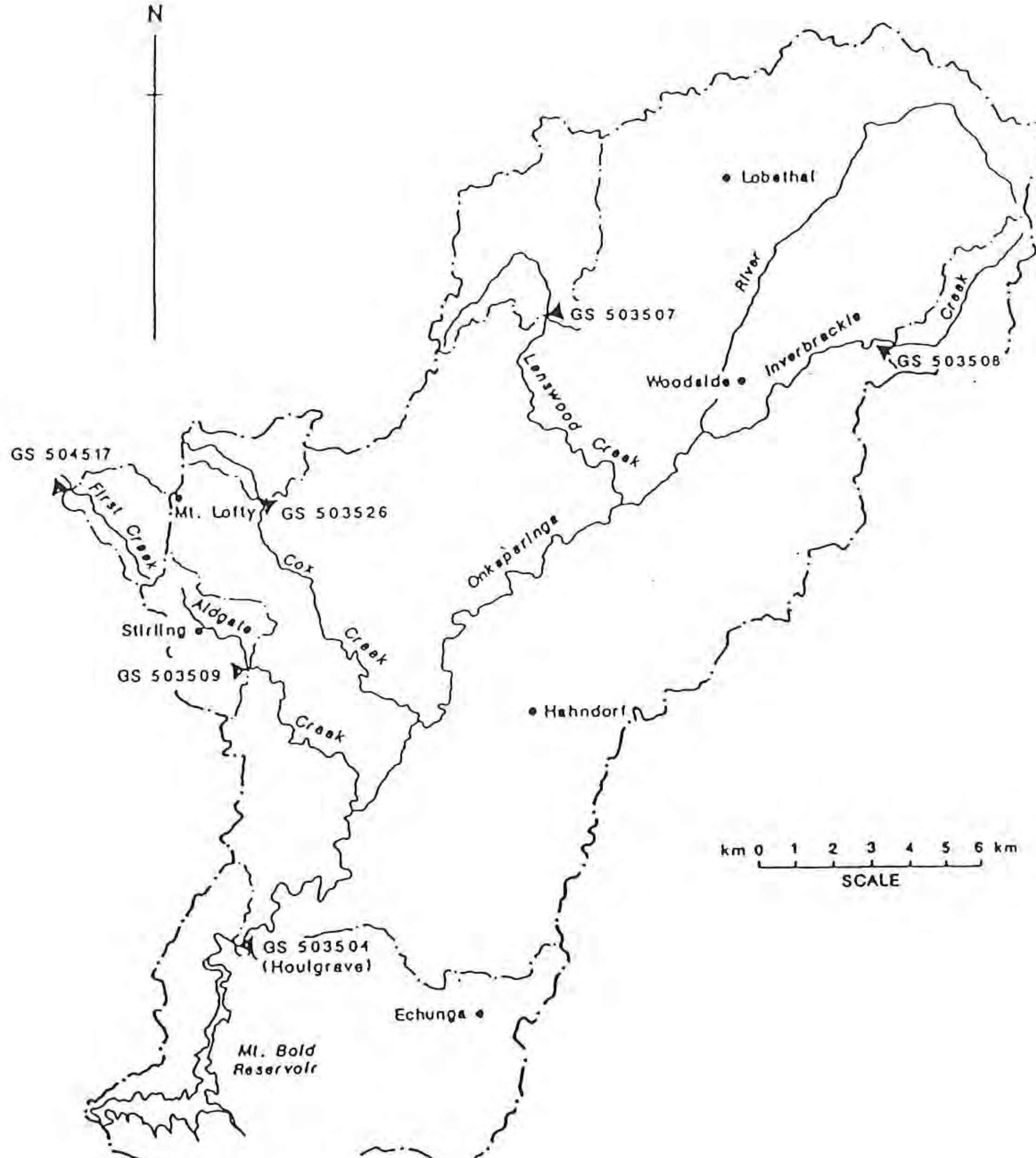


Figure 6.2 The Onkaparinga River catchment to Mt Bold Reservoir (Source: Maguire et al., 1986)

6.2 Previous Flood Studies in the Onkaparinga River Catchment

Hydrological modelling of the Onkaparinga River catchment has been undertaken for many different reasons over a long period of time.

Hill (1993) recently performed extreme flood estimation on the Onkaparinga River and estimated the probable maximum flood (PMF) using an estimate of the probable maximum precipitation (PMP). The RORB runoff routing model was calibrated using a number of events by sensitivity fitting. This is perhaps the most detailed study of the catchment to date and much of the data used by Hill will form the basis of the data presented and analysed in this study.

As part of Hill's literature review, a number of hydrologic studies of the catchment were summarised. For example, Kotwicki (1984) used the RORB model to undertake flood frequency analysis up to the Mount Bold Reservoir. More recently, a number of engineering consultants have studied different aspects of the hydrology of this catchment (B.C. Tonkin & Associates, 1986; Lange Dames and Campbell Australia Pty. Ltd., 1990).

Daniell and Hill (1993) prepared a flood inundation study for the Onkaparinga Flood Study Steering Committee. This study contained a historical view of flooding in this catchment through the use of newspaper documents.

6.3 Catchment Instrumentation

Instrumentation within the Onkaparinga River catchment has been operational for many years by SA Water Corporation (formerly the E&WS) and the Bureau of Meteorology. Rainfall and streamflow records are available for many locations within the catchment. Rainfall records are made using pluviometers and daily read raingauges.

Much of the instrumentation began operation only in the 1970s, however since then, many of the stations have ceased operation. Data is stored on the data archiving system HYDSYS, which allows storage and retrieval of time series data and is capable of manipulating the raw data for various hydrological calculations. HYDSYS was used in this study and a description can be found in HYDSYS Pty. Ltd. (1994).

Twelve extreme events used by Hill (1993) for RORB calibration, were chosen as the historical events used for this study. Therefore, the catchment instrumentation used for this study was dictated primarily by those which Hill used. The remainder of this section describes the location of this instrumentation and the amount of data available.

6.3.1 Pluviometers

Pluviometers are important for determining the temporal distribution of rainfall. The location of all pluviometers operated by the E&WS and those operated by the BoM is shown in Appendix E, but for this study not all of the available pluviometers were used.

The pluviometers for this study used data loggers and their respective periods of record are shown in Tables 6.1 and 6.2.

Table 6.1 E&WS pluviometers for the Onkaparinga River catchment used in this study

Number	Station Name	Commenced	Ceased
AW426638	Mt Barker Effluent	18/03/86	-
AW503502	Scott Creek	08/03/91	-
AW503508	Inverbrackie Creek	13/09/84	-
AW503521	Gallasch Creek	30/06/77	04/11/82
AW503525	Sutton Creek	23/07/82	-
AW503529	Burnt Out Creek	12/01/78	17/11/88
AW503533	Echunga Creek	25/01/84	-
AW503534	Mt Bold (Island)	04/10/88	-
AW504550	Ackland Hill	07/02/85	-
AW504552	First Creek Mt Lofty	12/09/84	-
AW504558	Angas Creek Station	16/10/80	-
AW504559	Sixth Creek Cherryville	22/09/81	-

Note: "-" indicates that the pluviometers are still operational

Table 6.2 BoM pluviometers for the Onkaparinga River catchment used in this study

Number	Station Name	Commenced
023101	Killara Park	01/08/89
023108	Longwood	26/07/89
023862	Lobethal	16/07/92
023865	Stringybark	11/06/91
023866	Verdun-Sutton	16/07/92

6.3.2 Streamflow Gauging Stations

A number of streamflow gauging stations have been operational at some time in the Onkaparinga River catchment. In the 1980s many became inoperational due to a lack of funding and other factors.

The gauging station used for this study was the Houlgraves Weir, just upstream of the Mt Bold Reservoir. It has a continuously digitised record since April 1973. The rating of Houlgraves Weir is considered good, with 89 gaugings available as of September 1992 (Hill, 1993).

6.4 Events used in this Study

To achieve a hyetograph that was spatially representative of the whole catchment, hourly rainfall was weighted from each of the operational pluviographs for each storm in accordance with the spatial representation of the pluviographs defined by Hill (1993). Each pluviograph was weighted in accordance to the area of the sub-catchments that each of the pluviographs were assigned to. The raw data was extracted from HYDSYS, based on hourly rainfall and hourly instantaneous stream flow values.

Appendix F shows the number of operational pluviographs used to calculate the catchment hyetograph of each storm and the fraction of the catchment area that each pluviograph contributed to the overall catchment hyetograph. Appendix G shows the weighted catchment hydrograph and the corresponding hydrographs for each of the 12 events from the commencement of the event. For some of the storms, once the weighted hyetograph was calculated, the commencement of the rainfall event was not well defined. Therefore, it was decided to estimate the event commencement subjectively by 'eye'.

Table 6.3 shows a summary of the important hydrologic characteristics of the 12 storms highlighting some of the parameters calibrated in the RORB model by Hill (1993), and the parameters established using the raw hydrograph-hyetograph data extracted from HYDSYS. From Table 6.3 it is evident that there is a considerable amount of variation between the hydrologic characteristics of these storms. Of particular importance from a modelling aspect was the number of pluviographs operational for each of these 12 storms, in particular, how the number of operational pluviographs increased over time, especially in the 1990s. It should be noted that two of the storms (24/7/81 and 24/6/87) were assumed to be a result of two rainfall bursts (Hill, 1993).

Figure 6.3 shows a single plot of all 12 hydrographs highlighting the hydrologic variability of the storms, clearly showing the magnitude of the 30/8/92 storm relative to the other storms.

Table 6.3 Hydrologic characteristics of the 12 storms used in the analysis

	RORB Calibration Hill (1993)		Instantaneous hourly hydrograph characteristics					Weighted hourly hyetograph characteristics						
			Peak Flow		*Commencement of Rising Limb*		*Flow*	*Rain Volume*			*Rain Duration*		*Intensity*	
	IL	CL	*Magnitude*	*Timing*	*Magnitude*	*Timing*	*Volume*	*Total*	*To Rising limb*	*To Peak Flow*	*Total*	*To centroid*	*Average*	*Peak*
EVENT	*(mm)*	*(mm)*	*(m^3/s)*	*(hours)*	*(m^3/s)*	*(hours)*	*(m^3)*	*(mm)*	*(mm)*	*(mm)*	*(hours)*	*(hours)*	*(mm/hr)*	*(mm/hour)*
24/7/81 (1)	18	1.32	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
24/7/81 (2)	12	0.27	121	19	12	5	6,876,000	24	12	21	29	6.8	0.8	4.9
3/8/81	18	0.36	98	29	8	15	5,176,000	27	10	26	30	16.5	0.9	4.4
8/8/81	21	0.32	135	14	6	5	7,153,000	37	20	31	23	4.9	1.6	6.8
25/8/83	25	0.97	88	15	2	6	4,605,000	44	25	44	12	5.7	3.7	7.8
8/9/83	15	1.96	121	30	13	25	5,795,000	24	5	24	23	17.9	1.0	8.4
24/6/87 (1)	20	1.94	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
24/6/87 (2)	5	1.61	220	38	12	22	11,569,000	70	20	55	50	24.3	1.4	5.1
15/7/87	20	1.52	151	27	3	7	9,038,000	46	12	43	30	13.4	1.5	5.3
24/5/88	46	4.55	158	43	1	19	4,967,000	168	48	167	44	27.3	3.8	16.3
15/8/90	15	0.61	82	20	6	8	6,166,000	37	12	30	30	9.7	1.2	4.7
30/8/92	22	1.27	428	31	3	7	17,948,000	73	21	67	30	19.9	2.4	7.1
16/9/92	15	0.81	80	16	3	5	7,245,000	36	18	31	23	5.7	1.6	5.4
8/10/92	20	0.91	193	31	3	17	8,477,000	51	12	44	42	19.9	1.2	6.2

Note:

(1) 1st burst of event

(2) 2nd burst of event

Timing is relative to the start of the rainfall event

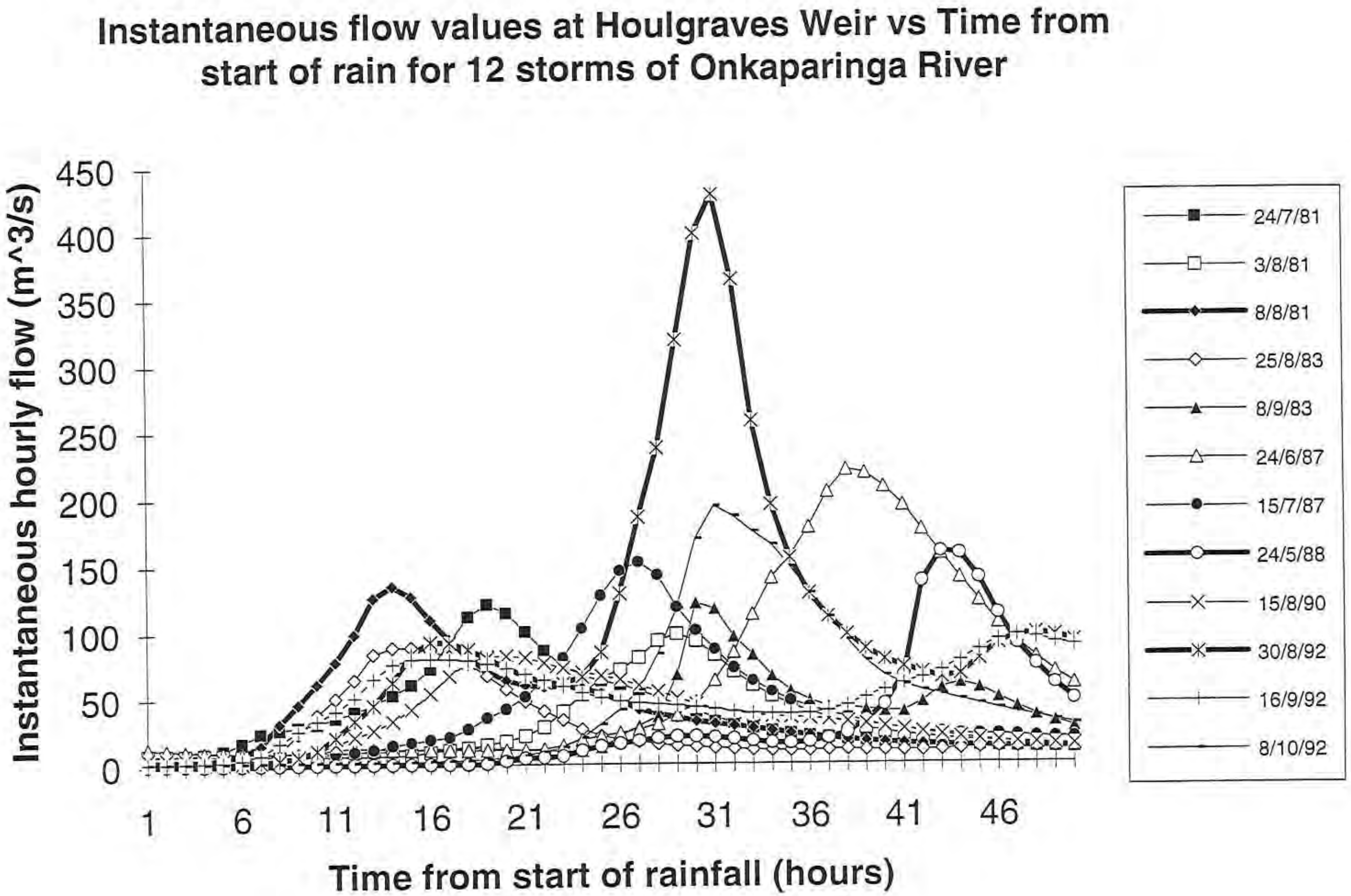


Figure 6.3 Plot of the 12 examined storms for the Onkaparinga River showing the variable hydrological characteristics of the hydrographs

6.5 Summary

This chapter has summarised the hydrometeorologic conditions within the Onkaparinga River catchment describing the land use of the catchment, briefly outlining some of the significant flood studies that have been undertaken which are relevant to this study, and the instrumentation available to carry out this research.

It is evident that a considerably larger historical data set is available compared with that of the Brownhill, Glen Osmond, Keswick and Parklands creek catchment as described in Appendix A. Although the historical data set is larger, the hydrologic characteristics including the magnitude of the flood events are all considerably different. In addition, the density of operational rainfall stations has increased in the last 5-10 years since the Bureau of Meteorology have become responsible for flood forecasting and monitoring the catchment.

The data obtained from this chapter will be used in the remainder of this thesis during analysis.

Chapter 7

Application of Soil Moisture Indices to Real-Time Flood Forecasting

7.1 Introduction

The aim of this chapter is to investigate antecedent catchment moisture conditions and to develop simple empirical relationships that may be used for future development of the flood warning system in the Onkaparinga River catchment and neighbouring catchments. The relationships obtained in this chapter will then be used to remove some of the subjectivity associated with flood forecasting in the remaining chapters, by giving an indication of the future rainfall-runoff response at the commencement of each examined storm. This may lead to future real-time updating techniques becoming simpler to operate and may allow the initial model parameters, particularly the losses, to be estimated with more accuracy. In this chapter, particular attention will be paid to initial loss estimation. Initial losses will be calculated using two methods and the subsequent results compared.

This part of the study is split into three components:

1. Determination of soil moisture indices (both antecedent precipitation index and pre-storm baseflow);
2. Estimation of initial loss from these calculated soil moisture indices; and
3. Derivation of other empirical relationships using these soil moisture indices.

7.2 Estimation of Initial Loss

The estimation of initial losses from storms is very subjective (Mein et al., 1995) and has recently been discussed by Hill (1994). The biggest difficulties occur when determining the start and finish times of the initial loss period. Mein et al. (1995) also emphasised how the spatial variation of rainfall affects the accuracy of the estimation of losses.

Hydrograph fitting, using a rainfall-runoff model or hyetograph-hydrograph analysis, are two methods that can be used to determine the initial loss of a storm based on historical data. The latter is generally more complicated and is discussed by I.E.Aust (1987) and Hill (1994), whilst the former relies much on the accuracy of the model.

A relatively standard procedure for real-time flood forecasting defines the initial loss as the depth of rainfall up to the time of rise of the hydrograph (B.C. Tonkin & Associates, 1977). This is a simple visual hyetograph-hydrograph technique and was used for developing flood warning procedures on the Torrens River, Adelaide. It is quite subjective in terms of when the rainfall begins, and when the hydrograph rise begins.

For this study, two methods of initial loss estimation were used and correlated against the soil moisture indices:

- RORB modelling by Hill (1993); and
- 'Rainfall to hydrograph rise' using the weighted catchment hyetograph.

Table 7.1 shows a reasonable comparison between the initial loss modelled by Hill (1993), and that estimated from the 'rainfall to hydrograph rise'. Differences between the two values can be attributed to RORB modelling errors, subjectivity of the start of event rainfall and rising limb, and differences in spatial representation of the rainfall (weighted catchment rainfall versus individual stations).

Table 7.1 Initial loss values for the Onkaparinga River catchment using two methods: RORB calibration by Hill (1993) and the rainfall to hydrograph rise

	Initial Loss (mm)	
Storm	Hill (1993)	Rainfall to hydrograph rise
24/7/81[1]	18	N/A
24/7/81[2]	12	12
3/8/81	18	10
8/8/81	21	20
25/8/83	25	25
8/9/83	15	5
24/6/87[1]	20	N/A
24/6/87[2]	5	20
15/7/87	20	12
24/5/88	46	48
15/8/90	15	12
30/8/92	22	21
16/9/92	15	18
8/10/92	20	12

Note: [1] indicates 1st burst

[2] indicates 2nd burst

7.3 Calculation of Soil Moisture Indices

7.3.1 'Catchment' Antecedent Precipitation Index

Raudkivi (1979) recommended calculating API using 20-60 preceding days of rainfall. To test sensitivity, calculations were performed for 7, 14, 30 and 60 day antecedent periods to compare the accuracy of using different length data sets.

The first part of the study involved calculating the 'catchment API' using the available storms. At each operational pluviograph for each storm, a 'pluviograph API' was calculated for the four (4) antecedent periods using Equation 4.3. An overall 'catchment API' was calculated by a weighted average of the 'pluviograph API' values. Weighting of each 'pluviograph API' was calculated in accordance with the location of the pluviographs from the RORB model set up by Hill (1993). Another approach could have been to first weight the catchment pluviographs, and then calculate the 'catchment API', however this was not investigated.

Due to a number of reasons, pluviographs (mainly for the earliest events) prior to storm commencement were inoperational for a period of time, resulting in a discontinuous rainfall record. Only the 7 day antecedent period contained full rainfall records from each of the pluviographs operational during the examined storm events. For the four antecedent periods of each storm, at least two of the same pluviographs were used to calculate 'catchment API' in order to give representativeness in terms of spatial rainfall variability. However, even for a few storms, no 'catchment API' was calculated for certain antecedent periods because less than two pluviographs were operational.

The starting value for the API calculations (API_0), was arbitrarily set at 30 mm and a value of 0.9 was arbitrarily chosen for the recession factor (K) since the storms occurred in either winter or spring.

Table 7.2 shows the calculated APIs for the four different antecedent periods and the number of pluviographs used in the calculations.

Table 7.2 Antecedent precipitation index (API) calculated for the examined storms on the Onkaparinga River catchment using four separate antecedent time periods

		Antecedent Precipitation Index (mm)			
Storm	No. of Pluviographs	60 day	30 day	14 day	7 day
24/7/81[1]	3	33.7	39.5	21.1	19.1
24/7/81[2]	3	56.0	64.1	50.7	45.4
3/8/81	3	43.3	41.8	43.4	31.3
8/8/81	3	38.4	36.6	32.1	31.5
25/8/83	2	*	*	*	24.3
8/9/83	3	*	*	70.9	56.4
24/6/87[1]	6	22.1	21.5	21.1	22.9
24/6/87[2]	6	71.3	71.0	68.8	71.9
15/7/87	7	34.7	32.8	20.4	27.9
24/5/88	8	66.2	68.9	71.1	73.1
15/8/90	8	40.1	38.8	39.7	37.0
30/8/92	8	*	31.1	23.7	20.5
16/9/92	8	48.8	47.7	41.2	25.5
8/10/92	8	47.3	45.5	39.5	27.3

Note: * indicates not calculated because of lack of operational pluviographs

[1] indicates 1st burst

[2] indicates 2nd burst

The three storms which showed discontinuous pluviograph records occurred on the 25/8/83, 8/9/83 and 30/9/92. Therefore, no API was calculated for these storms for some of the antecedent periods which is highlighted in Table 7.2.

The storms on 24/7/81 and 24/6/87 contained two rainfall bursts. For both of these storms, the 1st and 2nd bursts did not occur on the same day, hence an API value was calculated for both the 1st and 2nd rainfall bursts. One would expect, the 2nd burst API to be greater than the 1st burst API because the 2nd burst API contains the rainfall from both bursts, whereas the 1st burst API is calculated using rainfall from only the 1st burst.

From Table 7.2 for a number of the storms it can be observed that there is very little practical difference in the calculated APIs for the different antecedent conditions. This would indicate that for future on-line situations using a shorter rainfall record may yield adequate results for flood forecasting, which would be advantageous if a situation arises where there is prior loss of data. The minimum API value for all antecedent periods is about 20 mm and the maximum being about 70 mm, but most lie between about 20-30 mm. A value of 25 mm would therefore probably give a rough estimate as an input value to a forecasting model.

7.3.2 Pre-Storm Baseflow Discharge

As discussed in Section 4.4.2, pre-storm baseflow can be estimated from the commencement of surface runoff, therefore it has the advantage in that it does not rely on rainfall input.

In this study, the commencement of surface runoff was assumed to occur at the start of the rising limb of the hydrograph. For the Onkaparinga River catchment, determining the point where surface runoff began was difficult. In many of the storms the hydrograph rise occurred in two parts; an initial slow rise (which lasted up to about 10 hours in some cases) then a steep rapid rise. This was also noted by Mein et al. (1995). The slow first rise was probably due to direct rainfall interception into the river itself, or due to surface runoff contributing from saturated source areas located close to the river banks. Therefore the rapid rise in the hydrograph was selected as the start of surface runoff.

The pre-storm baseflow estimated visually by Hill (1993) in RORB analysis was also used and compared with the value estimated from the first rapid rise of the hydrograph. Table 7.3 shows the pre-storm baseflow for the two suggested methods. There is reasonable correlation between the both methods of estimating pre-storm baseflow. The three exceptions are for the two multiple rain burst events (24/7/81 and 24/6/87) and the storm on 8/9/83. The initial loss values estimated by Hill (1993) contained very little variation. Using this method the maximum value of pre-storm baseflow was 5 m^3/s.

Table 7.3 A summary of the pre-storm baseflow for each examined storm on the Onkaparinga River using the values visually determined by Hill (1993) and the first rapid rise in the hydrograph

	Pre-Storm Baseflow (m^3/s)	
Storm	Hill (1993)	First rise in the hydrograph
24/7/81[2]	2	12
3/8/81	3	8
8/8/81	4	6
25/8/83	1	2
8/9/83	4	13
24/6/87[2]	1	12
15/7/87	1	3
24/5/88	1	1
15/8/90	5	6
30/8/92	3	3
16/9/92	2	3
8/10/92	2	3

Note: [2] indicates 2nd burst

7.4 Estimation of Initial Loss from Soil Moisture Indices

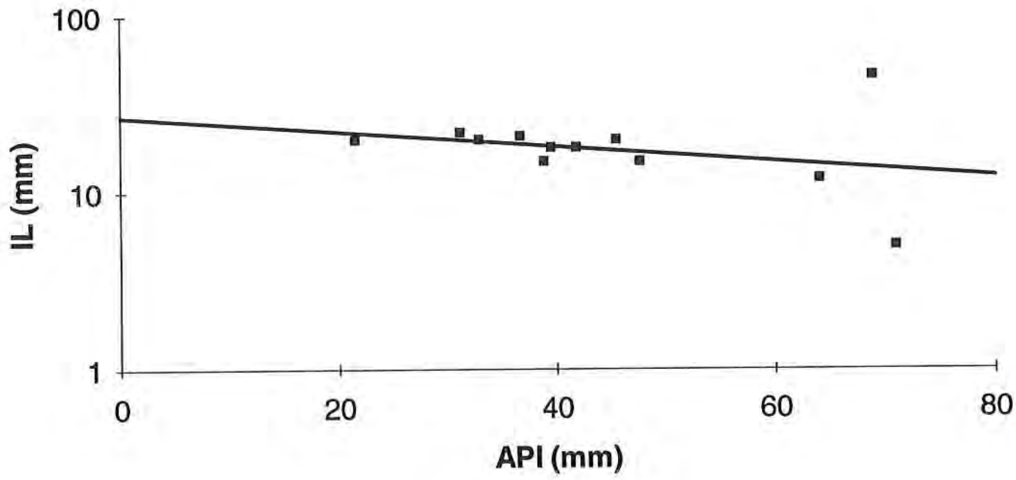
7.4.1 Antecedent Precipitation Index

This section describes the derivation of the exponential relationships between the initial loss and the 'catchment API' for both of the exponential equations described in Section 4.5.3. Correlations were performed using both methods of initial loss estimation and a comparison was made between the two.

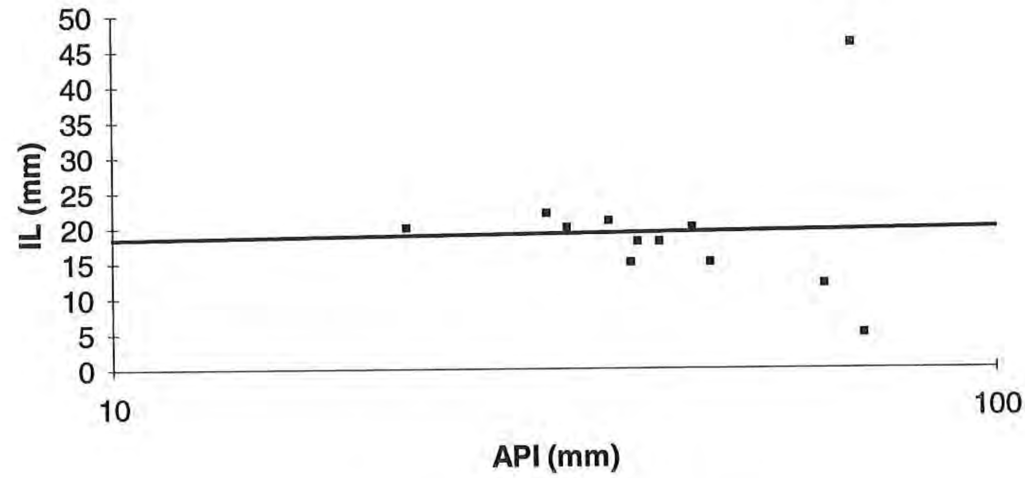
It should be noted that the 'rainfall to hydrograph rise' uses less points in the correlations since it does not separate the multiple rainfall bursts of the storms on 24/6/87 and 24/7/81 because the rain event is considered as one burst.

Initially, exponential regression analysis was performed for each of the four antecedent periods using only the available APIs as shown in Table 7.2.

These results were not particularly encouraging with very poor correlations observed. A more detailed investigation into the regression analysis revealed that the two rain storms containing the largest API values (24/6/87 and 24/5/88) did not fit the regression line at all well. Figure 7.1 illustrates this for one case, with each exponential relationship showing a different regression fit.



a) Log (IL) Vs API - ($R^2 = 0.11$)



b) IL Vs log (API) - ($R^2 = 0.0005$)

Figure 7.1 Initial loss (estimated from RORB modelling) Vs 30 day API using all operational pluviographs

As a result, the storms on 24/6/87 and 24/5/88 were removed from the analysis and new correlations were performed. By removing these two storms, improved relationships were developed. An example of this is shown in Figure 7.2.

The 7 day antecedent period used 12 storms, whereas for the 60 day period used 9 storms, therefore a true comparison of the relationships developed for estimating the initial loss would have required the same storms.

To increase the number of storms used in the analysis, for each antecedent period, if the API value was unavailable, the next available API value was adopted. For example for the 30 day antecedent period, API values were not calculated for storms on 25/8/83 and 8/9/83. To increase the number of storms used in the regression analysis, a 14 day API value was used for the 8/9/83 storm, and a 7 day API value was used for the 25/8/83 storm. However, little improvement was made probably because some of the added values, calculated from a shorter antecedent period are less 'accurate' than if the correct antecedent period value had been used.

The correlation coefficients (R^2) for the analysis can be observed in Table 7.4 and 7.5 for both methods of estimating the storm initial loss. The overall results show that the relationships developed were quite poor, in some cases no correlation was observed. The highest R^2 value obtained was 0.68 for the 30 day API removing the 24/5/88 and 24/6/87 storms as shown in Table 7.4, which is not regarded as a good correlation but may be of some operational use in the Onkaparinga River catchment. The derived equation for this relationship is shown in Equation 7.1.

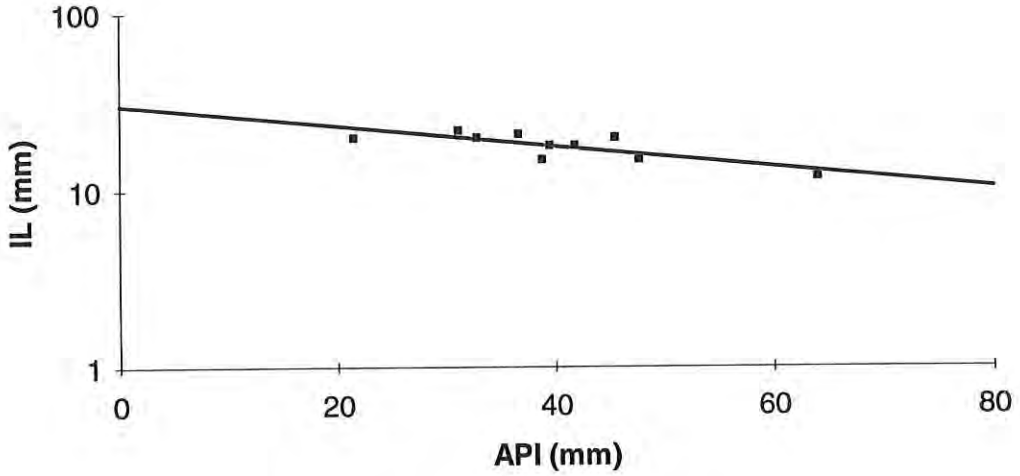
$$\mathrm{IL} = (30.3).10^{-0.00577\mathrm{API}} \tag{7.1}$$

where:

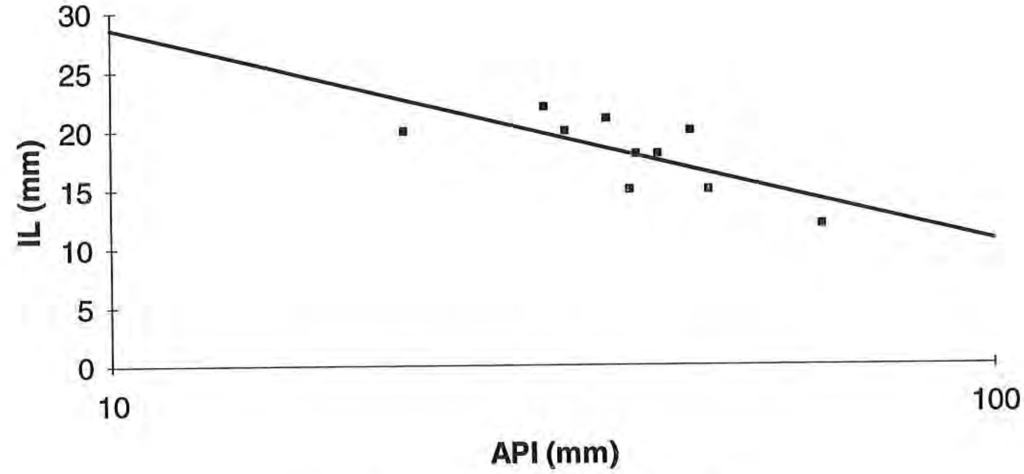
IL = Initial loss

API = 30 day antecedent precipitation index.

The derived IL-API relationships for all forms of regression can be found in Appendix H.



a) Log (IL) Vs API - ($R^2 = 0.68$)



b) IL Vs log (API) - ($R^2 = 0.50$)

Figure 7.2 Initial loss (estimated from RORB modelling) Vs 30 day API using all operational pluviographs except 24/5/88 and 24/6/87 storms

Table 7.4 Correlation coefficients (R^2) for IL-API relationship using initial loss calibrated from RORB

Antecedent Period	All available storms		All available storms except 24/5/88 & 24/6/87		All available storms plus antecedent period 'down'	
	log IL Vs API	IL Vs log API	log IL Vs API	IL Vs log API	log IL Vs API	IL Vs log API
7 Day	0.26 (14)	0.06 (14)	0.40 (12)	0.40 (12)	*	*
14 Day	0.08 (13)	-	0.46 (11)	0.47 (11)	0.10 (14)	-
30 Day	0.11 (12)	-	0.68 (10)	0.50 (10)	0.13 (14)	-
60 Day	0.10 (11)	-	0.54 (9)	0.36 (9)	0.14 (14)	0.01 (14)

'-' Indicates no correlation observed

'*' Indicates analysis was not performed

() Indicates number of storms used in regression

Table 7.5 Correlation coefficients (R^2) for IL-API relationship using initial loss from 'rainfall to hydrograph rise'

Antecedent Period	All available storms		All available storms except 24/5/88 & 24/6/87		All available storms plus antecedent period 'down'	
	log IL Vs API	IL Vs log API	log IL Vs API	IL Vs log API	log IL Vs API	IL Vs log API
7 Day	0.07 (12)	0.08 (12)	0.54 (10)	0.56 (10)	*	*
14 Day	0.09 (11)	0.06 (11)	0.53 (9)	0.39 (9)	0.05 (12)	0.02 (12)
30 Day	0.13 (10)	0.19 (10)	0.10 (8)	0.15 (8)	0.06 (12)	0.01 (12)
60 Day	0.21 (9)	0.31 (9)	0.02 (7)	0.01 (7)	0.06 (12)	-

'-' Indicates no correlation observed

'*' Indicates analysis was not performed

() Indicates number of storms used in regression

The two methods used to estimate the initial loss as shown in Tables 7.4 and 7.5 did not show many similarities except for the fact that the correlations from both methods were poor. By altering the antecedent period, some interesting observations were made. Using the 'rainfall to hydrograph rise' as the initial loss estimator, extremely poor correlations were obtained for 30 and 60 day antecedent periods, compared with those generated using the initial loss from RORB modelling. This was most evident when the storms on 24/5/88 and 24/6/87 were removed. For this situation, when the initial losses were generated from RORB calibration, the correlations improved when the antecedent period was increased, even though the number of data points used in the analysis was less. However when all of the available storms were used, although the overall correlations were not as good as when the 24/5/88 and 24/6/87 storms were removed, the opposite trend was observed. The linear relationships relating log IL to API gave the best correlations.

7.4.2 Pre-Storm Baseflow Discharge

In this section, two different correlations were performed. Firstly, the initial loss was estimated by calculating the 'rainfall to hydrograph rise' and then correlated against the pre-storm baseflow estimated from the initial rapid rise in the hydrograph. Secondly, the initial loss used to calibrate the RORB model of Hill (1993) was correlated against the pre-storm baseflow at the commencement of surface runoff when baseflow was removed by Hill (1993) in RORB modelling.

Using pre-storm base flow, all 12 storms were used in the regression analysis. As a means of comparison, the removal of the two storms from the regression as in Section 7.4.1, was again tried. The results of the analysis can be observed in Table 7.6.

Table 7.6 Correlation coefficients (R^2) for the exponential IL-BF relationships

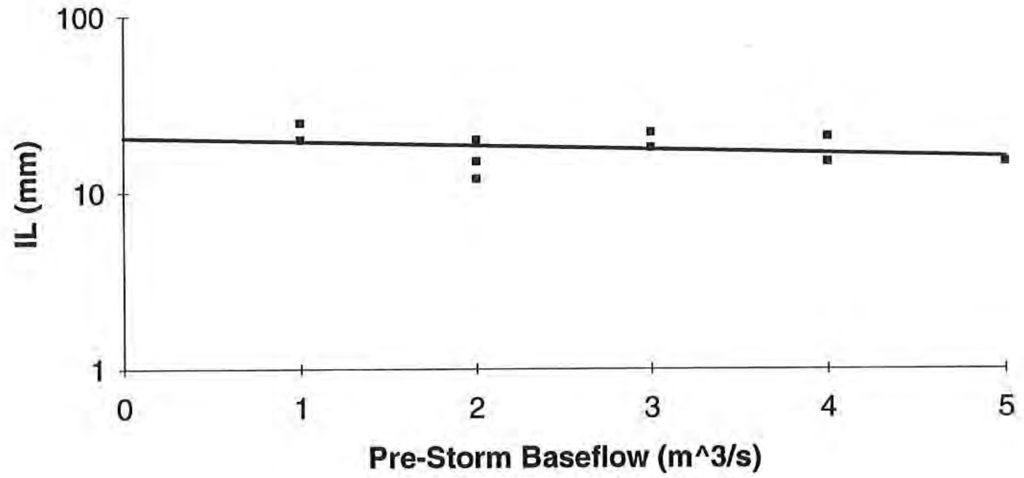
	R^2 using all available storms		R^2 using all available storms except 24/5/88 & 24/6/87	
IL estimator	log IL Vs BF	IL Vs log BF	log IL Vs BF	IL Vs log BF
RORB model	0.05 (12)	0.08 (12)	0.10 (10)	0.15 (10)
Rain to hydrograph rise	0.23 (12)	0.52 (12)	0.49 (10)	0.49 (10)

Note: ( ) Indicates number of storms used in regression

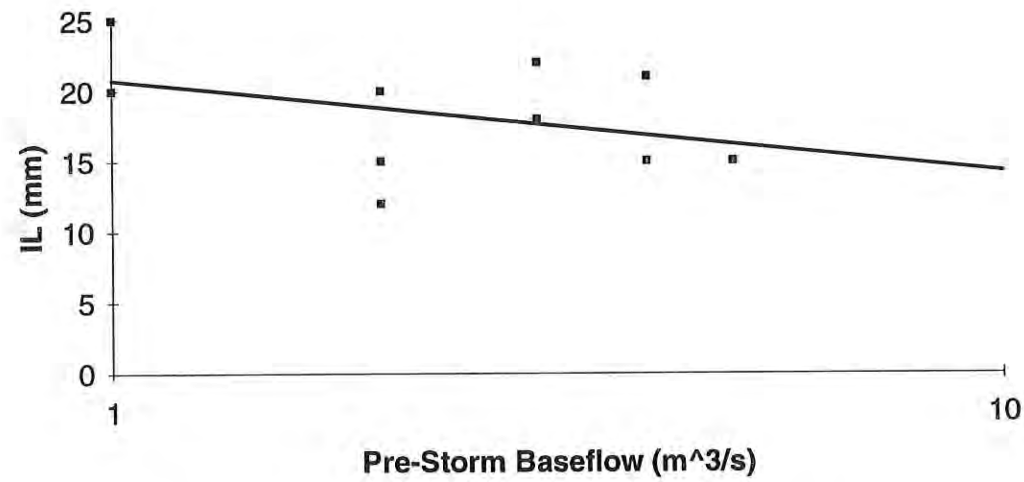
A number of features can be observed from these results. Again the correlations developed were extremely poor, with the maximum R^2 being 0.52, lower than the maximum achieved by using API. The full results can be found in Appendix H.

By using the initial loss estimated from RORB and the pre-storm baseflow estimated by Hill (1993), poor correlations were developed. The main reason for this is because pre-storm baseflow contained smaller variations between each storm compared with that estimated from the initial rapid rise in the hydrograph as shown in Table 7.6. Table 7.6 shows that both methods of estimating the initial loss were similar, meaning the $\Sigma(Y_{est}-Y_{av})^2$ term of Equation 4.8 decreases. Since there is very little change in the $\Sigma(Y-Y_{av})^2$ term, R^2 decreases.

For this situation, an IL Vs log BF relationship gave better overall results than a log IL Vs BF relationship. Typical results are shown in Figures 7.3 and 7.4.

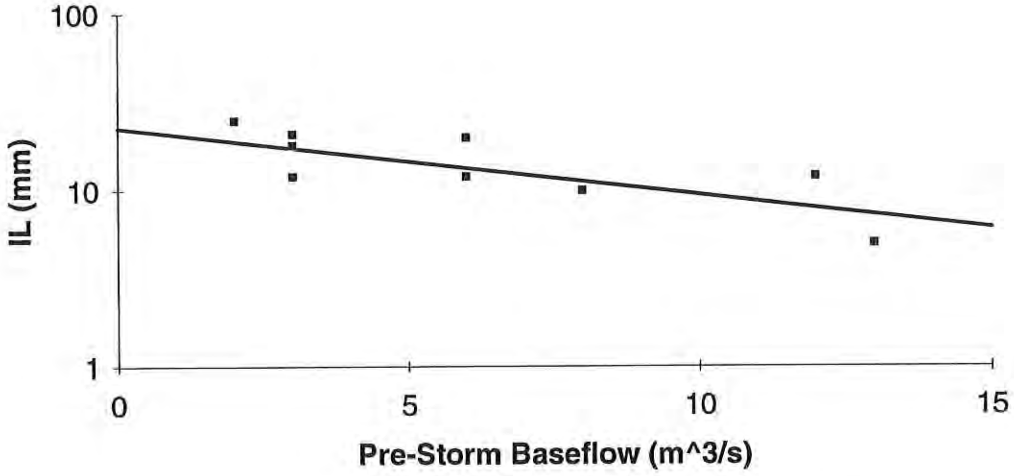


a) Log (IL) Vs Pre-Storm Baseflow - ($R^2 = 0.10$)

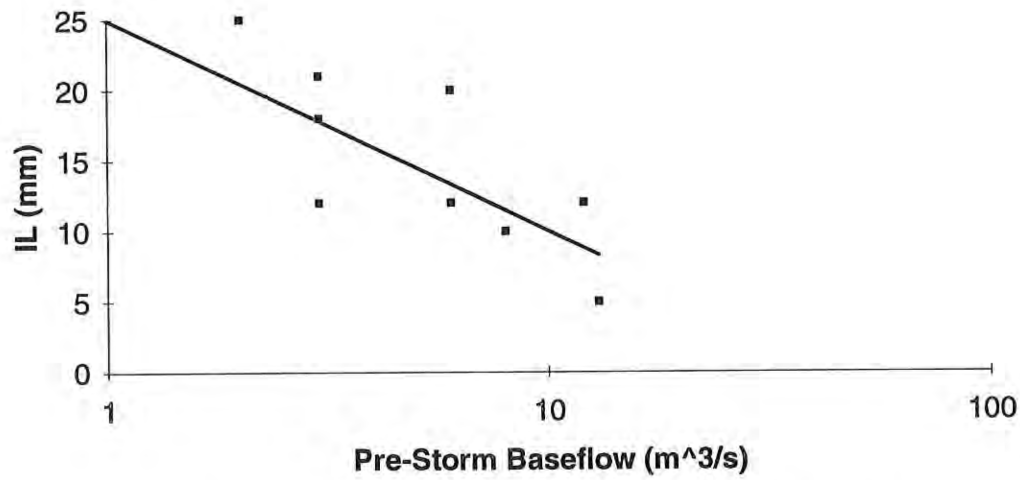


b) IL Vs log (Pre-Storm Baseflow) - ($R^2 = 0.15$)

Figure 7.3 Initial loss (estimated from RORB modelling) Vs pre-storm baseflow using all operational pluviographs except 24/5/88 and 24/6/87 storms



a) **Log (IL) Vs Pre-Storm Baseflow - ($R^2 = 0.49$)**



b) **IL Vs log (Pre-Storm Baseflow) - ($R^2 = 0.49$)**

Figure 7.4 Initial loss (estimated from 'rainfall to hydrograph rise') Vs pre-storm baseflow using all operational pluviographs except 24/5/88 and 24/6/87 storms

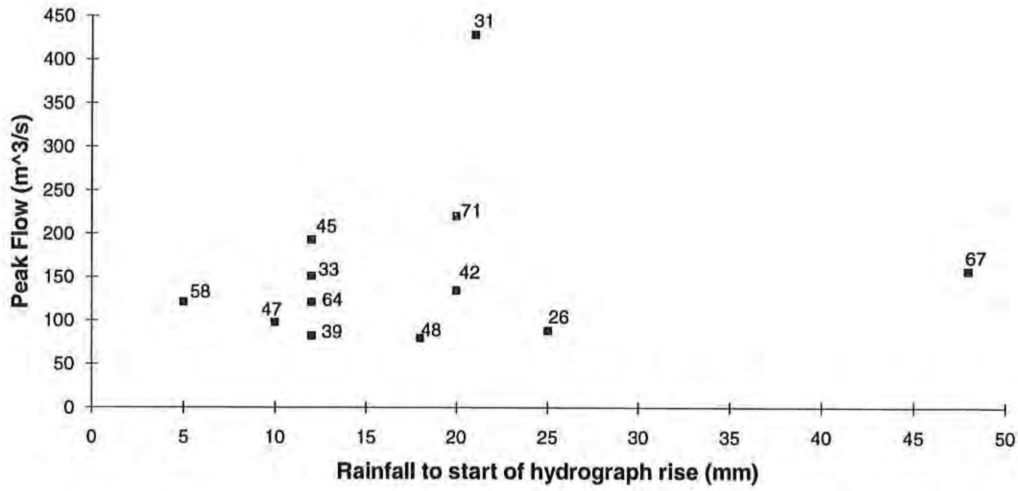
7.5 Empirical Rainfall-Runoff Relationships

The aim of this section is to develop a simple rainfall-runoff relationship linking catchment rainfall and antecedent precipitation index to predict three parameters: peak magnitude, peak timing and flow volume. This is similar to the work done by BoM (1963a), where graphical relationships were developed for predicting the peak stage for the Macleay River as shown in Figure 4.3 using API isopleths.

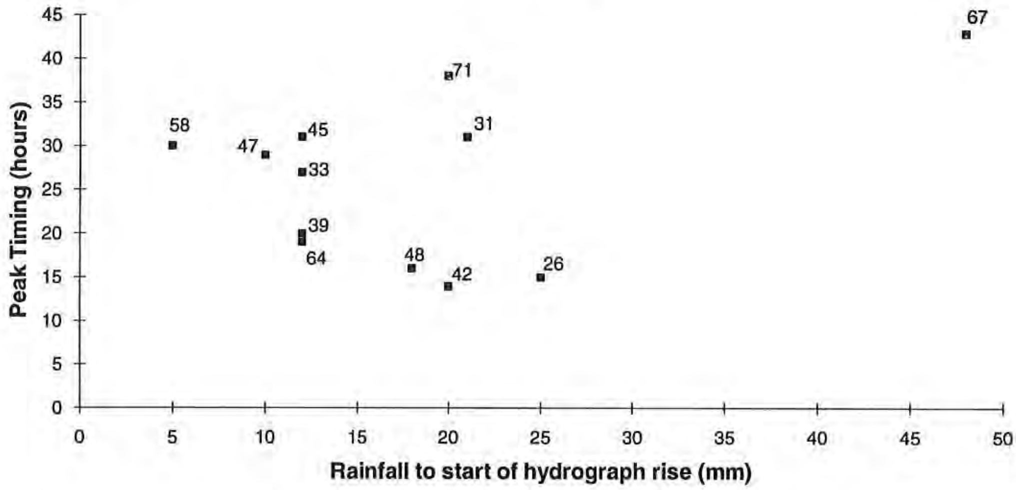
For the Onkaparinga River, a similar attempt was made using 30 day API. The 'rainfall to the hydrograph rise' was also included in the correlation.

The results of this analysis are shown in Figure 7.5. No conclusive relationships are demonstrated from any of these graphs, which is indicated by the fact that isopleths (lines of equal API) could not be drawn through any of the points. Removal of certain storms was not carried out because the accuracy of such a relationship would be further reduced.

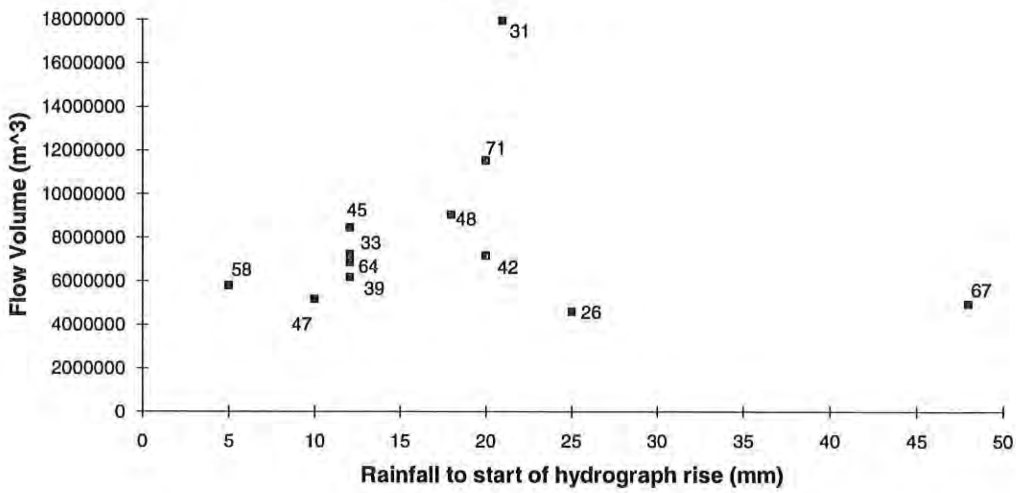
Other rainfall-runoff type relationships were not trailed because there were not enough storms to work with.



a) Peak Flow



b) Peak Timing



c) Flow Volume

Figure 7.5 Combined API and 'Rainfall to the start of the hydrograph rise' relationships for the Onkaparinga River catchment to predict a) Peak flow, b) Peak timing and c) Flow volume

7.6 Conclusions

The results of this section highlight that there is no simple relationship between the initial loss and both antecedent precipitation index and pre-storm baseflow. The relationships developed were dependent on what storms were used in the regression analysis, and the methods used to estimate the initial loss. There was little difference in using antecedent precipitation index or pre-storm baseflow as a means of predicting initial loss. Obtaining different correlations when certain storms were removed indicated how variable the historical data set was. No direct link was observed between the accuracy of the results and the length of antecedent rainfall used to establish the IL-API relationships.

The fact that only 12 storms were used for the analysis, probably limited the accuracy of the developed relationships. Mein et al. (1995) discovered that the confidence of derived relationships were dependent on the uniformity of the data points, particularly when only 10-12 storms were used. It is obvious that for this study, a similar result was found which was perhaps the biggest limiting factor.

Hill (1994) discussed how the start of surface runoff is highly dependent on the spatial variation of rainfall because in most storms, less than the whole catchment contributes runoff because not all of the catchment receives a sufficient volume of rainfall to 'wet' it up. In this study, this was perhaps the biggest limiting factor. The number of pluviographs available before 1990 was considerably less than those available since 1990. A weighted rainfall representation was used, which would have directly affected the calculated antecedent precipitation index values, and the initial loss estimated from 'rainfall to hydrograph rise'. Runoff generated from source areas close to the point where flow is measured, gives a quicker response than the overall catchment response. In the Onkaparinga River catchment, the majority of the rainfall is concentrated in the highest, steepest regions of the catchment. This would indicate that the rainfall-runoff time delay from the commencement of rainfall to the start of runoff, is more indicative of the travel time of the hydrograph, rather than the commencement of surface runoff.

Since the relationships obtained from within this chapter are not well developed, their application to not only the remainder of this thesis, but also to future operational forecasting is limited. It was hoped to derive more accurate relationships between the initial loss and the soil moisture indices and then use them later to help forecast some of the examined floods using the RORB model. By using these derived relationships, the subjectivity of estimating the initial loss at the commencement of the storms used for RORB modelling, could have been removed. In conjunction with this analysis, the estimation of continuing losses could have also been attempted had more encouraging results been achieved in estimating initial loss.

Since the Onkaparinga River has very low pre-storm baseflows with very little variation, the use of pre-storm baseflow as a catchment response indicator at the commencement of a storm for this catchment is not recommended. This would also be typical with most other watercourses in adjacent catchments because of their ephemeral nature.

This study does provide information which can be translated to potential similar studies that may commence on adjacent catchments such as the combined Brownhill, Glen Osmond, Parklands and Keswick Creek catchment, particularly to the rural part of the catchment. Firstly, many more storms are required to derive comprehensive and accurate results and secondly, the density of rainfall stations within any catchment must be greater than that that found in the Onkaparinga River catchment.

Chapter 8

Complete Hydrograph Simulation using an Artificial Neural Network Model

8.1 Introduction

The first part of using an artificial neural network model for this study, was to predict the complete storm hydrograph at one time using the whole hyetograph as an input, similar to the study by Foley and Brown (1993), as discussed in Chapter 5.

The main objective of this chapter is to gain a feel for which part of the model is most important and how sensitive the whole model is to change, particularly the model inputs, the neural network parameters and how much data is needed for training.

The importance of antecedent precipitation index (API) as a model input was also investigated to see if it can improve the models ability to simulate the rainfall-runoff response. More importantly, the results generated in this chapter are then to be applied to real-time flood forecasting using an artificial neural network model, which will be discussed in Chapter 9.

8.2 Development of the Artificial Neural Network Model

A number of factors were considered when setting up the ANN model. These factors included the:

- Type of input and output parameters;
- Method of training for the artificial neural network;
- Selection of appropriate storms to test;
- Rainfall-runoff relationship;
- Neural network parameters; and
- Neural network architecture.

8.2.1 Input and Output Parameters

Instantaneous hourly flow values from Houlgraves Weir on the Onkaparinga River were chosen to represent the runoff component of the model. Baseflow was not removed, firstly because rainfall losses were not considered, and secondly the baseflow component as a proportion of the total flow was insignificant. Two spatial rainfall distributions were considered:

- Weighted catchment representation; and
- Single station (AW504558).

For the weighted catchment representation, hourly rainfall from the available pluviographs from each event were weighted as discussed in Section 6.4.

Appendix F shows that no pluviographs were fully operational during all of the 12 storms. Station AW504558 was operational for the largest number of storms (8) and was therefore used for the single rainfall station analysis.

Antecedent Precipitation Index (API) was also used as an input variable. The model was tested with and without the API catchment indicator. Thirty day API was used, however when unavailable, either 14 or 7 day API was used as discussed in Section 7.4.1.

8.2.2 The Method of Training the Artificial Neural Network

Fifty hours of rainfall-runoff data was available from each storm, therefore the training set from each storm contained 50 hours of information. Six (6) training approaches were used in the analysis:

Method 1 (All storms using weighted catchment rainfall) : The training set contained data representing all of the storms except for the test storm, therefore 11 storms were contained in the data set. The weighted catchment rainfall representation was used as model input.

Method 2 (All storms except 30/8/92 using weighted catchment rainfall) : Essentially the same as Method 1, except the 30/8/92 storm was not included during training. The 30/8/92 storm was removed since it is the most extreme and uncharacteristic of the storms.

Method 3 (Single rainfall station-AW504558) : The training set contained data representing only those storms when station AW504558 was operational. Station AW504558 was used instead of the weighted rainfall representation as model input.

Method 4 (Similar time to peak storms) : The training set contained data representing only those storms that had similar time to peak characteristics (T_P). This was undertaken to examine the timing aspects of the hydrograph. Table 8.1 shows the different time to peak for each of the 12 storms. Two distinct groups can be separated, each containing five storms. Two storms (24/5/88 and 24/6/87) were not placed into either of the two groups. The implications of the two distinct groups meant that a storm tested from one group was only trained on the remaining storms from that same group. Therefore the training set consisted of 4 storms. In doing this, the number of storms used for training was considerably less than the other training methods.

Table 8.1 Separation of data based on similar time to peak

Lowest time to peak storms		Highest time to peak storms	
Storm	T_P (hours)	Storm	T_P (hours)
8/8/81	14	15/7/87	27
25/8/83	15	3/8/81	29
16/9/92	16	8/9/83	30
24/7/81	19	30/8/92	31
15/8/90	20	8/10/92	31

Method 5 (Similar hydrograph peak magnitude storms) : The test storm was trained on a training set containing only those storms with similar hydrograph peak magnitudes. For this, it was envisaged that an improvement in the magnitude of the hydrograph peak would be observed. Two groups were separated as shown in Table 8.2. One group contained the smallest storms, whilst the other group contained the next largest storms. The 30/8/92 storm was not included in the data set because of it being so much larger than the other storms.

Table 8.2 Separation of data based on similar hydrograph peak magnitude

Lowest magnitude storms		Highest magnitude storms	
Storm	Flood Peak (m^3/s)	Storm	Flood Peak (m^3/s)
15/8/90	80	24/7/81	118
25/8/83	86	8/9/83	119
3/8/81	95	8/8/81	132
16/9/92	96	15/7/87	148
-	-	24/5/88	156

The two groups and training mechanisms were based on the same concept as for Method 4. This time however, the group containing the lowest magnitude storms consisted of 4 storms only.

Method 6 (Similar 30 Day API) : The test storm was trained on a training set containing only those storms with similar 30 Day API. Two groups were separated as shown in Table 8.3, so that one group contained the 6 lowest values and the other group contained the six highest values. This time, API was not included as an input as this was taken into account when splitting the storms into the two groups.

Table 8.3 Separation of data based on similar 30 day API

Lowest API storms		Highest API storms	
Storm	30 Day API (mm)	Storm	30 Day API (mm)
25/8/83	24	8/10/92	46
30/8/92	31	16/9/92	48
15/7/87	33	8/9/83	71
15/8/90	39	24/7/81	64
8/8/81	37	24/5/88	69
3/8/81	42	24/6/87	71

8.2.3 Selection of Appropriate Storms to Test

Table 8.4 shows the 6 training methods and the storms available for testing from each method. For a consistent comparison of the 6 training methods, the same storms had to be tested from each method. Of the 12 storms, 7 storms were available for all 6 training methods, however only 6 were chosen for comparison. A '√' indicates availability and a '-' indicates unavailability.

Table 8.4 Storms available from each of the training methods

Method	**24/7/81**	**3/8/81**	**8/8/81**	25/8/83	**8/9/83**	24/6/87	**15/7/87**	24/5/88	**15/8/90**	30/8/92	16/9/92	8/10/92
1 (W)	√	√	√	√	√	√	√	√	√	√	√	√
2 (W)	√	√	√	√	√	√	√	√	√	-	√	√
3 (S)	√	√	√	-	√	-	√	-	√	-	√	√
4 (W)	√1	√2	√1	√1	√2	-	√2	-	√1	√2	√1	√2
5 (W)	√2	√1	√2	√1	√2	-	√2	√2	√1	-	√1	-
6 (W)	√2	√1	√1	√1	√2	√2	√1	√2	√1	√1	√2	√2

Note:

(W) denotes 'weighted catchment rainfall'

(S) denotes 'single station rainfall'

{i.e. **1 (W)** denotes training Method 1 which uses weighted catchment rainfall}

√1 denotes this storm is within Group 1 of the corresponding Training Method

√2 denotes this storm is within Group 2 of the corresponding Training Method

8.2.4 Rainfall-Runoff Relationship

Two runoff prediction relationships were used to compute the complete storm hydrograph. Fifty hours of hydrograph were forecasted, starting at the commencement of rainfall, at time t. Equation 8.1 includes API as an input, whereas Equation 8.2 does not. Method 6, only used Equation 8.2.

$$\{Q(t),....,Q(t+49)\} = f\{API, R(t),...,R(t+49)\} \tag{8.1}$$

$$\{Q(t),....,Q(t+49)\} = f\{R(t),...,R(t+49)\} \tag{8.2}$$

Equation 8.1 shows API input placed at the start of the data string, and was therefore the first number in each line. This was also performed with API at the end of the data string, however no difference in the model's performance were observed.

8.2.5 Neural Network Software

Two software packages were used; NeuralWorks Professional II/Plus and NeuralWorks Explorer which ran on an IBM compatible 486 DX2-66 machine. NeuralWorks Explorer is an educational program and Professional II/Plus is merely an extension of Explorer, capable of more sophisticated operations. Both software packages automatically normalise the input and output parameters using an in-built function. The normalisation procedure is a layer operation where the values corresponding to the output of a complete layer are scaled so that the total output is some fixed value, therefore the total activity in the layer remains approximately constant (NeuralWare Inc., 1991). For this study the MinMax function was used, which scaled the real world data outputs into a range between -1.0 to 1.0 which was suitable for the type of transfer function adopted. The mode in which these software packages were used required the setting up of two files; a test file and a training file. Both files are text files with each data entry separated by spaces containing a *.nna* extension. The training file contains the training sets (input-output combinations) which the ANN uses to learn from. When the learning procedure is complete, the ANN computes the output based on the input fed into the test file and compares the predicted output with the desired output (which is also contained within the test file).

8.2.6 Neural Network Parameters

All parameters were set to the default setting of the software. The following parameters were arbitrarily chosen for the ANN model.

Learning Rule:	Cumulative delta
Transfer Function:	Sigmoid
Convergence Criteria:	2 % RMSE

8.2.7 Neural Network Architecture

A fully connected backpropagation network was adopted. A single hidden layer was used. NeuralWare Explorer can only have a combined total of 75 nodes from the input and hidden layer. Since 50 nodes (or 51 nodes in the case of API input) were used in the input layer, 20 nodes were arbitrarily chosen as the number of nodes in the hidden layer. Figure 8.1 shows the neural network used when API was included, otherwise the API input node was not used.

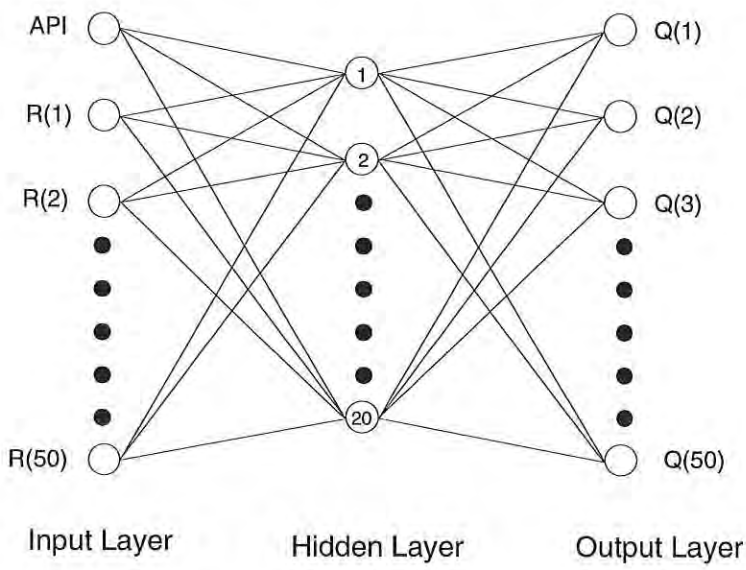


Figure 8.1 Fully connected neural network model adopted for hydrograph prediction with API as an input

8.3 Results

Table 8.5 shows the results from averaging the performance criteria from each of the 6 test storms. Figure 8.2 shows these results in graphical format.

Table 8.5 Summary of results of each of the six training methods in terms of the CD, the RMSE and errors in timing, volume and magnitude when predicting the whole hydrograph

Training	CD		RMSE		Timing Error (hours)		% Error Volume		% Error Peak	
Method	API	No API	API	No API	API	No API	API	No API	API	No API
1 * (11)	-0.72	-0.31	49.5	37.4	2.8	5.3	45.4	8.5	84.9	-5.5
2 (10)	-0.10	-0.16	32.0	36.5	3.8	3.3	3.9	20.3	**-2.0**	6.1
3 (7)	**0.39**	**0.27**	**24.8**	**27.3**	5.3	2.2	**2.6**	8.6	-13.6	-19.0
4 * (4)	-0.02	0.11	34.4	33.1	**1.0**	**0.5**	35.2	30.6	25.2	22.7
5 (3/4)	0.11	0.15	28.6	28.3	2.7	4.7	-3.6	**-0.8**	-17.2	-20.5
6 * (6/6)	-	-0.13	-	40.1	-	3.7	-	22.8	-	**2.1**

Note:

a) * denotes storm on 30/8/92 was included in the training set;

a) ( ) denotes the number of storms used in each training data set;

c) (3/4) denotes the first number '3' corresponds to the number of storms used for training from one group, whilst '4' corresponds to the number of storms used for training from the other group; and

d) Bolded values indicate the best performed training methods for each performance criteria.

The overall results of the analysis were not particularly encouraging. Method 1 (Training on all storms using weighted catchment rainfall) performed the worst of all. However, by removing the storm on 30/8/92 (Method 2) a general improvement was observed. Based on the CD and the RMSE, Method 3 (Single station rainfall) performed best. Method 3 also performed best in terms of percentage error in flow volume. Method 4 (Training set containing storms with similar time to peak) as expected produced the smallest errors in peak timing. By using Method 5 (Training set containing similar hydrograph peak storms) no improvement in the peak hydrograph was calculated, however the percentage error in flow volume were reduced. Method 5 was the only training method that underestimated both the flow volume and peak magnitude.

It was apparent that the API input failed to significantly improve the overall performance. In fact, the prediction of some hydrographs deteriorated by including API as a model input. Method 6 (Training set containing similar 30 day API storms only) surprisingly failed to improve the overall results in terms of the CD and the RMSE, however it did produce the least error in predicting the hydrograph peak.

In Chapter 7, API was found to be a poor measure of catchment response, a direct result of poor spatial representation, leading to errors in calculating API, which was probably carried over into this part of the study. The network may also have become confused and unable to differentiate between the different magnitude and separate purposes of the API and rainfall input. The fact that the two inputs differ markedly in size (i.e. the API is a large number in comparison with the rainfall increments) should not have been a factor, since the normalised procedure was specifically used to account for this problem.

The results shown in Table 8.5 are averaged results, and no single storm showed the same relationships when the training methods were varied because each of the storms tested were so different. Figure 8.3 illustrates typical plots for predicting the storm of 8/9/83, which highlights the difference between the errors shown for this storm compared with the averaged results depicted in Table 8.5. Figures 8.4 and 8.5 illustrate how the variation of the training data affected the predicted hydrograph. Figure 8.4 shows two predicted hydrographs with multiple peaks. It shows the storm on 15/7/87 which was trained on the storms occurring on 24/7/81, 8/8/81, 8/9/83 and 24/5/88 using Method 5 (Training set containing only similar hydrograph peak magnitude storms). It can be seen that the four training storms correspond well to the multiple peaks of the predicted hydrograph. This means that the length of time to the burst was modelled well and perhaps even the various sub-catchment outputs, therefore the generalisation of the overall rainfall-runoff response was not found by the model.

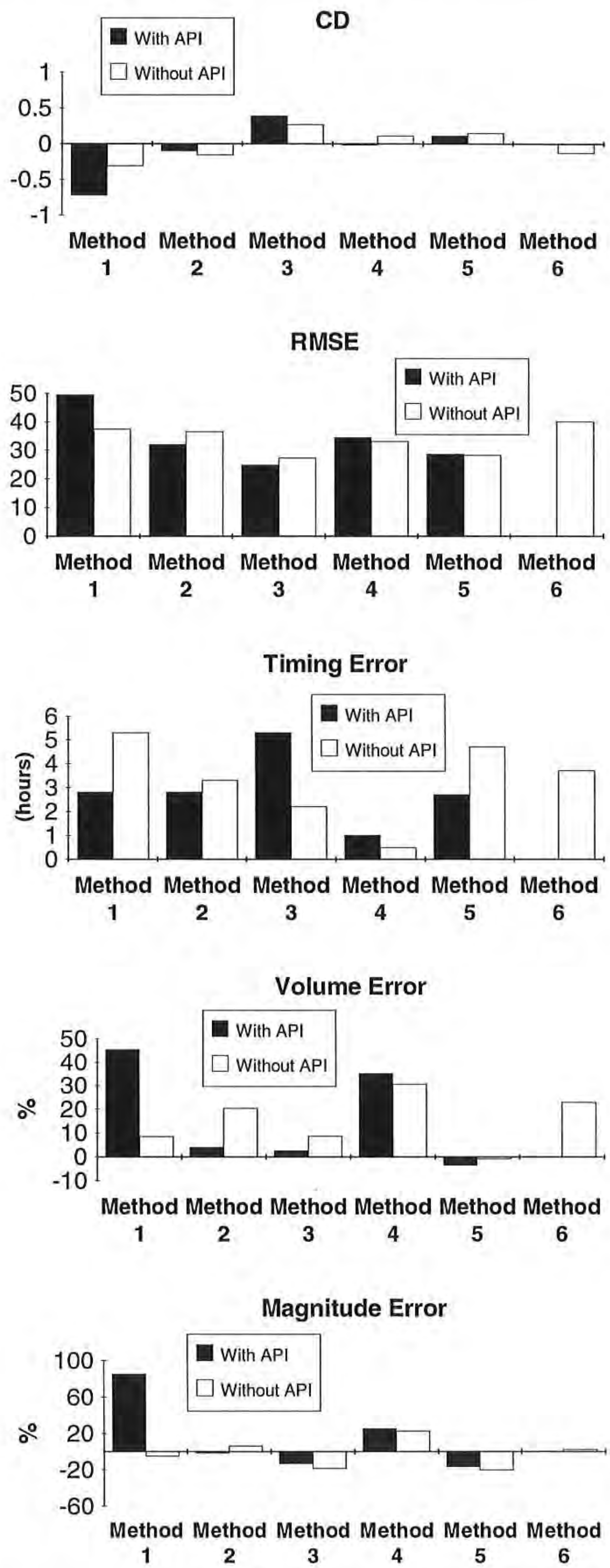


Figure 8.2 Performance of the 6 training methods based on the CD, the RMSE and errors in timing, magnitude and volume for the cases of API input and no API input simulating the whole hydrograph

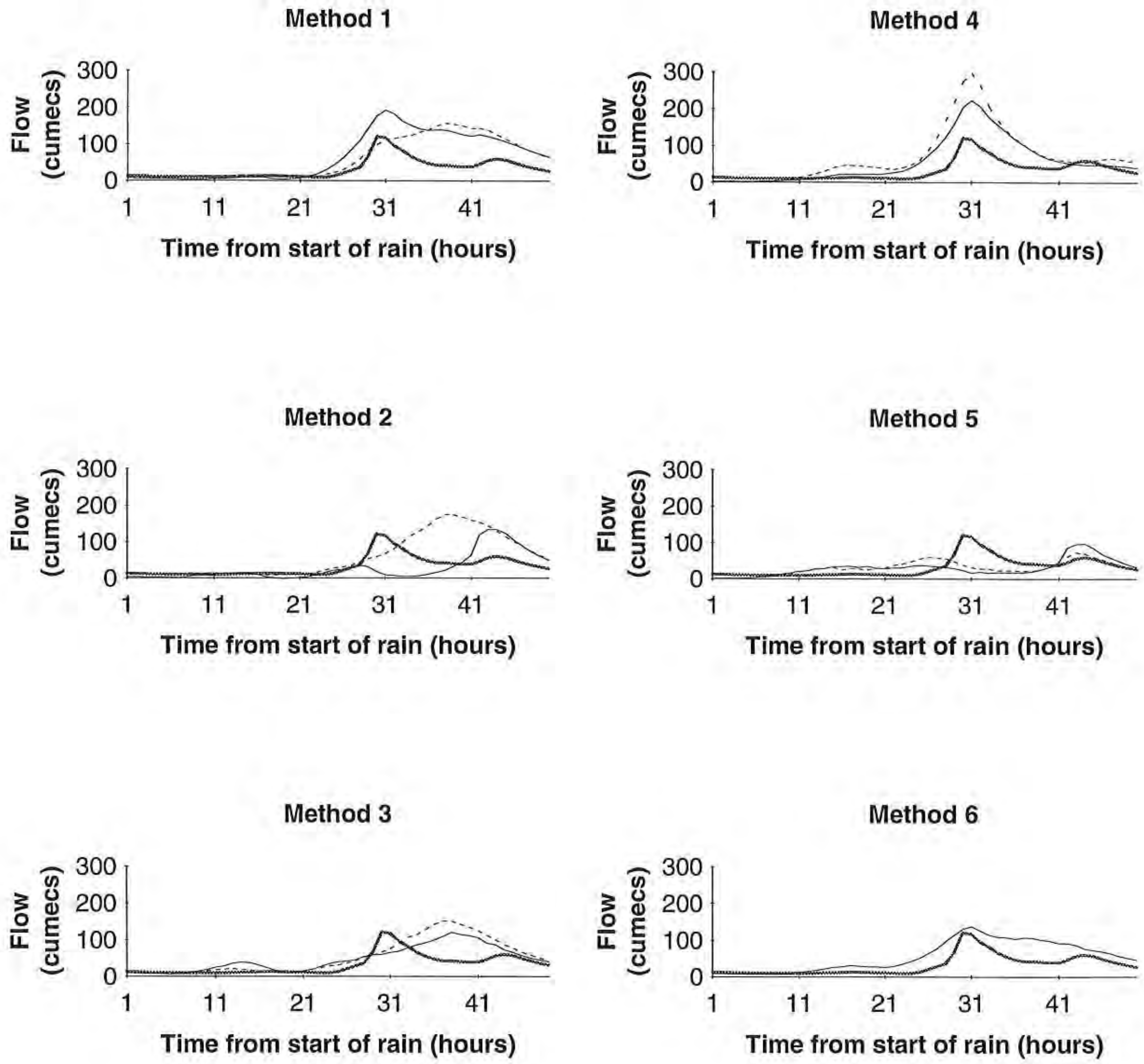


Figure 8.3 The results of simulating the hydrograph of the 8/9/83 storm for the six training methods

(Note: Bolded line represents actual hydrograph, dotted line represents training with API whilst other solid line represents training without API)

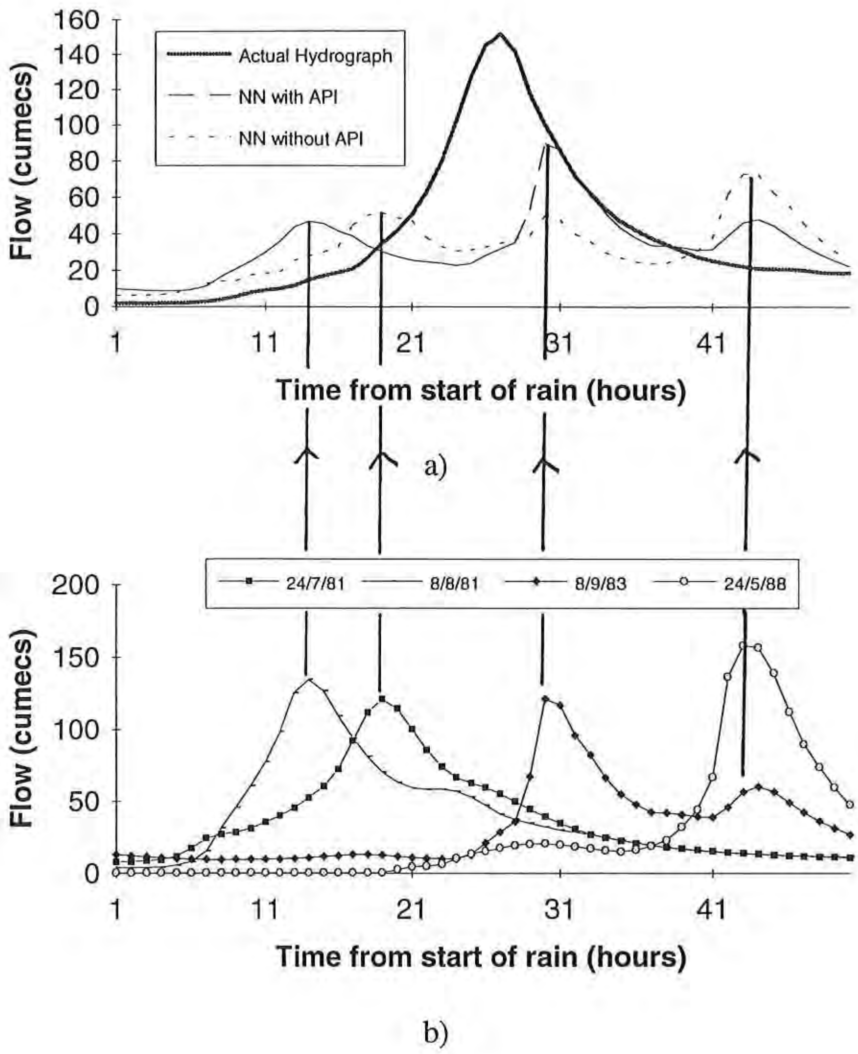


Figure 8.4 A comparison of the tested hydrograph on 15/7/87 using Method 5, with the hydrographs that make up the training set; a) Hydrograph tested both with and without API input; b) Hydrographs within the training set

8.4 Conclusions

Two main observations were shown. The first was the failure of the API input component to enhance the results. In fact, many of the results deteriorated with its inclusion. The second observation was how the results changed by altering the training data set, including the spatial rainfall distribution over the catchment.

It is obvious that the quality and the quantity of the training set is also important. The sensitivity to the number of storms used for training was found, and the variability of the data set altered. The general conclusion is that a highly variable training set will affect the results and through grouping the data into sets with similar characteristics, the performance may be improved. An important observation was that even though the number of storms used for training was reduced by splitting the data into similar time-to-peak characteristics, timing errors were reduced. Whether or not further improvements to the result would occur if more data was included (i.e. more storms) is unclear.

Instead of using API as an input to the model to separate storms with similar potential rainfall-runoff characteristics, the storms themselves could be normalised based on the wetness of the catchment, using say a value of 1 for a fully saturated catchment, and a value of 0 for a dry catchment. This would remove any subjectivity as to whether there were problems with the way the API input value was normalised relative to the rainfall input.

Perhaps the biggest limiting factor was the accuracy of the rainfall input. With such varied spatial rainfall representation for each storm, it would not be surprising if this was the dominating factor for contributing to the variability in the output results.

The next chapter, Chapter 9 will investigate using an artificial neural network for real-time flood forecasting. The results observed in this chapter will be used to develop a strategy for this. The value of antecedent precipitation index as a model input to improve the real-time forecasting capabilities seems doubtful. It is anticipated that the results of further application in Chapter 9 will again be limited to the variability of the rainfall input and the number of storms available for analysis.

Chapter 9

Real-Time Runoff Forecasting using an Artificial Neural Network Model

9.1 Setting up the Model

In addition to the factors applied in Chapter 8 to establish the neural network model for a complete hydrograph simulation, a number of additional aspects must be considered for developing the model for real-time computations. These additional factors include:

- An improved rainfall-runoff prediction relationship;
- Determination of a rainfall-runoff time delay lag;
- The length of time to forecast; and
- Adjustments to the number of training sets from each hydrograph.

9.1.1 Input and Output Parameters

Again, instantaneous hourly flow values from Houlgraves Weir and hourly rainfall were adopted. Baseflow was not removed because rainfall losses were not considered. The removal of baseflow would have probably made little difference to the overall result because it is relatively small compared with the peak total flows.

Theoretically, the inclusion of an antecedent catchment indicator such as antecedent precipitation index (API) or pre-storm baseflow (BF) should assist in determining how the Onkaparinga River catchment will respond, however this was not the case, as already seen in Chapter 7. Indeed, it was shown that in some cases the inclusion of API as a model input caused a reduction in the model's performance. In addition to this, the time required to set up the models, run them and interpret the results, meant that some optimisation of and assumptions about what was to be tested had to be made. Therefore, due to the poor results observed when including API for simulating the whole hydrograph in Chapter 8, it was decided not to include API as an input for this part of the study, even though in theory it would appear that API input is a fundamental factor in developing such a model. As in Chapters 7 and 8, rainfall was weighted from all relevant pluviograph stations to maximise the number of storms available for training.

9.1.2 Selecting of Appropriate Storms to Test

Only three of the available storms were used for testing. Each of the remaining nine storms were used for training purposes only. Ideally, all storms should have been tested in turn, but time did not permit such an extensive study.

The plot of the twelve available storms shown in Figure 6.3, shows the considerable difference in the hydrologic characteristics of each storm in terms of peak magnitude, peak timing and flow volume. The start of each event was determined subjectively as discussed in Section 7.2 and the next 50 hours of rainfall and runoff was available for input into the ANN model.

The three storms selected for testing occurred on 8/8/81, 24/5/88 and 30/8/92, because each was hydrologically unique from a flood forecasting aspect. The storm on 8/8/81 had a short time to peak with a moderate peak magnitude and would be more typical of a flash flood type situation. The hydrograph of 24/5/88 peaked very late in relation to when the rainfall started, and had only a moderate peak magnitude. In Chapter 7 little correlation was found between the soil moisture indices and initial loss for the 24/5/88 storm. This is visually evident by noting that this storm had an extremely high volume of rainfall but did not produce a large peak flow or flow volume. The storm on 30/8/92 was the most extreme and the most typical of a damaging event from within the data set. It generated the highest peak magnitude and flow volume. Testing of this storm was ideal to determine whether the artificial neural network could perform as an extrapolation tool.

9.1.3 Determination of the Rainfall-Runoff Time Delay

Fujita and Zhu (1992) simplified the hydrological system into a relationship between rainfall, runoff and an associated rainfall-to-runoff time delay. A generalised relationship to describe the basin outflow Q(t) in terms of the rainfall R(t) is shown in Equation 9.1.

$$Q(t) = f\{R(t-a)....R(t-b)\} \tag{9.1}$$

where:

a,b = Rainfall-runoff lags

The rainfall-runoff lag measures the rate of conversion of rainfall into basin runoff. This occurs because rainfall over a catchment does not produce an immediate response in terms of an increase in runoff at downstream gauging stations (Chander and Shanker, 1984), and is found even in the most intense storms. There is an initial response time for the rainfall excess to become evident as actual runoff, caused by the situation of the saturated contributing areas.

A number of different definitions for rainfall-runoff lag have been documented. The following are three such examples:

Lag 1 (Bencherqi et al., 1993): Time from the centroid of the hyetograph (calculated up until the hydrograph peak) to peak of hydrograph;

Lag 2 (Chander and Shanker, 1984): Time from the start of rainfall to the start of the first rapid rise in the hydrograph; and

Lag 3 (B.C. Tonkins & Associates, 1977): Time from maximum rainfall intensity to the maximum flow.

Only Lags 1 and 2 have been considered in this study. The idea was to examine when the catchment became wet and then contributed at different times in different parts of the catchment. A diagrammatic representation of the lags considered is shown in Figure 9.1.

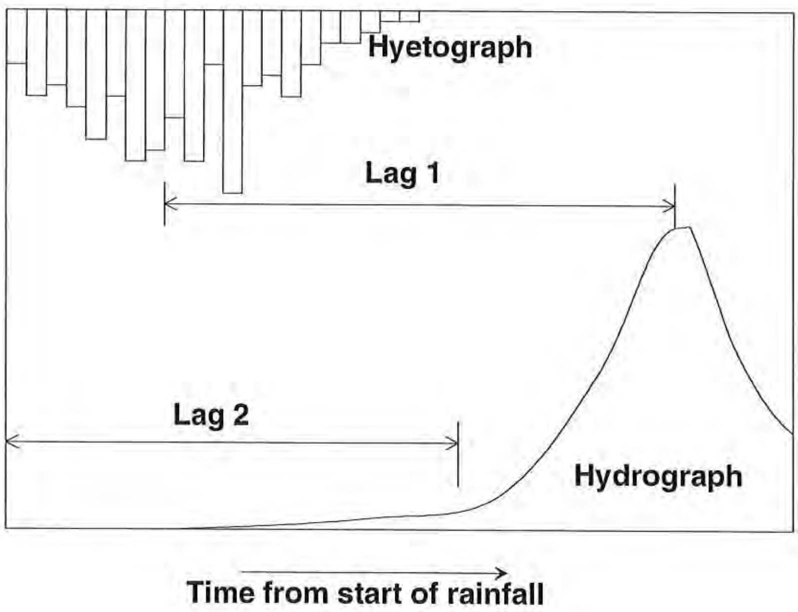


Figure 9.1 Diagrammatic representation of the two rainfall-runoff lags considered in this study

Table 9.1 shows the two lag parameters calculated for each event (rounded off to the nearest hour) as well as an overall average value for each lag parameter.

Table 9.1 Computed rainfall-runoff lags for each of the 12 storms

Storm	Lag 1	Lag 2
24/7/81	7	5
3/8/81	17	15
8/8/81	5	5
25/8/83	6	6
8/9/83	18	25
24/6/87	24	22
15/7/87	13	7
24/5/88	27	19
15/8/90	10	8
30/8/92	15	7
16/9/92	6	5
8/10/92	20	17
AVERAGE	*14*	*12*

Note: Shaded storms are the test storms as defined in Section 9.1.2

From Table 9.1 there is reasonable correlation between most of the two calculated lags for each storm, and the overall averaged values. Based on these results, an estimate for the rainfall-runoff time delay would be in the order 13 hours. This would indicate that on a physical basis, both lags are similar.

When comparing individual storms, there is quite a marked difference between the calculated lags. The minimum calculated lag was 5 hours, and the maximum was 27 hours. The majority however fell below 20 hours. Chander and Shanker (1984), however found similar rainfall-runoff lags for different storms, even though the rainfall distributions were varied. The vast difference in calculated lags again highlights the highly variable nature of the hydrologic characteristics of these storms on the Onkaparinga River catchment.

Also considered, in setting up the artificial neural network for real-time forecasting, was an approximate duration of rainfall that contributed to the outflow at a particular time. Two different lags were compared with two different rainfall duration's as shown in Equations 9.2 and 9.3. Equations 9.2 and 9.3 use 10 and 5 previous rainfall increments respectively.

$$Q(t) = f\{R(t-5), R(t-6), \ldots\ldots, R(t-14)\} \tag{9.2}$$

$$Q(t) = f\{R(t-1), R(t-2), \ldots\ldots, R(t-5)\} \quad (9.3)$$

An alternative method which was not investigated could have been to calculate the API of the storm to be forecasted, then based on the rainfall-runoff lag for historically known storms with a similar API, select an appropriate rainfall-runoff lag. Figure 9.2 shows the correlation between the 30 day API and both of the lags defined in this section for the twelve available storms, from which no visible correlation is evident.

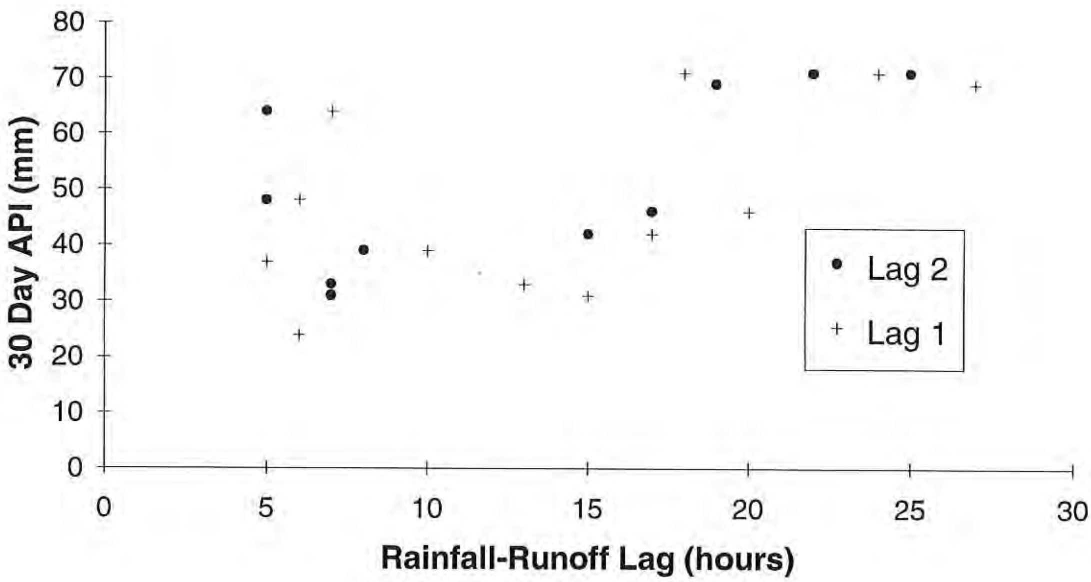


Figure 9.2 The correlation between the 30 day API and both rainfall-runoff lags defined in Section 9.1.3 (Lag 1 and Lag 2)

9.1.4 Runoff Prediction Relationships

The model developed by Fujita and Zhu (1992) for iterative runoff forecasting was modified in this study for use as a multi-step ahead forecasting tool, and is expressed in Equation 9.4. It was assumed that at time t, the basin runoff Q(t) and rainfall R(t) are known.

$$\{Q(t+1)\ldots Q(t+n)\} = f\{R(t-a), \ldots, R(t-b), Q(t), \ldots, Q(t-c)\} \quad (9.4)$$

where:

a,b = Rainfall-runoff lag (time delay)
c = Number of previous runoff inputs
n = Number of hours forecasted

Forecasts were made for three cases with different combinations of input parameters:

- *'Rain and flow': Denoted (R/F)* - See Equation 9.4

- *'Rain only': Denoted (R)*

$$\{Q(t+1)...Q(t+n)\} = f\{R(t-a),...,R(t-b)\} \tag{9.5}$$

- *'Flow only': Denoted (F)*

$$\{Q(t+1)...Q(t+n)\} = f\{Q(t),...,Q(t-c)\} \tag{9.6}$$

The 'Flow only' case did not use the rainfall-runoff lag and the 'Rain only' case did not use the previous runoff inputs.

It may seem that when using artificial neural networks increasing the number of previous runoff increments will improve the accuracy of the next forecast. However, it was important to limit the number of previous runoff increments used for training because the network would have difficulties in 'mapping' the inputs (previous part of the hydrograph) to the outputs (future part of the hydrograph). An example of such difficulties are where a sudden change in the magnitude of the hydrograph occurs, including a rapid increase in the rising limb or immediately following the hydrograph peak.

Two different amounts of previous runoff data were used as input to each training set and compared.

- 1 input {Q(t)}
- 5 inputs {Q(t),.....,Q(t-4)}

In using five previous runoff inputs, the most recently known runoff value, Q(t) is used to provide the starting point for the next forecast, and the next four inputs {Q(t-1),....,Q(t-4)} are used as a means of giving the model an idea of what 'shape' the forecast should be as discussed in Section 5.8.2 in explaining the model by Fujita and Zhu (1992).

9.1.5 Length of Time to Forecast

Two lead time runoff forecasts were compared:

- A 1 hour single step forecast {Q(t+1)}; and
- A 5 hour multi-step forecast {Q(t+1),.....,Q(t+5)}.

9.1.6 The Method of Training the Artificial Neural Network

The three test storms were trained using four different methods.

Method 1 (All except current event): Training sets contained data representing all of the storms except for the test storm, therefore 11 storms were contained in the data set. No rainfall-runoff information regarding the current test storm was used during training.

Method 2 (All including current event): Essentially the same as Method 1 but also included training sets from the currently available (or known) rainfall-runoff information of the test storm, up until the forecast time.

Method 3 (Current event only): Training sets contained only the currently available rainfall-runoff information from the test storm, up until the forecast time. Training sets from the remaining 11 storms were not included.

Method 4 (Similar time to peak storms including the current event): Training sets contained only those storms that had similar time to peak characteristics (T_p). The training sets were divided into the same two groups as in Section 8.2.2. The storm of 8/8/81 fell within the group containing the low time to peak storms, and the storm of 30/8/92 fell within the group containing the high time to peak storms, and were therefore trained only on the remaining storms within their respective group. The storm on the 24/5/88 did not lie within one of these two groups, therefore was not tested using this method. Training sets from the currently known test storm information were also included in training.

Methods 1 and 2 involved training with variable hydrological data sets. Method 1 was more variable because it did not contain the currently available information from the test storm. Method 3 involved training on data sets with the least hydrologic variability, whilst Method 4 had an even more reduced variability.

Since Method 3 involved training on the currently available rainfall-runoff information from the test storm, the artificial neural network performed only as an extrapolation tool when forecasting the rising limb of the hydrograph.

9.1.7 Altering The Number of Training Sets From Each Hydrograph

It was also decided to test the sensitivity of the forecasts to the number of training sets (input-output combinations) from each of the storms. As in Chapter 8, 50 hours of rainfall-runoff information was available from each storm, therefore 50 possible training sets could be used from each of the training storms.

Two separate scenarios were considered:

Scenario 1: Only a limited number of training sets were used for training. When the test storm was trained on other storms, only 10 training sets were taken from these storms for training. At the forecast time t, the previous 10 input-output combinations (at t, t-1,....., t-9) from the other training storms were used, remembering that the commencement of each storm was normalised at t=0 hours.

When information from the test storm was included in training, the most recently available 10 input-output combinations were used. For example, if the forecast (t+?) was performed at time t, training sets comprised of input-output information from times (t, t-1,...., t-9) for both 1 and 5 hour forecasts.

Scenario 2: Used the maximum amount of training data. The complete hydrograph (50 input-output combinations) were used to develop all possible training sets from each of the training storms, except for the current test storm, regardless of when the forecast was made. When the current test storm was included in training, again the most 'recent' 10 input-output combinations were used, as in Scenario 1.

Table 9.2 shows the difference in the number of training sets for the four training methods of each training scenario. Scenario 1 contained approximately one quarter of the training sets as Scenario 2. The following lists the training methods in order of decreasing number of training sets; Method 2, Method 1, Method 4 and Method 3. Of particular note was how so few training sets were used for Method 3 as compared with the other methods.

Table 9.2 The number of training sets for each of the training methods for each scenario

	Number of Training Sets					
	Scenario 1			Scenario 2		
Training Method	Other Storms	Current Storm	*Total*	Other Storms	Current Storm	*Total*
Method 1	11×10=110	0	*110*	11×50=550	0	*550*
Method 2	11×10=110	10	*120*	11×50=550	10	*560*
Method 3	0	10	*10*	0	10	*10*
Method 4	4×10=40	10	*50*	4×50=200	10	*210*

9.1.8 Neural Network Parameters

As in Chapter 8, the default values of the software were used. The following parameters were arbitrarily chosen for the artificial neural network model:

Learning Rule:	Cumulative delta
Transfer Function:	Sigmoid
Convergence Criteria:	2 % RMSE

9.1.9 Neural Network Architecture

Two networks were trialed, a fully connected and a partially interconnected backpropagation network, with the networks shown in Figures 9.3 and 9.4 respectively. A single hidden layer was used with the number of hidden nodes set arbitrarily to the number of nodes in the input layer. The partially interconnected network is analogous to that used by Fujita and Zhu (1992) to separate the two independent input parameters from the output layer.

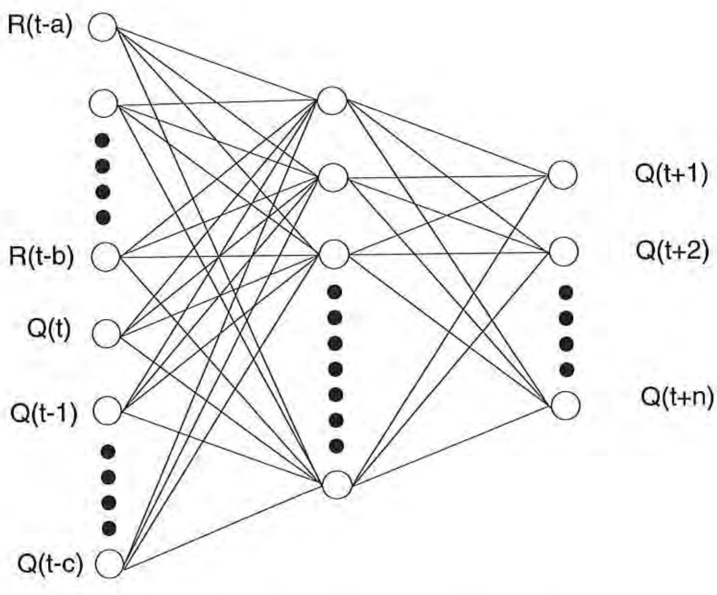


Figure 9.3 The fully connected ANN model used to forecast runoff

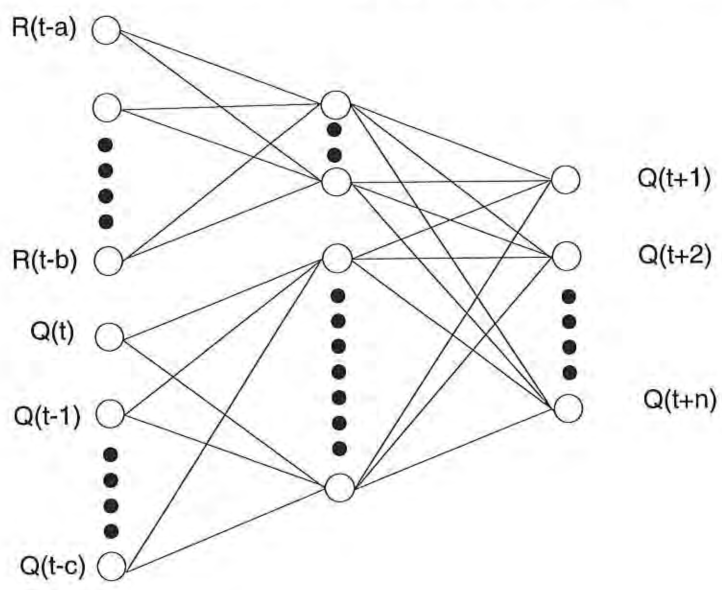


Figure 9.4 The partially interconnected ANN model initially trialed to forecast runoff

9.2 Analysis

A flood forecasting procedure normally commences after the exceedance of some pre-defined threshold in stage height or at the commencement of the rising limb of the hydrograph. For this part of the study, the commencement of forecasts began arbitrarily 5 hours after the commencement of rainfall (at t = 5 hours).

The biggest limitation with this study, was the many different combinations that had to be tested and compared. The time taken to complete each forecast was extremely lengthy because computations had to be performed at forecast times over the complete 50 hour duration of each storm. (i.e. for the 1 hour forecast, 45 forecasts were performed for each storm, assuming the forecasts commenced at t = 5 hours).

Not only did the training procedure for each forecast take some time, training and testing files also had to be created. This was an arduous and mentally impossible task if performed manually for so many cases. An Excel macro was developed to set up these files based on a simple template. Setting up the largest training files took approximately 20 minutes. An example of part of one of the training files used is shown in Appendix I.

To reduce the number of computations, a trial and error approach was used to minimise the analysis performed, however enough results were generated to gain a picture of how the model performed.

Initially, only the fully connected network was used. A number of observations were made with some test cases and if unsuccessful, further analysis was not undertaken. The observations were that:

- The model was unable to converge when training contained rainfall (R) as the only input. As a result, analysis using Equation 9.5, which used rainfall as the only input was discontinued altogether.

- Training which did not use the current storm as input (Method 1) did not perform well when rainfall and runoff (Equation 9.4) were used as input. At that time, it was thought that since the performance was poor using both rainfall and runoff as input, by using runoff as the only input, the model's performance would continue to diminish. As a result, to reduce the number of training methods tested, Method 1 was not continued using runoff (Equation 9.6) as the only input.

- When using only 1 previous runoff value as input for training purposes, convergence difficulties were encountered. The model was obviously unable to predict the next value based on only one previously known hydrograph value. This would generally be the case even for a trained forecaster (i.e. it is not possible to predict whether the value will increase or decrease because no historical trend is presented to the model).

Table 9.3 shows the analysis finally undertaken for the three test storms. The ticks(√) indicate computations were made, whilst a cross (×) indicates computations were not performed because of convergence difficulties. Training Method 4 was not carried out with Flow (F) as the only input because of time constraints.

Table 9.3 Summary of analysis carried out for each test case for each storm

Input Case	Rain/Flow (R/F)								Flow (F)			
Training Method	1		2		3		4		2		3	
Previous Runoff	1	5	1	5	1	5	1	5	1	5	1	5
	√	√	√	√	√	√	√	√	√	√	×	√
Test Case Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**		**11**

Using Scenario 1 for both rainfall-runoff lags, both 1 and 5 hour forecasts were computed for each case.

In operational forecasting, the 5 hour forecast is of more importance than the 1 hour forecast. Therefore, Scenario 2 was computed using the same test cases as in Table 9.3, except only 5 hour forecasts were performed. Training Method 3, using Scenario 2 was not performed because it is identical to that of Scenario 1.

Throughout the analysis, a total of 186 hydrographs were forecasted in real-time using the fully connected network. The actual time taken to train the various models ranged between about 1 to 10 minutes, but generally less than 5 minutes, depending on the number of inputs used, and the amount of training data utilised. For example, Scenario 1 took less time to train because it used less training data than Scenario 2. The rainfall-runoff lag containing more inputs {R(t-5),....., R(t-14)} obviously took longer to train than using the {R(t),....., R(t-4)} lag.

The partially interconnected network was trialed, but the output from the few trials that were made, were almost identical to the fully connected network. This was surprising in view of the success achieved by Fujita and Zhu (1992) in using this network. The time taken to set up the partially interconnected network in Professional II/Plus was very labour intensive because Professional II/Plus sets its default network as fully connected. At each forecast time the network had to be recreated (initiated) and then adjusted, which took a considerable amount of time, therefore its use for further forecasts was discontinued. Pictorial evidence of this is not shown because not enough 'runs' were performed using this model.

9.3 Results

Even with the reduced number of tests that were performed, it was difficult to generalise the overall performance of the model.

Two methods of examining the results are included, firstly an appreciation for the differences in the performance of the forecasted hydrographs from a visual aspect, and secondly a discussion of the results in more detail from a statistical point of view.

For each of the 11 test cases defined in Table 9.3, the same five performance criteria for each test storm were calculated as per Chapter 8. The averaged value from each test case was calculated. This formed the basis for generalising the overall results. From this, simple ranking systems were devised to summarise the results and are explained later in this chapter.

9.3.1 Visual Observations

It was difficult to summarise the results from a pictorial aspect as there are many slight variations in the results. Too many plots would be confusing, therefore only a few plots are shown to gauge the overall performance of the model.

Figures 9.5, 9.6 and 9.7 show some typical 1 and 5 hour forecasted hydrographs for the three test storms and for the three training methods using Scenario 1 only. Scenario 2 hydrographs cannot be used to make this same comparison because 1 hour forecasts were not performed for Scenario 2. A number of distinct observations were made regarding the performance of the forecasted hydrographs for Scenario 1. Perhaps the most obvious observation was that a 1 hour forecast was more accurate than a 5 hour forecast.

Figures 9.8, 9.9, 9.10 and 9.11 are typical plots showing the difference in performance between using Scenario 1 and Scenario 2 (for 5 hour forecasts only). Generally, the overall performance of the model was improved when Scenario 2 was used.

In most situations, the flow volume and peak magnitudes were underestimated. The only exception to this seems to be the 24/5/88 storm. As discussed in Section 9.1.2, this storm displayed quite unusual hydrologic characteristics because a large rainfall event produced only a moderate peak flow relative to the eleven other events.

In most cases, the peak of the hydrograph was forecasted after the actual peak occurred. The most accurately forecasted storm was generally the 8/8/81 storm. As expected, the least accurately forecasted storm in terms of predicting the peak was the large 30/8/92 storm, with the peak magnitude being underestimated in all cases. This would suggest that the model was unable to work as an extrapolation tool.

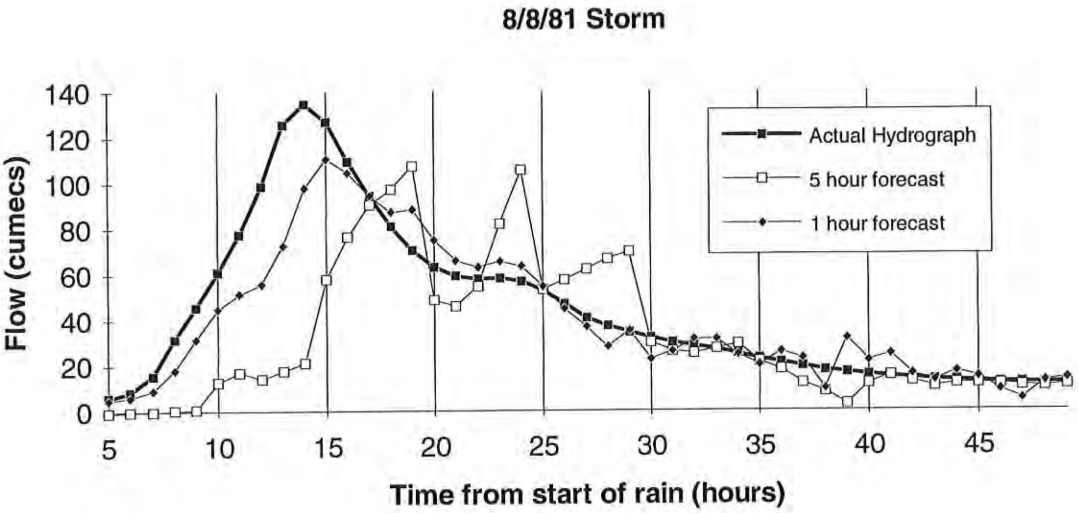
Generally, the hydrograph up until the start of the rising limb was well matched. However, once surface runoff commenced, the models performance deteriorated. In some cases 'negative' flows were observed.

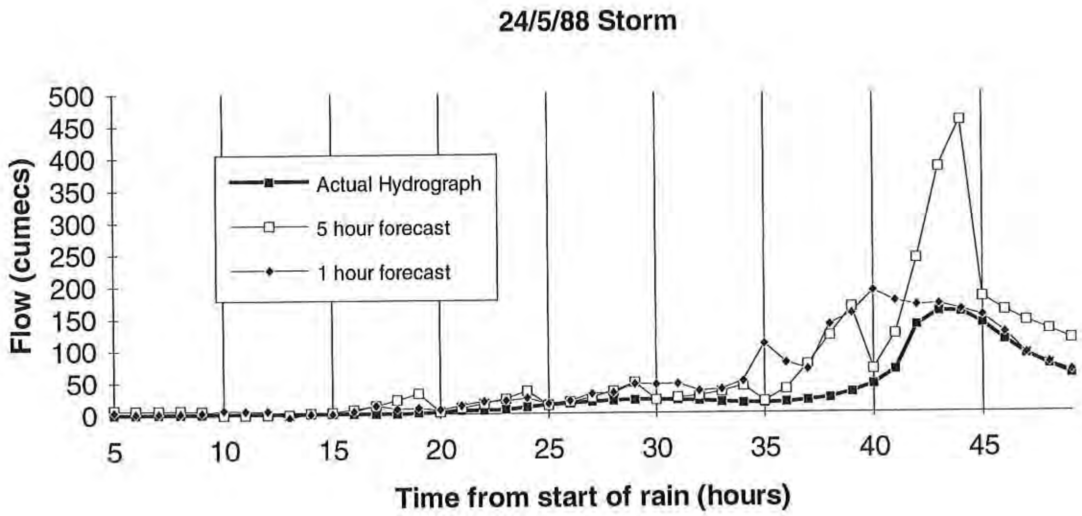
Little difference was observed between using 1 and 5 previous runoff inputs. Infact, in many of the cases, a more accurate forecast was achieved when only 1 previous runoff input was used. Forecasting using previous runoff (F) as the only input, behaved differently to those forecasted using rainfall and runoff (R/F).

Perhaps the biggest failure with these models was their inability to 'update' the next forecast with the addition of previous runoff inputs. As indicated for Scenario 1 in Figures 9.5 and 9.7 at each forecast time step, the hydrographs do not appear to be corrected based on the previously known part of the hydrograph. This is noticeable for both the 1 and 5 hour forecasts, but more so for the 5 hour forecast. Even the 5 hour forecasts using Scenario 2 as shown in Figures 9.8, 9.9, 9.10 and 9.11 displayed the same characteristic. For example, when a forecast was made on the rising limb, the next forecasted value, Q(t+1) was generally less than the previously known value (as explained in Figure 5.7), except for the 24/5/88 storm, where the predictions were almost always significantly greater than the actual hydrograph.

In terms of overall performance and updating ability, as expected, the 1 hour forecasts, using Training Method 3 (F) with 5 previous runoff inputs, performed best as shown in Figure 9.6. When the forecast occurred on the rising limb, the next forecasted value was greater than the previous one, and if on the falling limb, the next forecasted value was less than the previous value. For these 1 hour forecasts the hydrograph was translated forward by 1 hour. The 5 hour forecast was unable to update correctly, but was still translated ahead by about 5 hours. Although these observations were made for Scenario 1, the same would be expected to occur for Scenario 2 as well.

The best results made with Method 3 (F) have little significance or relevance from a practical or operational view point because, based on knowing the previous portion of the hydrograph, a trained forecaster could make hourly forecasts of equal accuracy to those in Figure 9.6, and for the 5 hour forecasts could possibly make even better predictions.





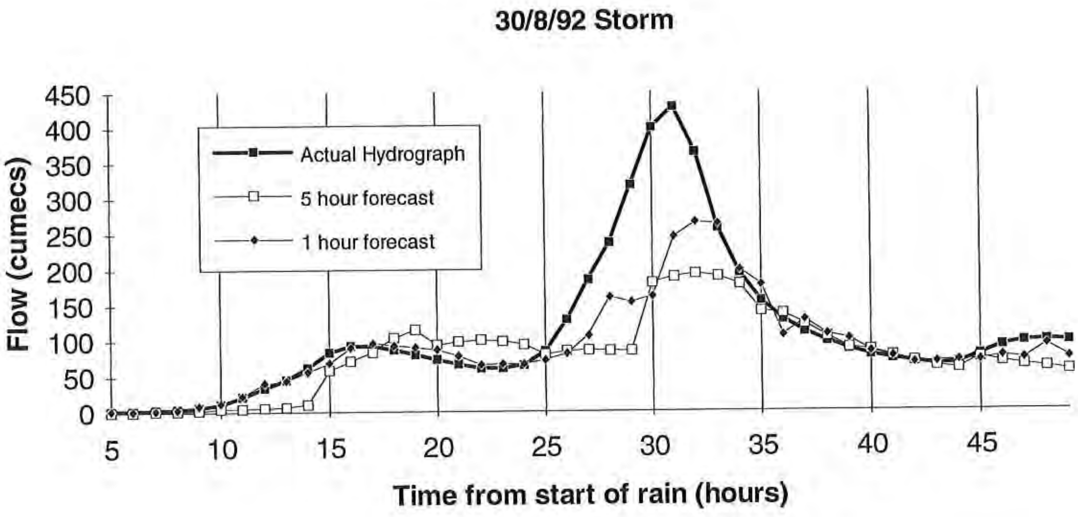


Figure 9.5 Method 1 (R/F), Lag {R(t),....., R(t-4)}, Scenario 1, 1 previous runoff values (Note : Vertical lines indicate the times when the 5 hour forecasts)

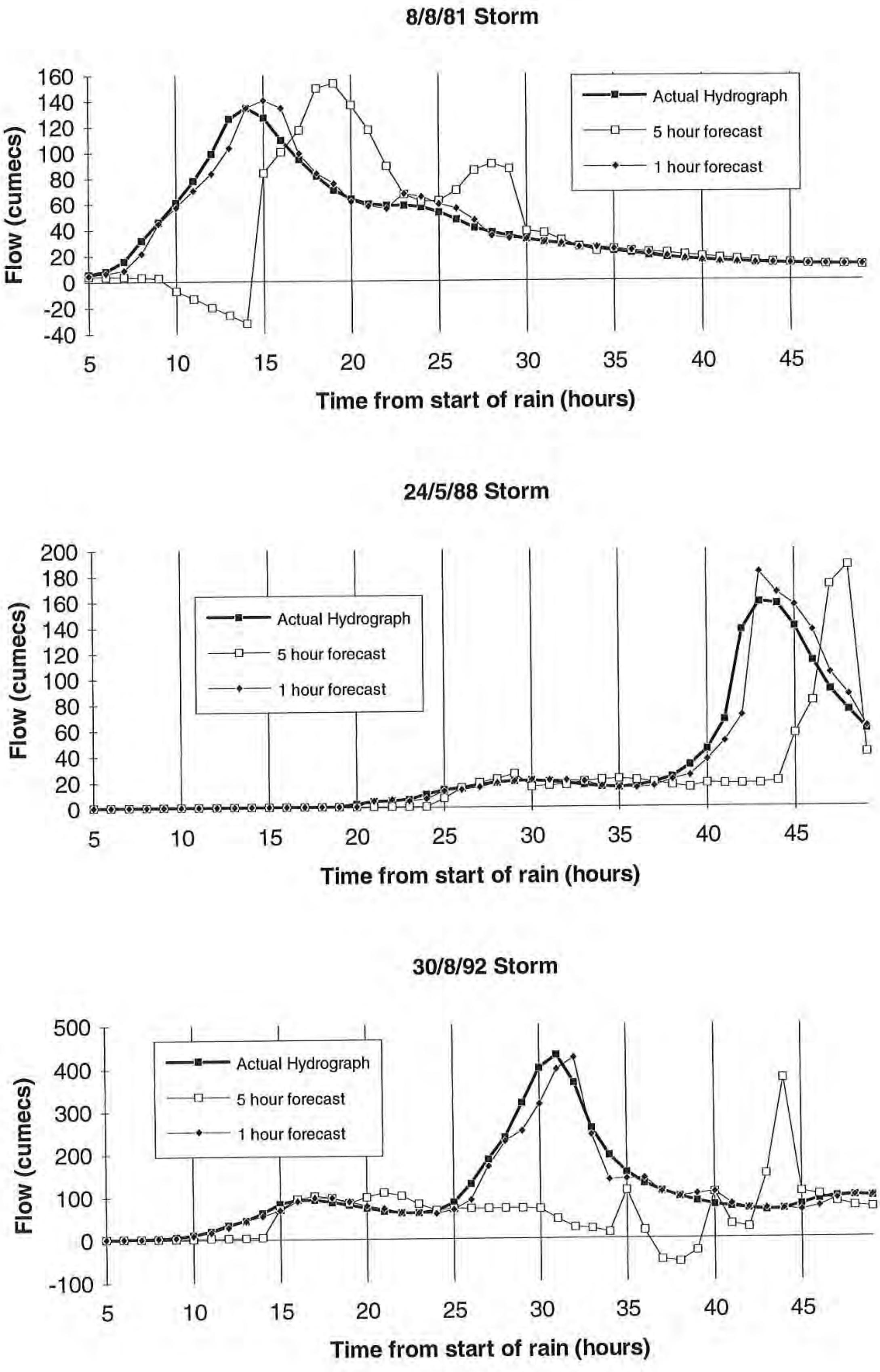
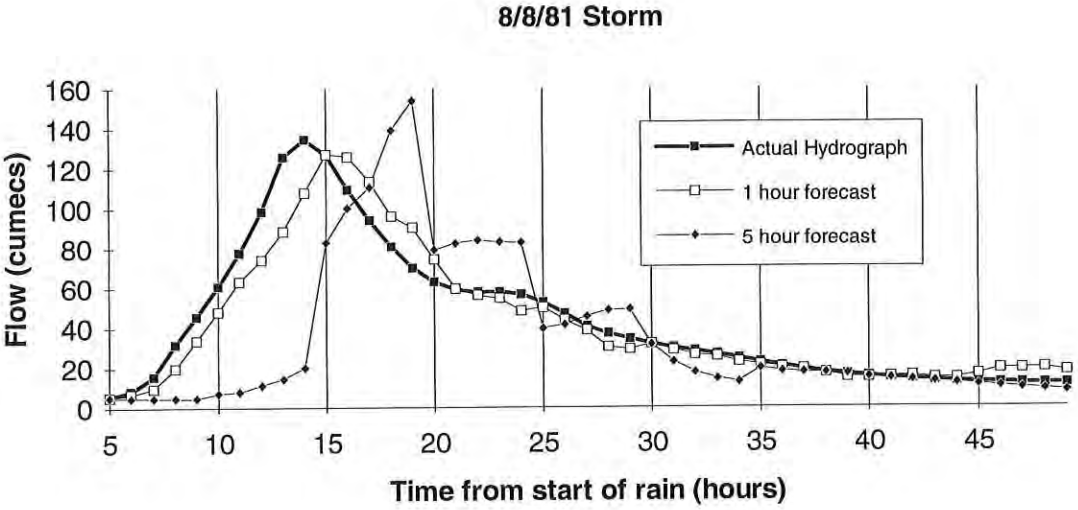


Figure 9.6 Method 3 (F), Scenario 1, 5 previous runoff values
(Note : Vertical lines indicate the times when the 5 hour forecasts are made)



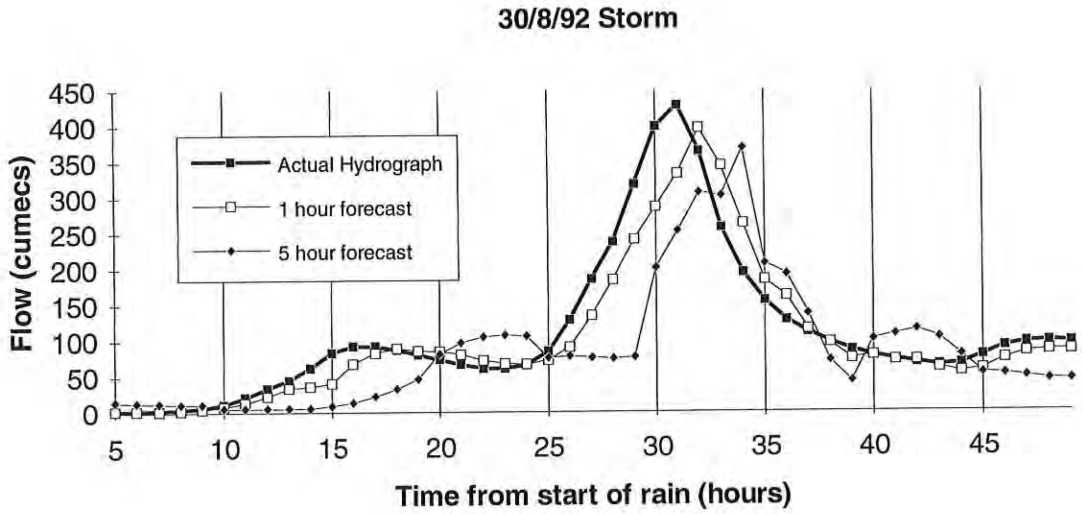
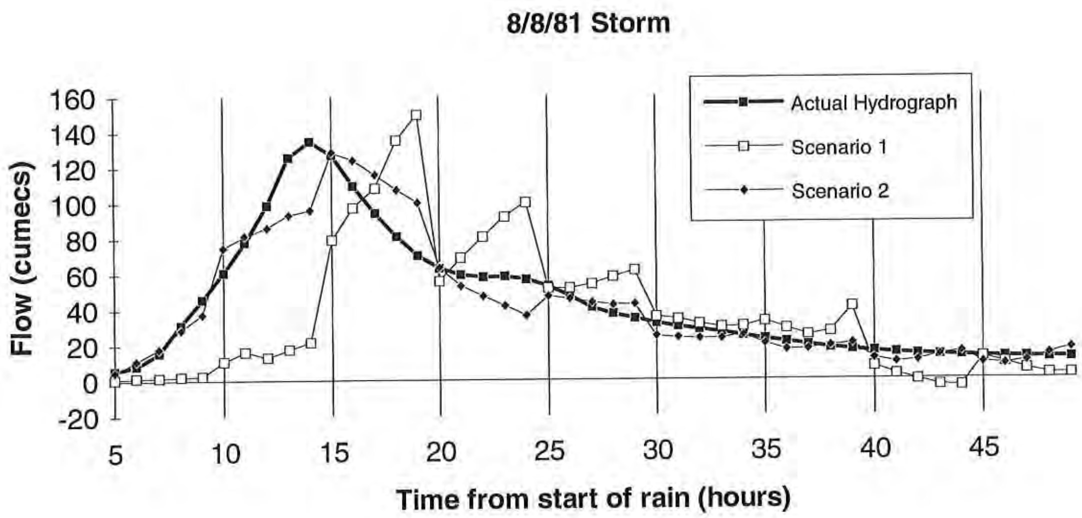
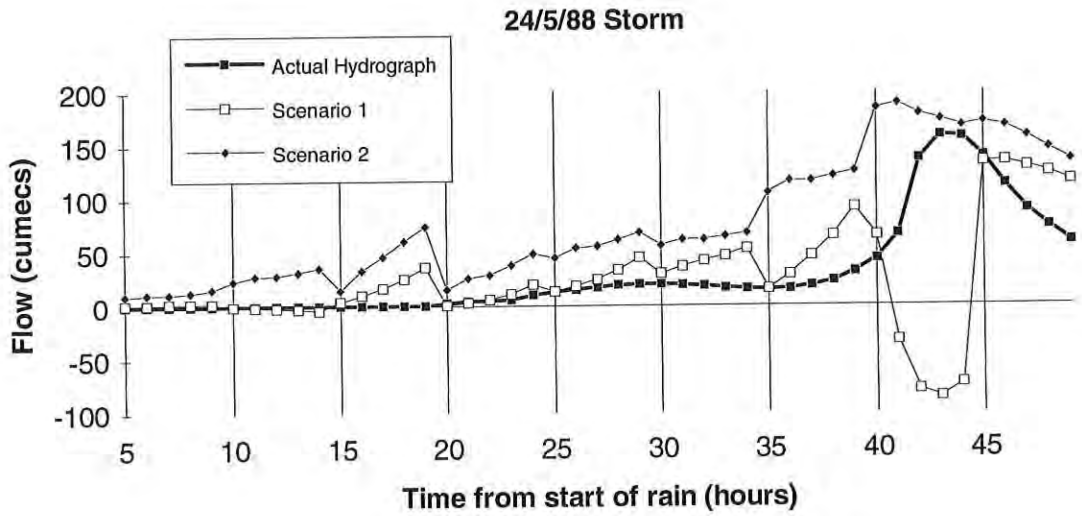


Figure 9.7 Method 4 (R/F), Lag {R(t),......,R(t-4)}, Scenario 1, 5 previous runoff values (Note : Vertical lines indicate the times when the 5 hour forecasts are made)





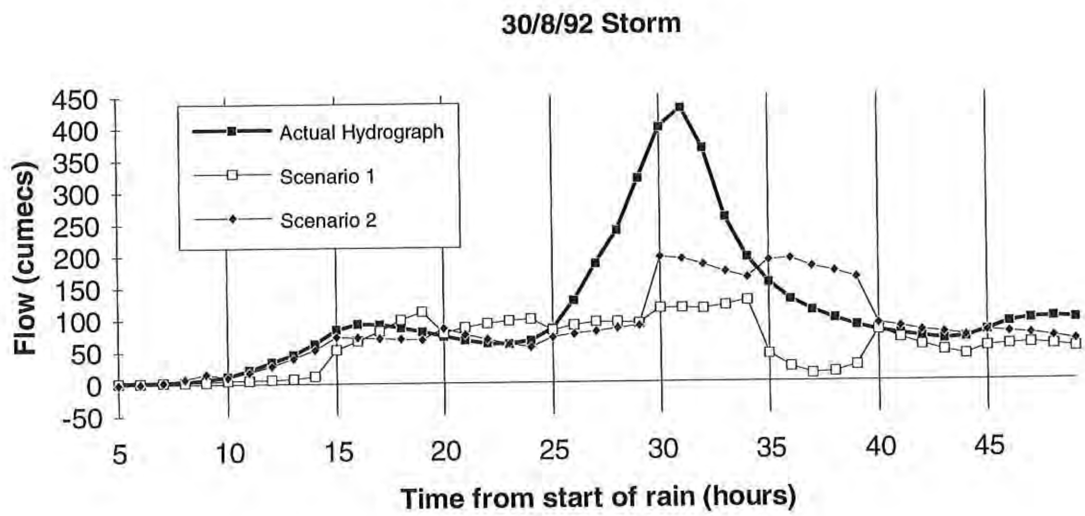


Figure 9.8 Method 2 (R/F), Lag {R(t),.....,R(t-4)}, 5 hour forecast, 5 previous runoff values

(Note: Vertical lines indicate the times when the 5 hour forecasts are made)

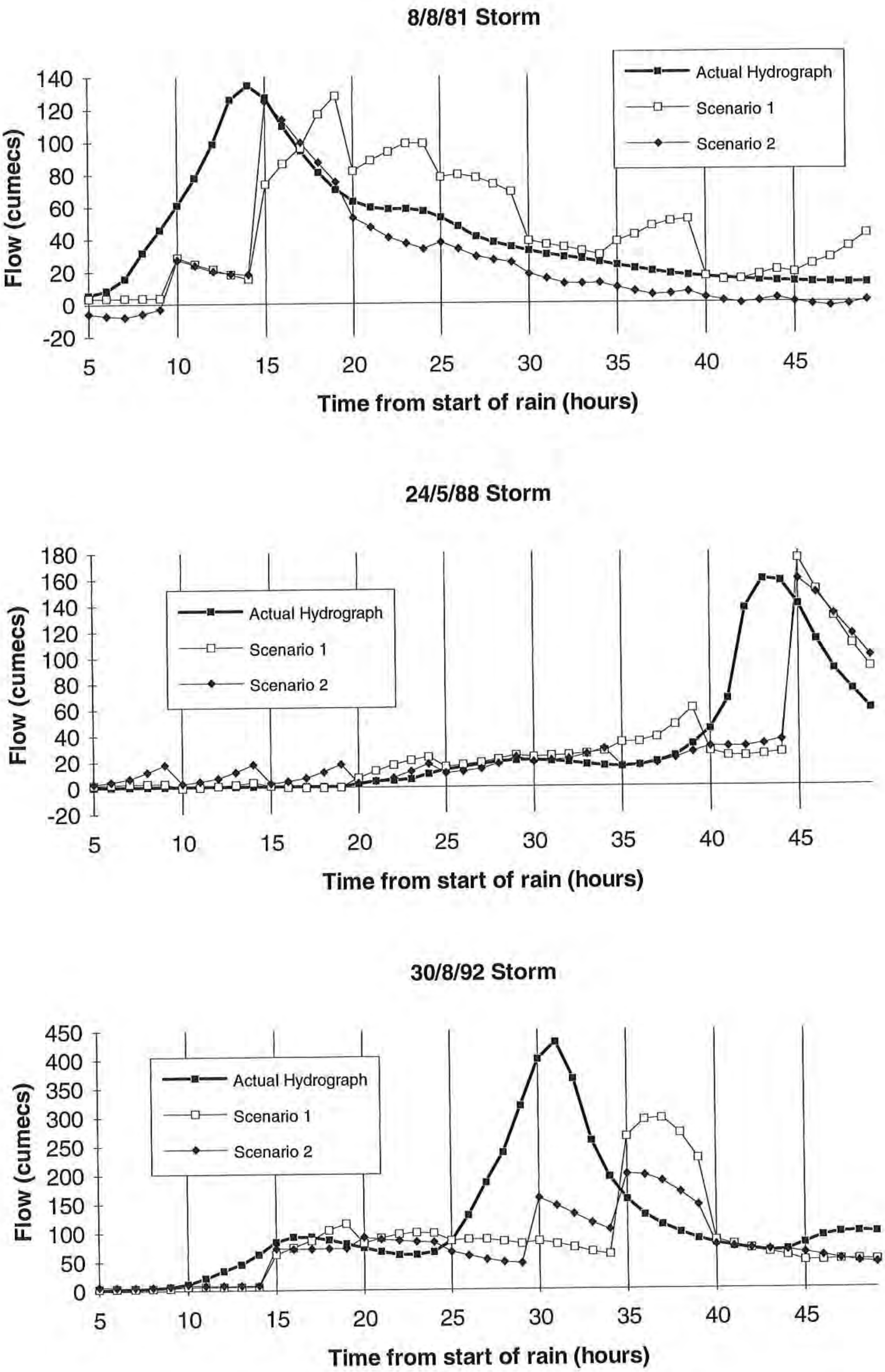


Figure 9.9 Method 2 (F), 5 hour forecast, 5 previous runoff values
(Note : Vertical lines indicate the times when the 5 hour forecasts are made)

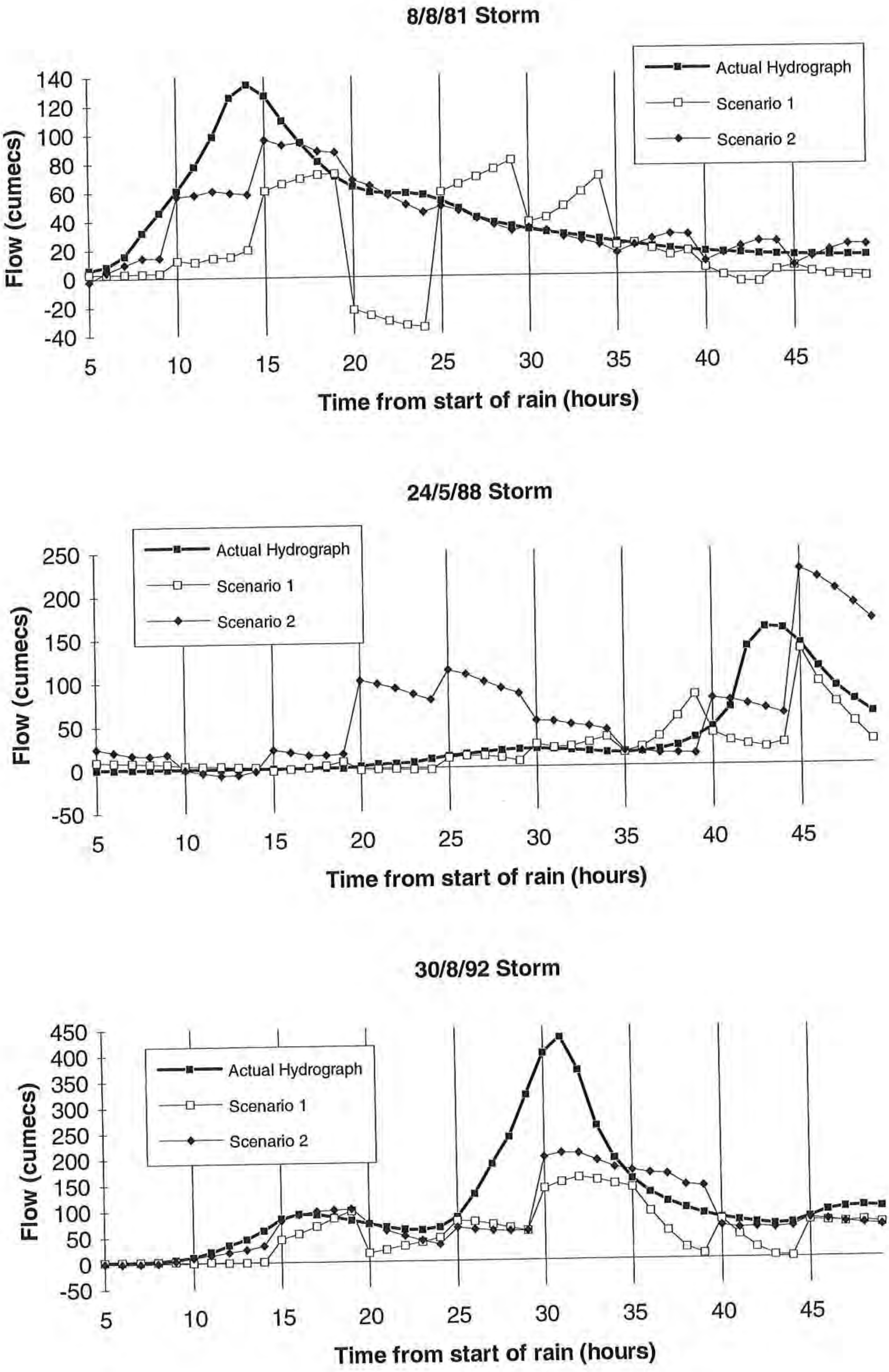
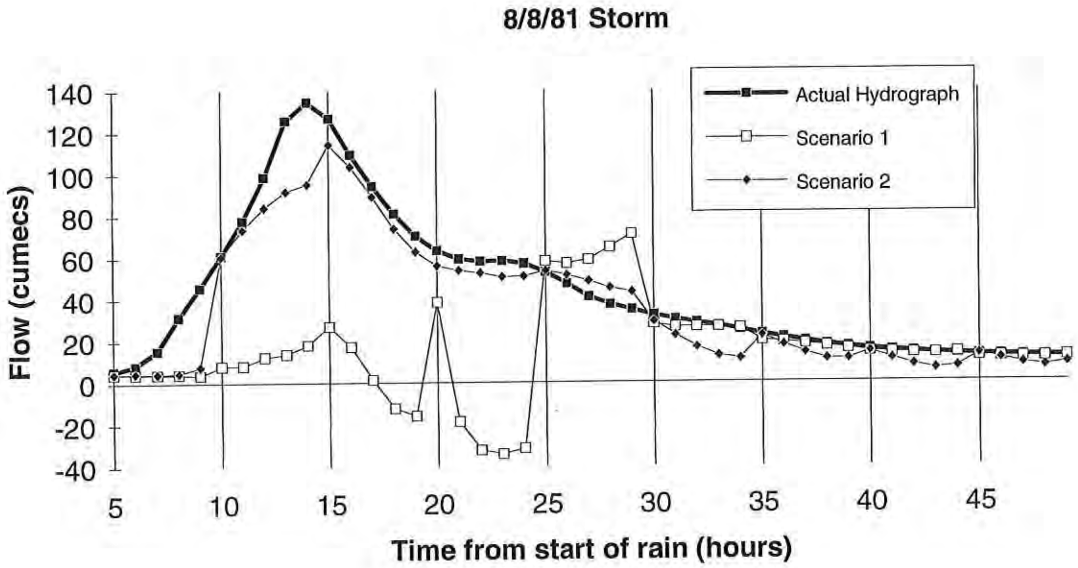


Figure 9.10 Method 2 (R/F), Lag {R(t-5),.....,R(t-14)}, 5 hour forecast, 5 previous runoff values

(Note : Vertical lines indicate the times when the 5 hour forecasts are made)



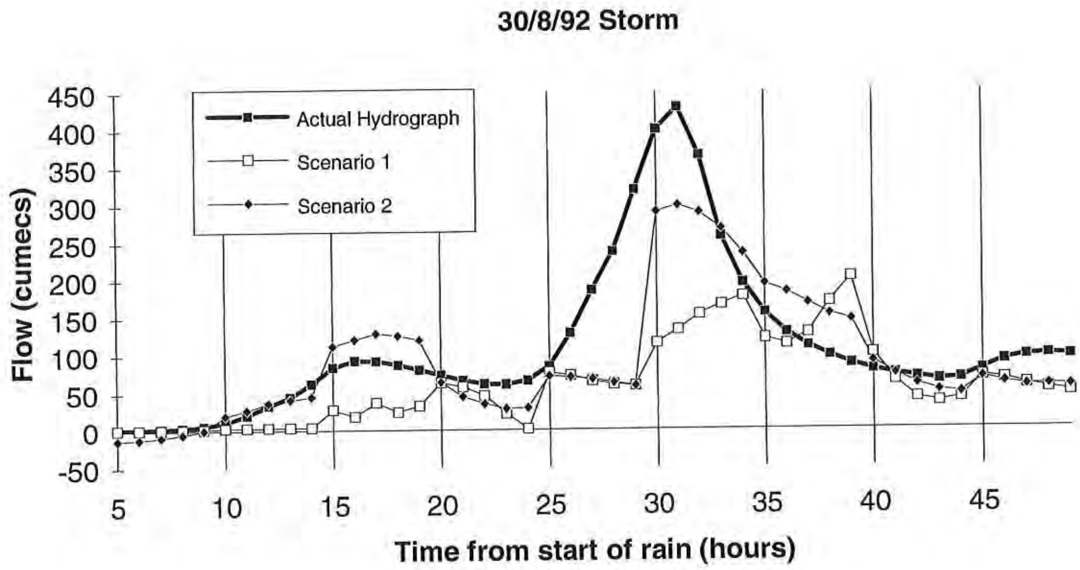


Figure 9.11 Method 4 (R/F), Lag {R(t-5),.....,R(t-14)}, 5 hour forecast, 5 previous runoff values

(Note : Vertical lines indicate the times when the 5 hour forecasts are made)

9.3.2 Comparison of the Scenarios

To statistically compare the difference between Scenarios 1 and 2, the performance of the 3 forecasted storms in terms of the criteria used in Chapter 8, was calculated and then averaged for each training method for 5 hour forecasts only. Only 5 hour forecasts were compared in this manner because 1 hour forecasts were not performed for Scenario 2. This is summarised in Figure 9.12 for both rainfall-runoff lags.

Here, Method 3 was not considered because the same number of tests were not performed for both (R) and (R/F) input cases, therefore a relative comparison could not be made.

It is quite evident, not only from Figures 9.8, 9.9, 9.10 and 9.11, but also from Figure 9.12, that Scenario 2 performed significantly better than Scenario 1 for each of the 5 performance criteria. This suggests that by using training sets from the whole duration of the training storms, a more accurate forecast can be obtained. It would still be expected that a similar result would be found if 1 hour forecasts were also compared.

9.3.3 Comparison of the Training Methods

To compare the performance of the 4 training methods, a ranking system was devised. For both 1 and 5 hour forecasts, the accuracy in terms of the 5 performance criteria was ranked for all 3 storms tested, with a value of '1' given to the best forecasted hydrograph. A value of '2' was given to the next best predicted hydrograph and so on. This was carried out for Scenario 1 storms only, including both rainfall-runoff lags. The result of this analysis is summarised in Figure 9.13. Storms that could not converge during training, were given the highest rank. The lower the overall rank the better the performance.

It should be noted that a direct comparison between the two types of input to the model; rainfall and previous runoff (R/F) and runoff only (F), cannot be made because the same training methods were not performed for both input types, as summarised in Table 9.3.

As shown in Figure 9.6, Method 3 (F) with 5 previous runoff inputs, was very accurate. However, because convergence difficulties were observed for Method 3 (F) with 1 previous runoff input, the ranking for Method 3 (F) is quite high, indicating poor performance.

The most interesting feature of these results was the fact that only the performance based on the CD and the RMSE, displayed a similar trend for both rainfall-runoff lags. No trends can be observed for peak magnitude, peak timing and volume.

The worst training method appeared to be Method 1 (R/F). Method 2 (R/F) generally performed better than Method 1 (R/F), which indicates that with the addition of the currently available storm information from the storm to be forecasted, an improvement in the forecast can be made.

From this ranking system, based on the CD and the RMSE, Method 4 (R/F) performed best, however for the other 3 performance criteria, Method 4 (R/F) did not perform as well. In terms of the other 3 criteria, there were considerable variations in what method performed best. However, it was surprising to observe that Method 4 (R/F) did not perform best in terms of peak timing errors, after all, the test storms were trained on storms with similar time-to-peak.

It was nevertheless encouraging to observe that Method 4 (R/F) performed well for the CD and the RMSE, since it is the CD and the RMSE that considers the 'shape' of the overall forecasted hydrograph, summarising the overall predictive ability of the model. The most encouraging fact about Method 4 (R/F), was that although the number of storms used in training was less than the other methods, it produced the best 'overall' result. The best explanation for this is through splitting the data into storms of similar time-to-peak, some of the variability within the training storms was reduced.

It was somewhat surprising to observe that Method 3 (R/F) based on the CD and the RMSE, performed next best, after Method 4 (R/F). Although Method 3 contained no hydrologic variability, it used the least number of training sets during training. The fact that Method 3 used the model as an extrapolation tool on the rising limb, would partially explain why it did not perform overall, as well as Method 4.

Table 9.4 shows an example of the difference in overall forecasted hydrograph performance for 1 hour forecasts using Method 2 (containing hydrologic variability) and Method 3 (containing no hydrologic variability) as well as their ability to update the forecast based on previous runoff inputs. This example is for the 24/5/88 storm using Scenario 1, 5 previous runoff inputs and {R(t),....., R(t-4)} rainfall-runoff lag. This is visually represented in Figure 9.14.

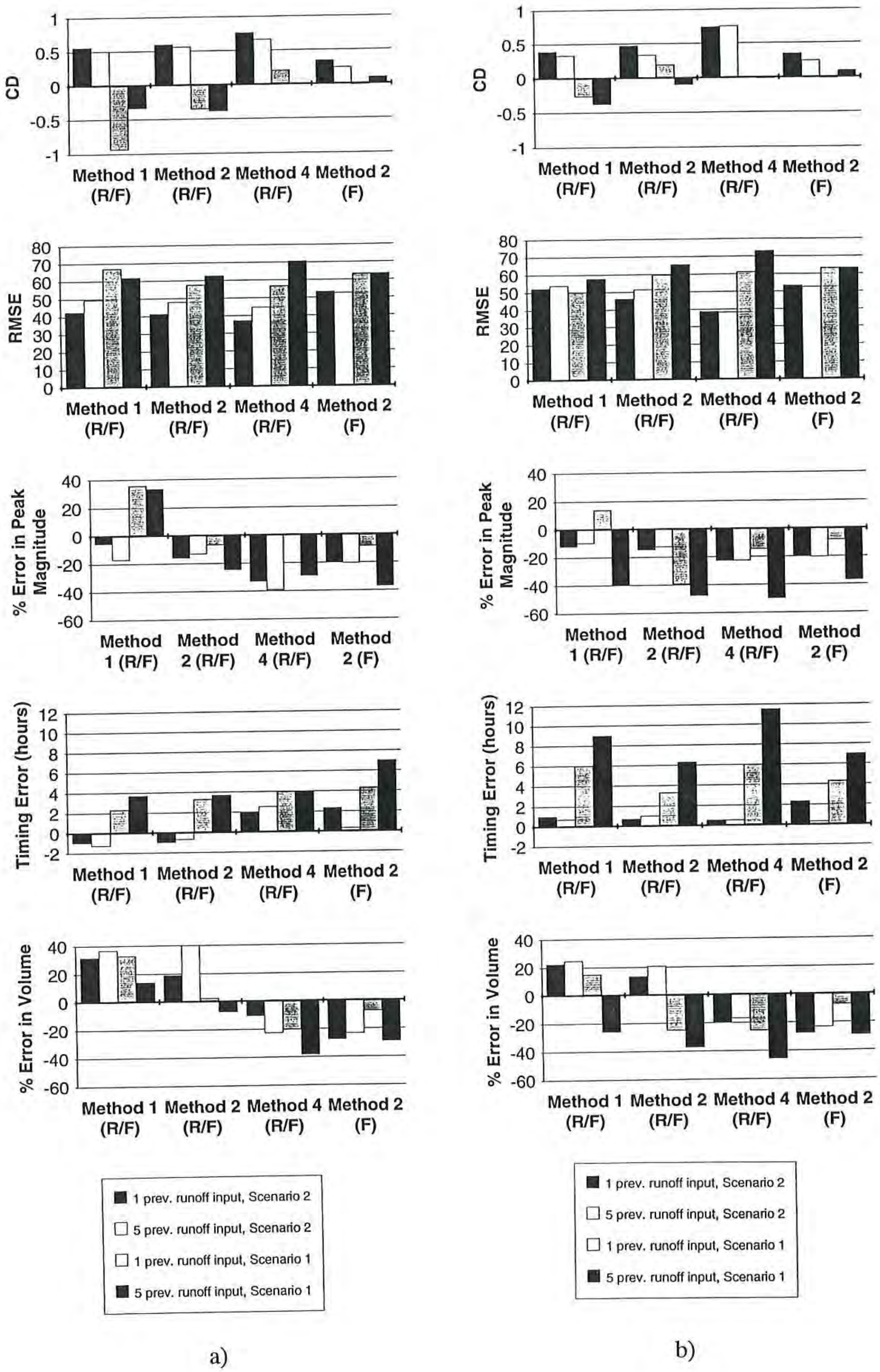
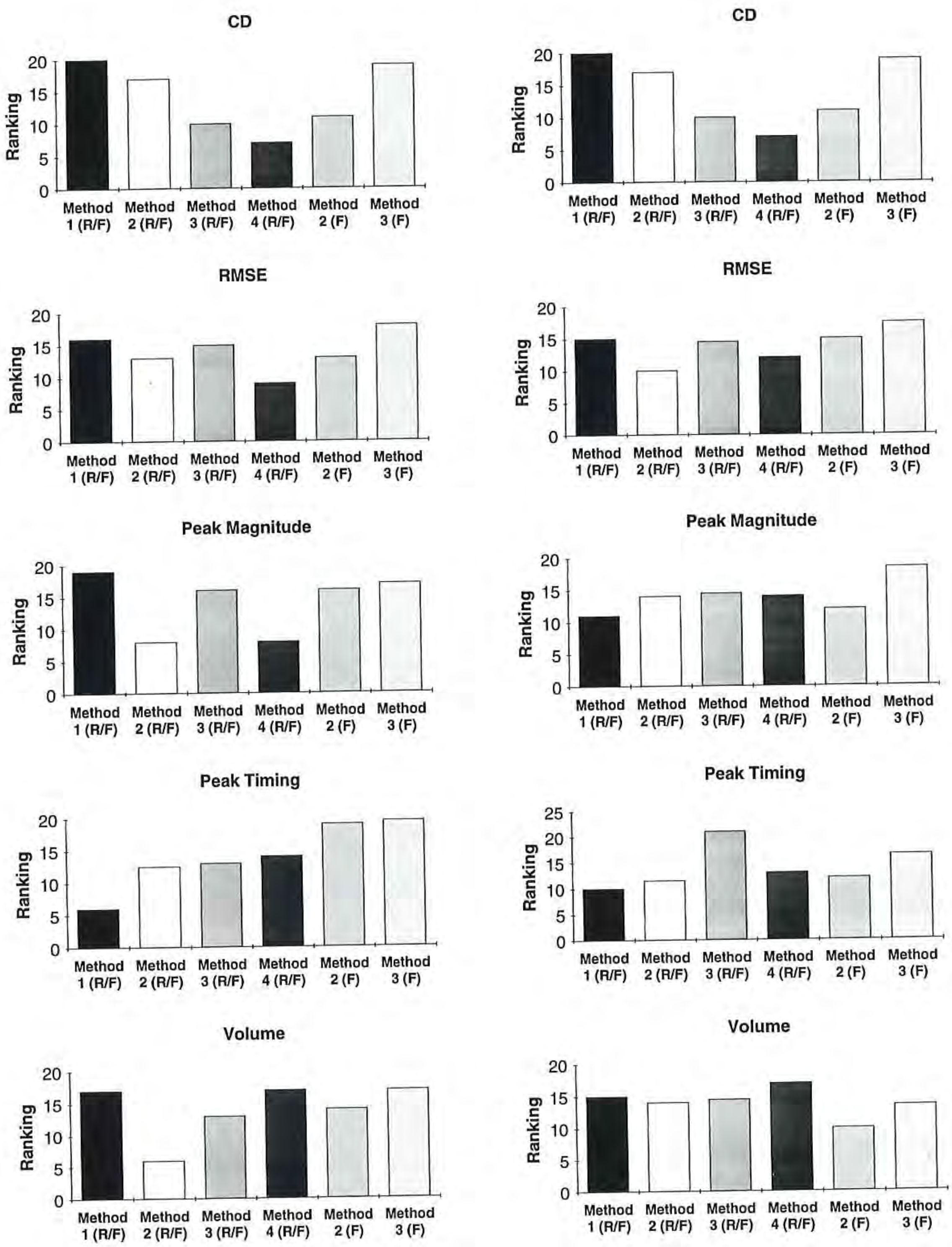


Figure 9.12 Comparison of the performance of both scenarios for 4 training methods a) {R(t),....., R(t-4)} b) {R(t-5),....., R(t-14)}



a) b)

Figure 9.13 Ranking of Training Methods for Scenario 1 for each performance criteria a) {R(t),....., R(t-4)} b) {R(t-5),....., R(t-14)}

Table 9.4 Performance of forecasted hydrographs for Method 2 and Method 3 using Scenario 1, 5 previous runoff inputs, Lag {R(t),....., R(t-5)}, 24/5/88 storm

Training Method	RMSE	CD	Updating Ability *
Method 2 (R/F)	30.4	0.677	4
Method 2 (F)	17.0	0.853	3
Method 3 (R/F)	13.4	0.909	2
Method 3 (F)	12.2	0.925	1

* '1' indicates best updating ability, '4' denotes worst updating ability

Table 9.4 indicates for that particular case, Method 3 performed better than Method 2. This can be explained by the fact that Method 3 contains no hydrologic variability during training. For both training methods, the inclusion of the rainfall input clearly reduced the models performance. Since Method 2 used many more training sets than Method 3, it appears that the accuracy of the forecast was more dependent on the quality of the data than the quantity. This result suggests that the model did not consider the inputs correctly. Perhaps there was some difficulty with the way the model considered the independent nature of the inputs, or maybe the poor spatial accuracy of the rainfall contributed in some way. Regardless of the rainfall input, with the inclusion of the previous runoff inputs, the model should have still updated correctly.

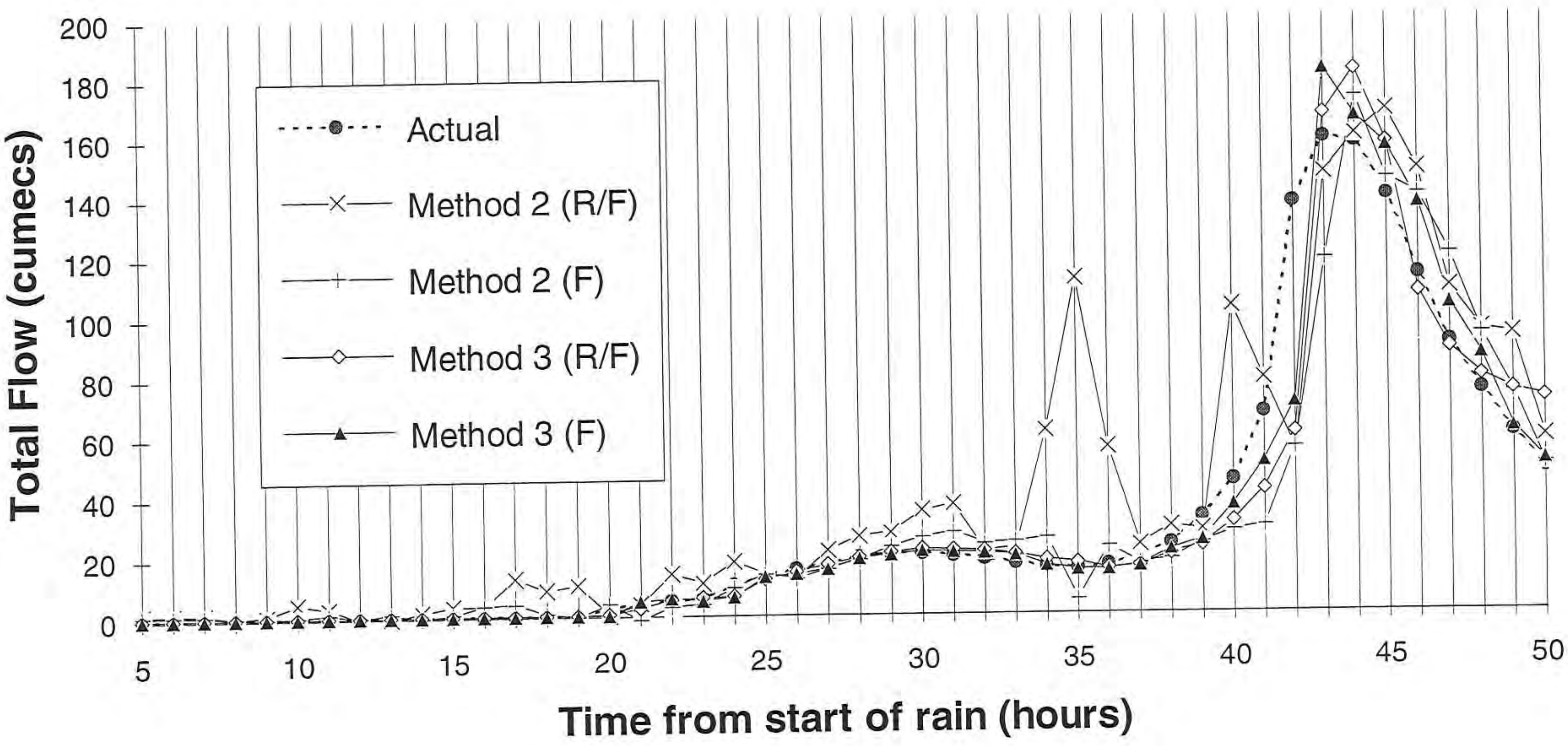


Figure 9.14 Comparison of the performance of training method 2 and 3 for a case where both rainfall and previous runoff inputs are used (Scenario 1, 1 hour forecast, 5 previous runoff inputs, lag {R(t),....., R(t-5)}, 24/5/88 storm)

9.3.4 Comparison of Rainfall-Runoff Lags

A similar ranking system was devised to compare the rainfall-runoff lags. The averaged performance criteria from Test Cases 1-8 (as defined in Table 9.3 in Section 9.2) were compared (i.e. those that used rainfall and previous runoff as input). Only the storms forecasted using Scenario 1 were considered in this comparison. A rank of '1' was given to the better performed lag, and a rank of '2' given to the other lag. The lower the overall summed rank, the better the performance for that criteria. Figure 9.15 shows a considerable difference between the performance of the two lags, however Lag {R(t),....,R(t-4)} performed the better of the two.

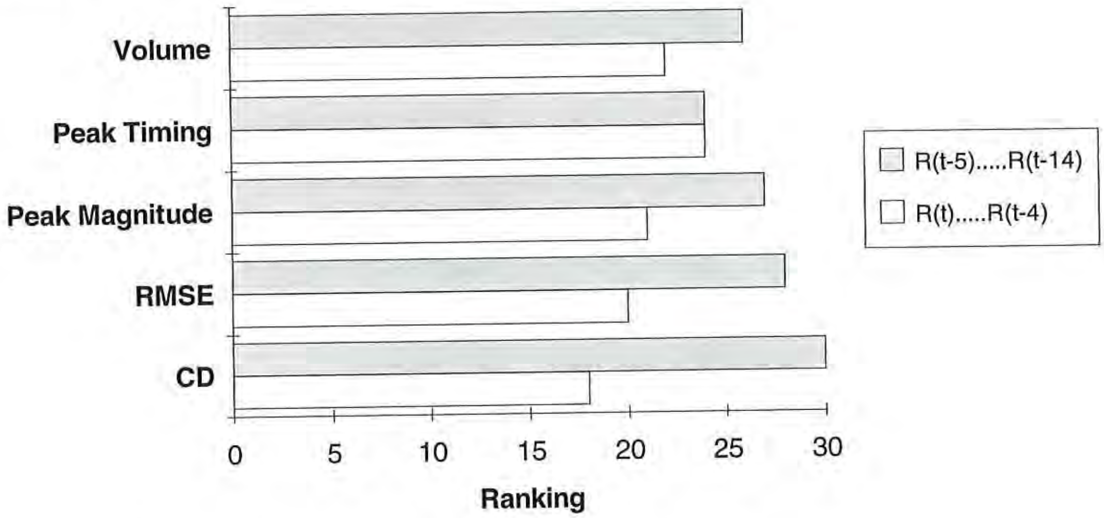


Figure 9.15 Performance of both rainfall-runoff lags relative to each performance criteria
(The lower the rank the better the performance)

Figure 9.15 is based on averaged results, but of equal importance was how the three individual storms performed on this basis. Figure 9.16 shows the rainfall-runoff performance for the 3 individual storms for each of the 5 performance criteria. This time, instead of using a ranking system, a lag performance percentage (%) was adopted. The lag performance percentage (%) meant that one of the lags performed better, a certain percentage (%) of the time. For this, the performance of each storm was similar. Lag performance relative to the peak magnitude, peak timing and volume marginally favoured the {R(t),.....,R(t-4)} lag for all three storms. Based on the CD and the RMSE, a different picture was observed. For the 8/8/81 storm, the {R(t),.....,R(t-4)} lag clearly performed the best, whereas the 30/8/92 storm favoured the {R(t-5},.....,R(t-14)} lag. There was little difference in lag performance for the 24/5/88 storm based on the RMSE and the CD.

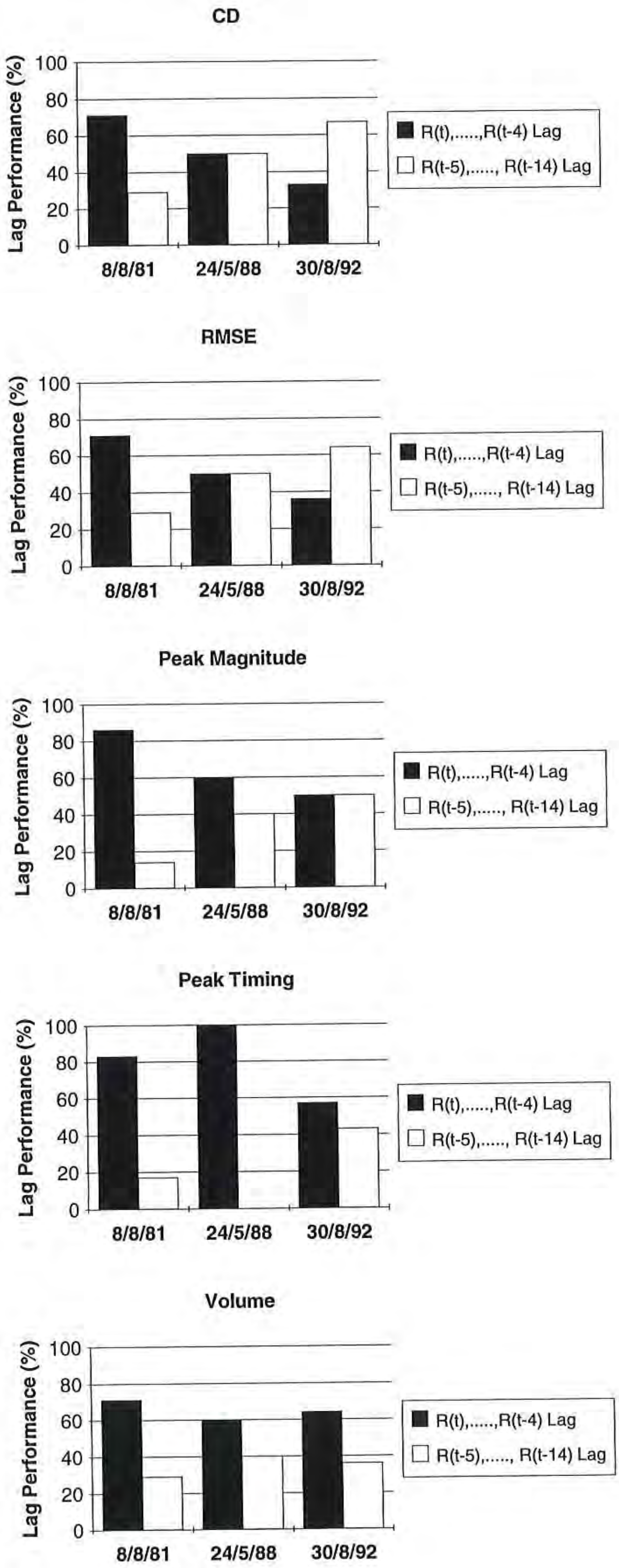


Figure 9.16 Relative performance of both rainfall-runoff lags for each of the three test storms

9.3.5 Sensitivity of Model Inputs

NeuralWorks Professional II/Plus enables a sensitivity analysis to be performed. Once the network has been trained, the relative significance of the inputs can be obtained. By using the 'Explain' function of the software, each of the model inputs can be increased in turn and the change in each of the outputs can be observed. The sensitivity of a given input can be given by Equation 9.7.

$$\text{Sensitivity} = \frac{\text{percentage change in output}}{\text{percentage change in input}} \times 100 \qquad (9.7)$$

The percentage change in input is specified by the user. For this case the default value of +5% was used. The percentage change in output is determined within the model, and the sensitivity is how much the output changed by altering the input.

This function was successfully used by Maier and Dandy (1995a), who used it for forecasting cyanobacteria (blue-green algae). It was used to help determine the lags at which maximum correspondence occurred between blue-green algae concentrations, and the input parameters which caused such problems.

For this study, the 'Explain' function was used to help understand why the model performed in the manner outlined in previous sections. The questions that needed to be answered were:

- Which of the previous runoff inputs were most significant ?;
- Which of the rainfall components were most significant, therefore giving an indication of the rainfall-runoff time delay for the catchment developed by the ANN model (For Scenario 2 only) ?;
- Whether the previous runoff and rainfall input components were considered as independent variables ?;
- Which of the inputs, either rainfall or previous runoff was most dominant ?;
- Which runoff output, for the 5 hour forecasts were most affected by the input variables?;
- Whether the sensitivity changed as the forecast time was incremented ?; and
- Whether the three forecasted storms produced similar sensitivities or not ?.

Figure 9.17 shows the sensitivity of two of the test storms (8/8/81 and 24/5/88) for the lag {R(t),...., R(t-4)} with 5 previous runoff inputs. Figure 9.18 shows the sensitivity of the 30/8/92 and 24/5/88 storm for the {R(t-5),....., R(t-14)} lag, again with 5 previous runoff inputs. The same is shown in Figure 9.19, except Scenario 1 is shown for the 30/8/92 storm with 1 and 5 hour forecasts. These figures are typical plots of the sensitivity results.

A number of features can be observed which are typical of all storms tested. The most recent previous runoff inputs were the most significant, this is shown by the fact that the sensitivity of Q(t) was always greater than Q(t-4).

For Scenario 2, the rainfall R(t-5) component, was most significant. An interesting facet was that the same rainfall input R(t-5), was most sensitive for all of the storms that were tested. Method 2 (R/F) used all storms including the current test storm, which suggests that the rainfall-runoff time delay is about 5 hours, not 13 as calculated in Section 9.1.2.

Figure 9.20 shows the sensitivity of using Scenario 2, Method 4 (R/F) for the {R(t-5),....., R(t-14)} lag using 5 previous runoff inputs. Again, the most sensitive rainfall input was the R(t-5) component.

For Scenario 2 storms, as the test storm proceeded, the sensitivities at different forecast times did not change significantly. For Scenario 1, the sensitivity of the inputs changed as the storm progressed. This is because the training data set changed as the storm progressed, whereas the training set for Scenario 2 remained constant (except for updates to the current test storm).

In Figure 9.19, a comparison of the sensitivities of the next forecast Q(t+1) for a 1 hour and 5 hour ahead forecast can be made. Some similarity exists between the sensitivity of the Q(t+1) value for both forecasts, and is typical of other examples, although these are not shown. For the 5 hour forecasts, the next forecast, Q(t+1) was the most sensitive to input changes.

These trends were observed for all storms tested, however for the same rainfall-runoff lag, each of the 3 storms tested showed quite a different degree of sensitivity. For example, the 30/8/92 storm shown in Figure 9.18 and 9.19 was more sensitive to input changes than the other storms shown. The degree of sensitivity was also different for the two rainfall-runoff lags.

In all cases, the previous runoff component of the model was at least as sensitive, if not more, than the rainfall component, indicating the importance of the previous runoff component. This may be the reason why training using rainfall only (R) failed to successfully converge.

All the sensitivity results suggest that the ANN model was able to differentiate between the two model inputs from a numerical aspect, but the independent functions of the inputs were not recognised, in particular the previous runoff component.

Figure 9.20 shows the sensitivities that correspond to the forecasted hydrographs of Figure 9.21 for the storms on 30/8/92 and 8/8/81 for Method 4 (R/F). For the 30/8/92 storm, the rainfall and runoff inputs have similar magnitude sensitivities, whereas for the 8/8/81 storm, the previous runoff component was considered more important than the rainfall component. From the predicted hydrographs in Figure 9.21, the 8/8/81 storm was forecasted more accurately than the 30/8/92 storm, in terms of correctly updating Q(t+1). The next forecasted values {Q(t+2), Q(t+3),....,Q(t+5)} were predicted accurately as well. This shows a situation where the previous runoff component appears to have been treated more importantly, leading to a more accurate update.

Figure 9.22 shows the typical difference in sensitivity that occurred when using 1 and 5 previous runoff inputs for the storm on the 8/8/81 for Method 2 (R/F), Scenario 2 with Lag {R(t),....., R(t-4)}. The sensitivities of the rainfall inputs were similar, however there is a relative difference in the previous runoff sensitivities. When using 5 previous runoff inputs, it appears that the importance of the previous runoff inputs is distributed amongst all inputs {Q(t),....., Q(t-4)}, therefore the sensitivity of the most recent runoff value, Q(t) is much less. This helps explain why 1 previous runoff input, gave better accuracy than 5 previous runoff inputs in terms of updating ability. The fact that less importance is given to the most recently known hydrograph value, means that the next forecast is unlikely to be updated correctly.

Other factors contributed to the model's inability to correctly update the hydrograph as the storm progressed. The fact that negative sensitivities were recorded for some inputs, may partly explain this. 'Negative' sensitivities in the rainfall inputs may result if zero rainfall fell just before the forecast time due to lagged values from one storm to another. Appendix I shows a training file with training sets containing many zero values which may create this 'negative' sensitivity phenomena. On the rising limb, negative sensitivities within the inputs would tend to negate the overall sensitivity and create a tendency for a lower hydrograph forecast. This would explain why some of the forecasts produced 'negative flows'. By removing the least important input nodes, the negative sensitivity inputs, may be reduced.

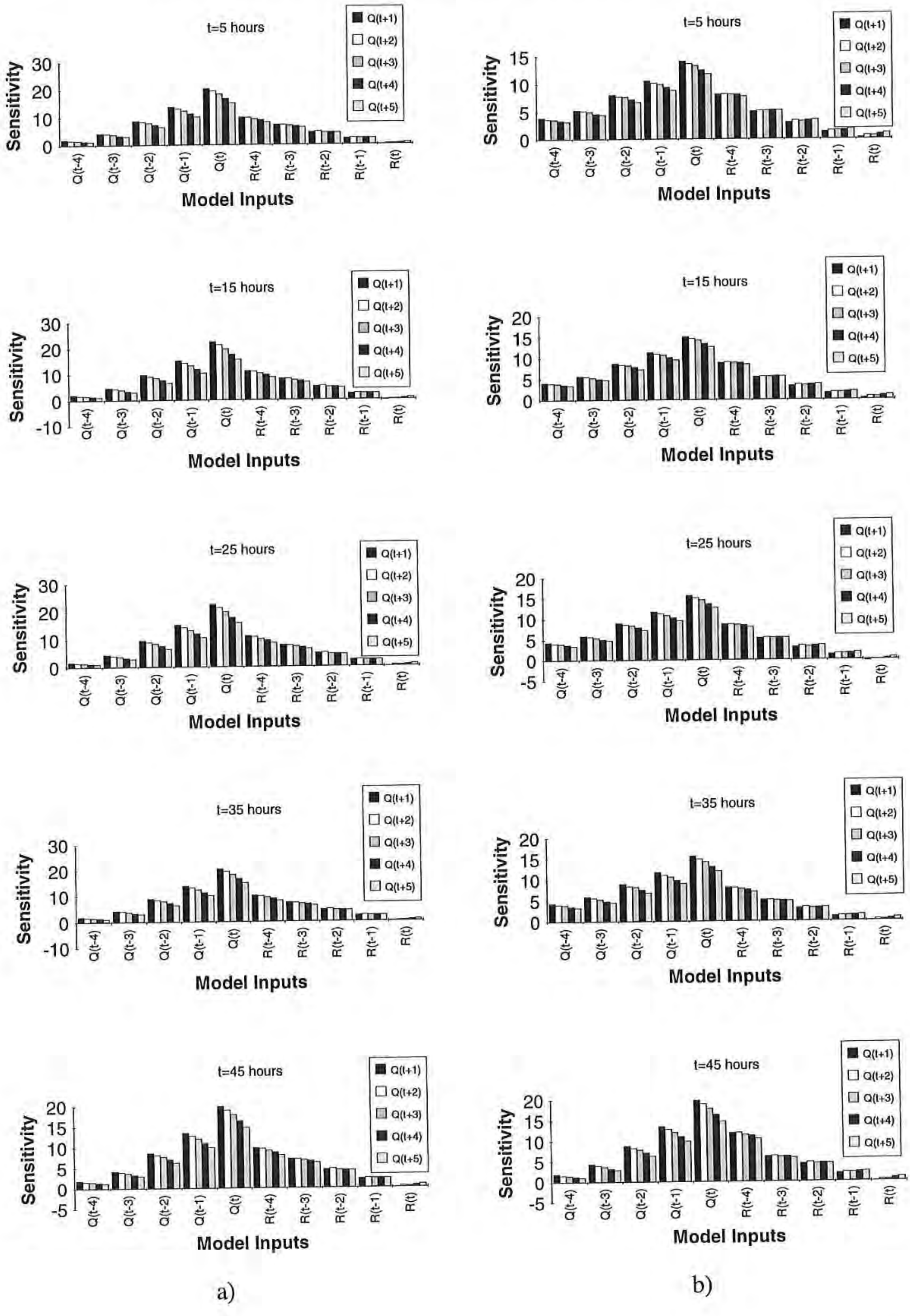
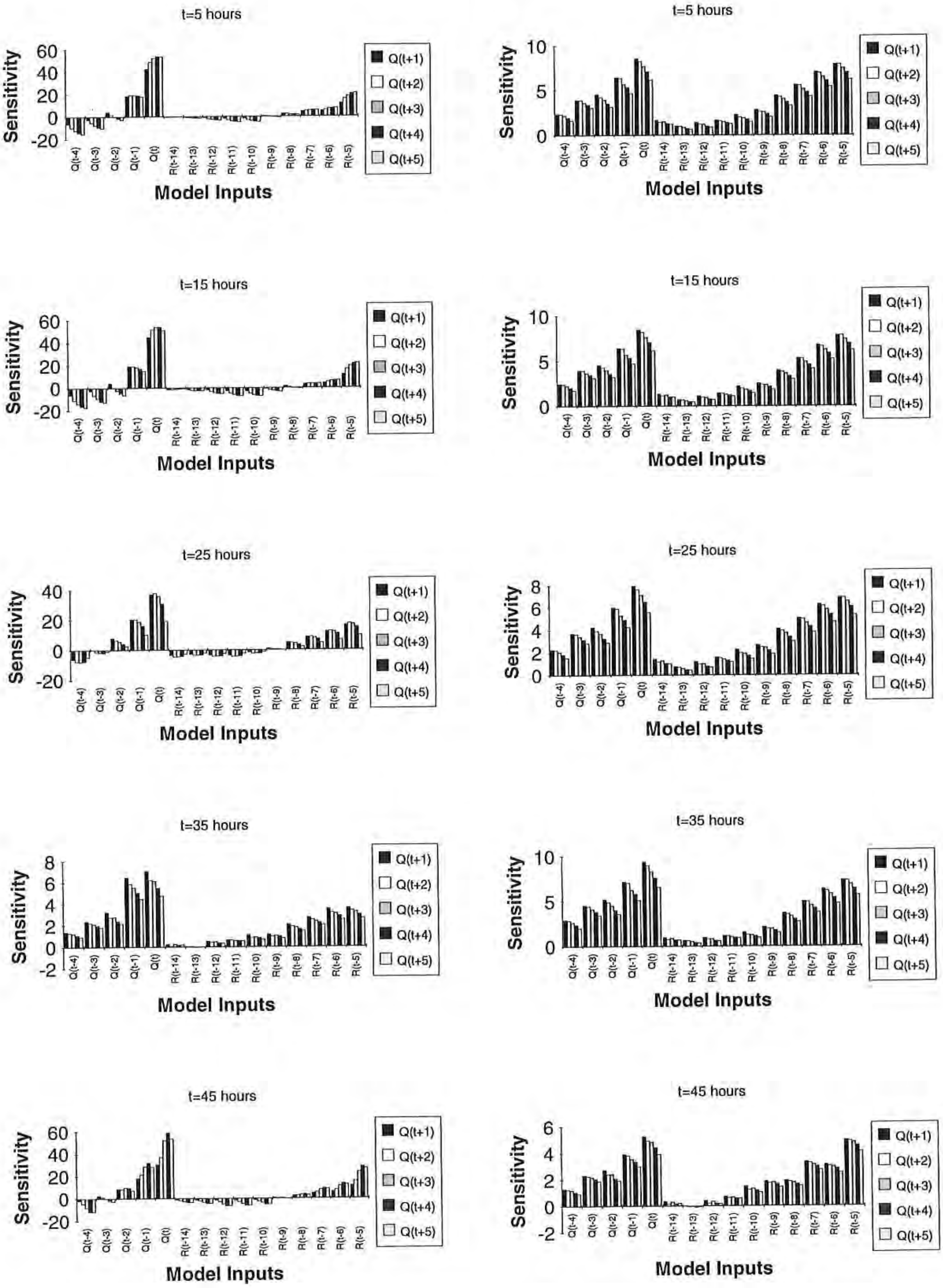


Figure 9.17 Sensitivity of Method 2 (R/F), Scenario 2, 5 Previous Flows, Lag {R(t),....., R(t-4)}; a) 8/8/81 Storm, b) 24/5/88 Storm



a) b)

Figure 9.18 Sensitivity of Method 2 (R/F), Scenario 2, 5 Previous Flows, Lag {R(t-5),....., R(t-14)}; a) 30/8/92 Storm, b) 24/5/88 Storm

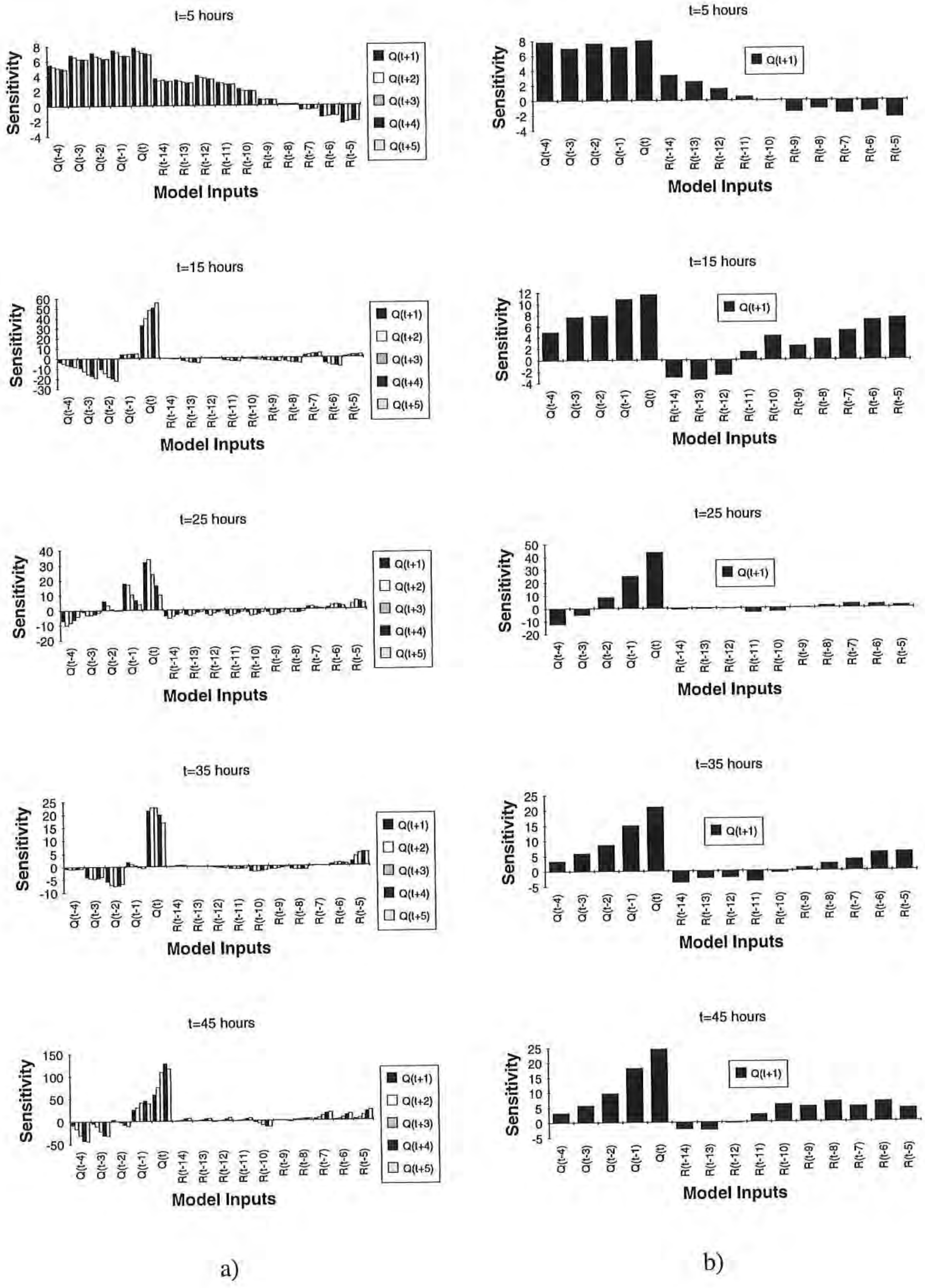
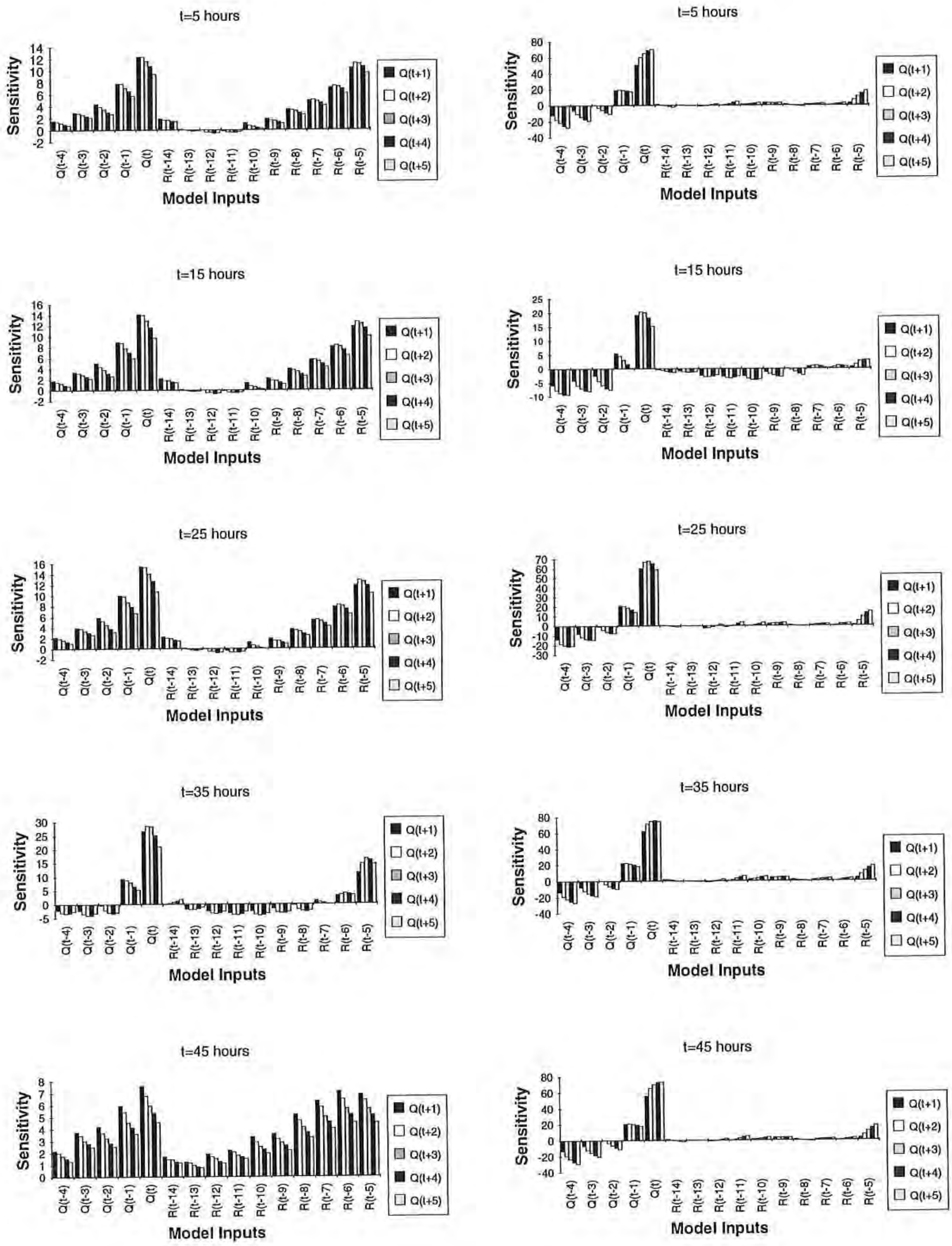
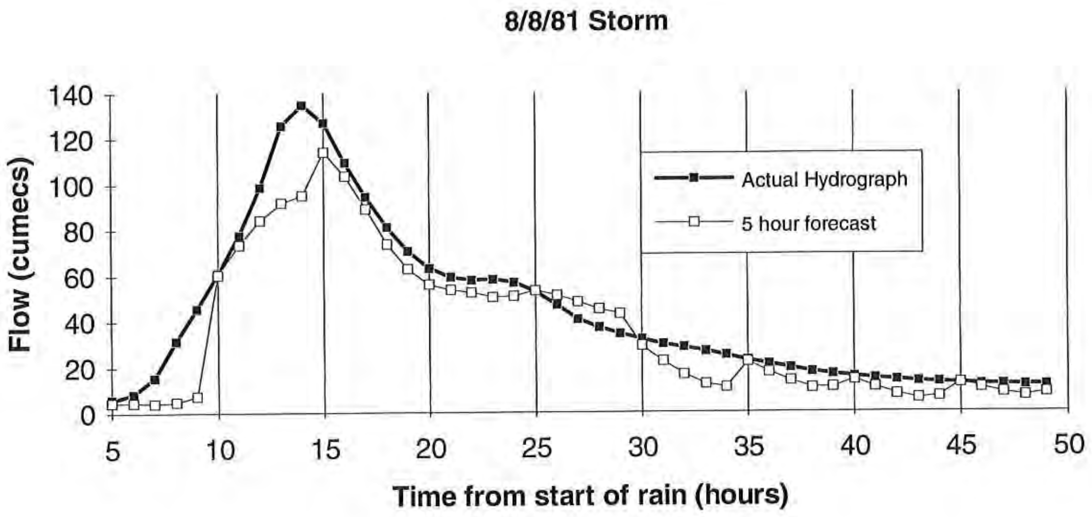


Figure 9.19 Sensitivity of Method 2 (R/F), Scenario 1, 5 Previous Flows, Lag {R(t-5),....., R(t-14)}, 30/8/92 Storm; a) 5 hour forecast b) 1 hour forecast



a) b)

Figure 9.20 Sensitivity of Method 4 (R/F), Scenario 2, 5 Previous Flows, Lag {R(t-5),....., R(t-14)}; a) 30/8/92 Storm, b) 8/8/81 Storm



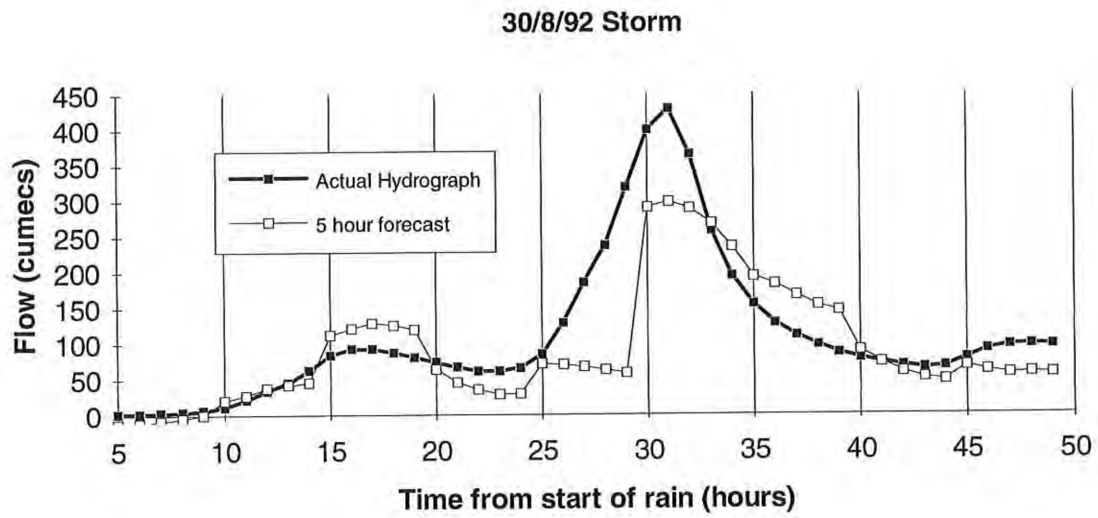
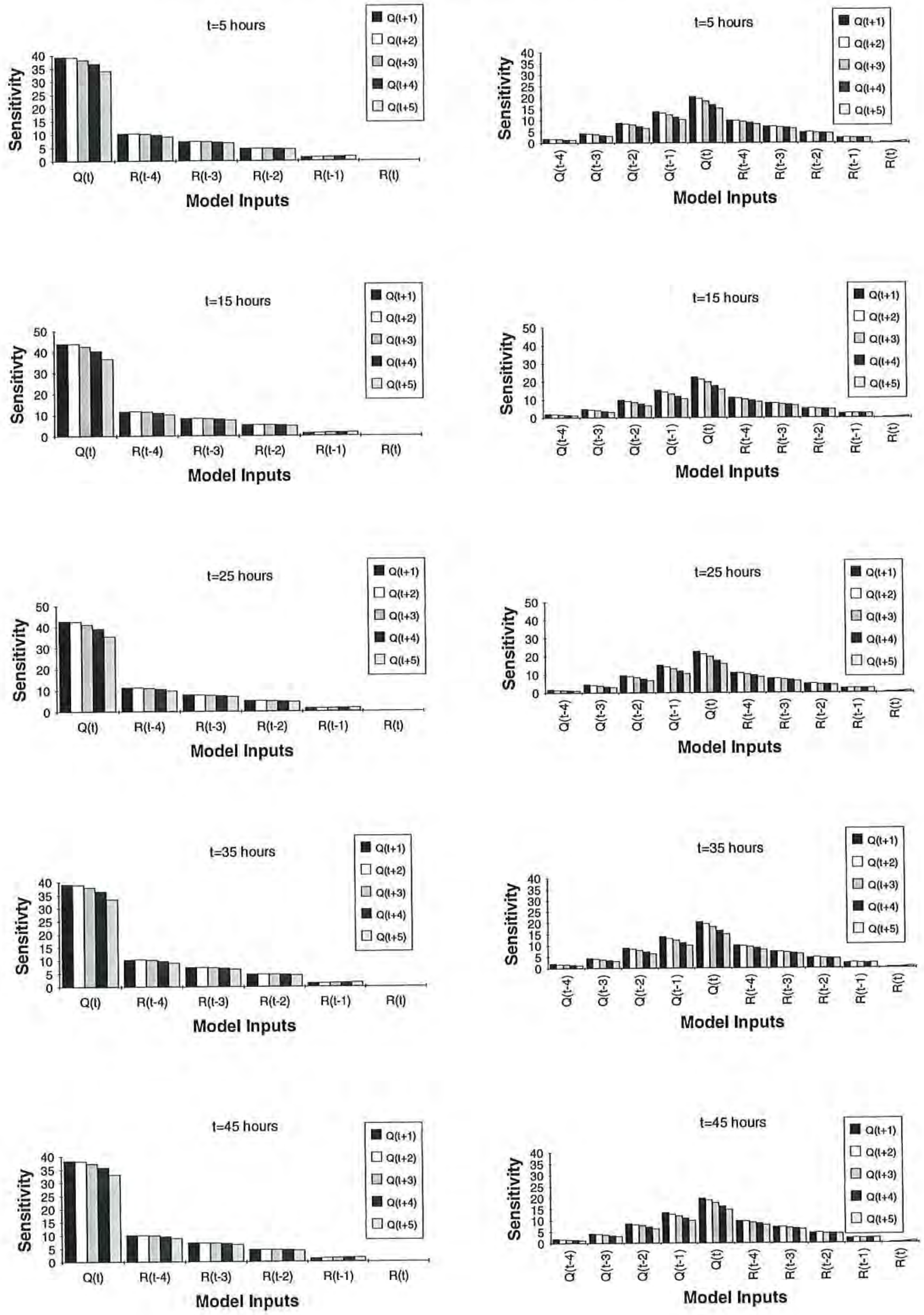


Figure 9.21 Method 4 (R/F), Lag {R(t-5),....., R(t-14)}, Scenario 2, 5 Previous Flow Inputs, 5 Hour Forecasts



a) b)

Figure 9.22 Sensitivity of Method 2 (R/F), Scenario 2, Lag {R(t),....., R(t-4)}, 8/8/81 storm; a) 1 previous flow inputs b) 5 previous flow inputs

9.4 Summary of Results

- Training using rain as the only input (R) was not successful;
- 1 hour forecasts performed considerably better than the multi-step 5 hour forecast;
- Hydrograph correction using 1 previous runoff input performed marginally better than 5 previous runoff input;
- Lag {R(t),.....,R(t-4)}performed marginally better than the {R(t-5),.....,R(t-14)}lag;
- The different training mechanisms significantly affected the results;
- Training using Method 1 (R/F) which used 'All storms except current' performed the worst;
- Including the 'current storm' information in training, improved the model's performance;
- Training that used 'Runoff only' (F) as an input compared equally well with 'Rain and Runoff' (R/F), for the 1 hour forecasts; and
- Scenario 2 which used the maximum number of training sets performed considerably better than Scenario 1.

9.5 Conclusions and Recommendations

Using the developed model, the accuracy of the ANN in real-time runoff forecasting on the Onkaparinga River catchment, was not as encouraging as first desired. A trained forecaster could probably forecast better through visual inspection of the previous portion of the hydrograph, better than even the most accurate predictions made by the ANN model. The exact reasons why the ANN performed in this manner are not fully understood, mainly because of the 'black-box' nature of ANNs. It does appear however that failure is a result of a combination of three main reasons, with no one reason highlighted as the main factor.

Firstly, the simplified rainfall-runoff model developed for the analysis, was probably not detailed enough. The rainfall-runoff process depends on many more parameters than those considered here.

Secondly, the structure of the ANN model appears to have limitations in terms of the network architecture, software parameters and the way training was performed.

Finally, and perhaps most importantly, was the variability of the storm data used for training in terms of both quality and quantity. The use of only a few storms with similar characteristics for training, most probably assisted Fujita and Zhu (1992) in producing encouraging results.

The runoff forecasts were highly dependent on the way in which the data was trained. The fact that there was variable performance in the different training methods, validates this.

Previous studies as outlined in Chapter 5 have shown that the more data available for training, the more accurate the results. For this study, the best results were obtained when storms were trained on similar time-to-peak storms (Method 4), and only the currently available storm information (Method 3). These two methods contained the least hydrologic variability, and the least amount of training data, therefore the quality of the training data was at least equally important as the quantity of data. This is emphasised by the inclusion of the currently available storm information, which also improved the performance of the forecasts.

For operational forecasting, the biggest practical problem with splitting the data set into specific groups before the commencement of a storm, is the difficulty in knowing how the catchment will respond. Dividing the storms into groups containing similar antecedent catchment moisture indices, such as those used in Chapter 8, should be tested for this situation when more data becomes available.

Two storms from the data set could have been removed to see if an improvement was made, namely the 24/5/88 and 30/8/92 storm. These two storms may have biased the results because of the high rainfall volume associated with the 24/5/88 storm and the extreme flow magnitude from the 30/8/92 storm.

The storms used for training had extreme flow conditions and occurred only in winter and spring on a 'wet' catchment. Ideally, training should have also included storms containing extreme rainfall, which did not necessarily result in extreme flow conditions. This would be typical of a summer storm resulting from monsoonal weather. By including such storms, all possible hydrologic situations are considered in the training set.

Perhaps the biggest disappointment with the model was its failure to use the previous runoff inputs to correctly update the hydrograph of the next forecast Q(t+1). Regardless of the rainfall input, it was thought that with the inclusion of the previous runoff inputs, the model should have updated correctly. Sensitivity analysis showed that the ANN was able to numerically differentiate between the rainfall and previous runoff inputs, but it appeared the model did not consider the two inputs as having distinct and independent purposes. Only a small difference in performance was observed between 1 and 5 previous runoff inputs, suggesting that the previous runoff input was not correctly considered as a means of assisting the starting value for the next runoff forecast, nor the future shape of the hydrograph.

Preliminary analysis showed that separating the two input parameters using the partially interconnected network, was also unable to assist in improving the accuracy of updating the forecast. By using a different software package which can allow for more efficient modifications to the network structure, a more detailed investigation can be made. To offset such phenomena, the inputs may need to be weighted in some way, such that more importance is given to the Q(t) component rather than the {Q(t-1),.....,Q(t-4)} components.

One question that had to be answered was; why did the recursive 5 hour forecasts fail to provide any accuracy? In forecasting many hours ahead, the recursive multi-step ahead method may not be applicable, and may explain why Fujita and Zhu (1992) adopted an iterated multi-step procedure.

Through sensitivity analysis of the model inputs, it was found that many of the rainfall inputs were not considered important by the ANN model. The rainfall input R(t-5), was found to be most important, suggesting the rainfall-runoff lag was about 5 hours. This contradicts the lags computed by conventional means as shown in Table 9.1. By removing some of the 'unimportant' rainfall inputs, the model may become more accurate.

Another significant source of error, relating to the model input, was how the catchment hyetographs were calculated. This is merely a spatial rainfall problem analogous to the problems discussed in Chapters 7 and 8. Sensitivity analysis could be used to observe the difference in performance when certain pluviographs are removed from the data set.

Accuracy may be improved by using forecasted rainfall as an input to the model. For 5 hour runoff forecasts on the Onkaparinga River, rainfall forecasts would theoretically be of no benefit since the rainfall-runoff lags for the available storms were usually in excess of 5 hours. Therefore, for this catchment the inclusion of rainfall forecasts would only be beneficial for longer runoff forecasts, but would be of use for catchments prone to flash flooding such as the Brownhill, Glen Osmond, Keswick and Parklands Creek catchment (which was the original intention of the modelling investigation).

Changing the input parameters is an aspect which should be trialed in the future. For example, instead of using total flows and total rainfall, effective rainfall (total rainfall-losses) could be applied along with surface runoff (total flow-baseflow) i.e. removing the losses up to the saturated condition of the source areas. Cumulative rainfall instead of incremental rainfall could be combined with cumulative flow volume. A large set of possibilities for change exist.

Using an upstream flow gauging station combined with a travel time delay, as is commonly done in flood forecasting as explained in Section 3.3.1, would probably also assist in the accuracy of the runoff forecast at the downstream end of the basin. By including an upstream gauging station, the effects of highly variable hydrologic characteristics would probably be removed. However, by doing so, the forecast becomes a combined flow and rainfall 'driven' model.

Once an accurate model is developed using the ANN, 'flash code', a 'C' program can be taken from the software which gives a detailed description of the relationship developed between the processing elements in terms of weights and inputs. The complexity of the 'flash code' is dependent on the number of inputs and outputs, as each processing element is represented as a function of all other processing elements. An example of a 'flash code' output from one of the forecasts can be found in Appendix J.

Chapter 10

Real-Time Forecasting using the RORB Rainfall-Runoff Model

10.1 Introduction

One reason why RORB has not been used as an objective forecasting tool, is that in its PC form, it is difficult and rather cumbersome to interact automatically with conventional computer operating systems. The other major drawback of RORB is that it is not internally consistent, and is only really of use to predict the outflow from the catchment. In real-time flood forecasting it is often useful to adjust the performance of the model using current hydrographs from flow gauging stations within the catchment as discussed in Section 3.5. This cannot be done easily with RORB unless separate RORB models are developed for each gauging station which is inefficient from an operational forecasting point of view. As an operational model, the use of RORB for real-time flood forecasting has been confined to manual operation, which uses mainly subjective procedures to adjust the models performance as the flood progresses. A summary of the use of RORB for real-time forecasting applications in Australia is not presented because, as already pointed out, its use is subjective and reliant on a knowledge of the characteristics of the catchment and parameters derived from historical events (Crapper, pers. comm., 1994).

The aim of this chapter is firstly to investigate the development of a real-time algorithm to use with RORB, considering that both the model parameters (k_c and m) and losses may need adjustment in time, and to determine which of these is more critical to the model's performance. Secondly, the algorithm had to be automated so that the procedure could operate with as little input as possible from the forecaster.

10.2 The RORB Rainfall-Runoff Model

The RORB model is a non-linear runoff routing model where the excess rainfall from the catchment is routed through a model which represents the catchment storage. The model approximates the catchment drainage network as a number of non-linear storage relationships.

The catchment storage model is obtained by dividing the catchment into a number of sub-catchments, defined by watersheds and drainage lines, and it is preferred that each sub-catchment be of equal area. Laurenson and Mein (1990) give recommendations on dividing the catchment into sub-catchments. Model nodes are placed at confluences of creeks on the main channels, significant points of interest, and at the centroids of the sub-catchments.

The centroid of each sub-catchment is assumed to be the point where the rainfall associated with each sub-catchment enters the model. For each sub-catchment, the excess rainfall is obtained by subtracting the rainfall losses from the hyetograph. Routing of the excess rainfall begins at the upstream end of the catchment and continues through the subsequent downstream model storages. At stream confluences, the resultant hydrograph is added until the catchment outlet is reached.

Each sub-catchment is assumed to have a storage-discharge relationship:

$$S = 3600\,kQ^{m} \tag{10.1}$$

where:

$S =$ Storage (m^3)

$Q =$ Discharge(m^3/s)

$m =$ Measure of the catchment's non-linearity (Dimensionless exponent)

$k =$ Dimensionless empirical coefficient

k is defined as a product of two parameters:

$$k = k_c \,.\, k_r \tag{10.2}$$

where:

$k_c =$ Dimensionless empirical coefficient which measures the storage and is applicable to the whole catchment network

$k_r =$ Relative delay time (applicable to each reach storage)

The relative delay time is represented by:

$$k_r = \frac{d_i - d_j}{d_{av}} \tag{10.3}$$

where:

$d_i - d_j$ = Reach length represented by the storage
d_i, d_j = Flow distance from node i, j to catchment outlet
d_{av} = Flow distance in the channel network from the catchment centroid to the outlet

The two model parameters that RORB requires for operation are m and k_c. The value of m is usually taken as between 0.6-1.2. The principal model parameter for fitting is k_c. Increasing k_c decreases the hydrograph peak and increases the lag. Decreasing k_c has the opposite effect. The choice of m has less effect than k_c in calibration. As values of k_c and m are inter-related, k_c is generally decreased when m is increased. This causes a slight delay in the rise of the hydrograph, and the tail of the recession curve, causing an advance in the time of the peak.

10.3 Development of the Real-Time RORB Model

A real-time RORB model must consider certain aspects of the model differently to a RORB model for design purposes. The model remains the same in terms of sub-catchment division and the runoff routing methodology, but modifications are needed to evaluate rainfall losses, rainfall input and the method by which surface runoff is estimated.

The three storms forecasted in Chapter 9 using the ANN model, were again chosen to be forecasted using RORB, namely the storms occurring on 8/8/81, 24/5/88 and 30/8/92.

10.3.1 RORB Model of the Onkaparinga River Catchment to Mt Bold Reservoir

The RORB model that Hill (1993) developed for extreme flood estimation, was used for this study. Hill used an initial loss-continuing loss model, and divided the catchment into 12 sub-catchments. Figure 10.1 shows the RORB model developed by Hill, displaying the location of sub-catchments, sub-catchment centroids and nodes.

Figure 10.1 RORB model developed for the Onkaparinga River catchment to Mt Bold Reservoir (Source: Hill, 1993)

10.3.2 Choice of Loss Model

RORB facilitates three different runs for loss modelling; FIT, TEST and DESIGN. In FIT and TEST runs, the loss parameters are determined by the model such that the volume of rainfall excess of a rainfall burst is equal to the volume of surface runoff from the surface runoff hydrograph. In a real-time situation, the future hydrograph is not known and the loss parameters can not be determined in this manner. In a DESIGN run, the user inputs the loss parameters, irrespective of whether the surface runoff hydrograph is known or not. In this study, the DESIGN run was adopted for this reason.

RORB can adopt two loss models; initial loss followed by either a continuing loss or a proportional loss. The continuing loss rate (mm/hr) is a capacity loss rate that occurs only if rainfall is equal to, or greater than that rate. For less intense rainfall periods, the loss rate is equal to the rate of rainfall. The proportional loss rate is a volumetric runoff coefficient, or a fraction of rainfall in each time period. A value of zero signifies the least runoff capacity, and unity, the greatest runoff capacity.

Dyer et al. (1994) concluded that based on 24 catchments across Australia, the initial loss-proportional loss model may give a better representation of the observed hydrograph than initial loss-continuing loss model. It was suggested that the initial loss-proportional loss model has a greater physical significance than an initial loss-continuing loss model. Despite this, a number of limitations lie in the use of initial loss-proportional loss models for real-time flood forecasting.

The biggest problem in using an initial loss-proportional loss model, is that only a limited number of studies have attempted to establish relationships for estimating the proportional loss at the commencement of a storm. The few studies undertaken have been essentially through API and soil moisture deficit (Srikanthan et al., 1994). Volumetric runoff coefficients are quite variable, therefore the forecaster usually must select values based on previous knowledge of the catchment. No significant studies have been undertaken on the Onkaparinga River catchment using RORB with an initial loss-proportional loss model, therefore an initial loss-continuing loss model was adopted for this study. Many of the parameters derived from the model calibrated by Hill (1993) were used throughout the remainder of this part of the study.

10.3.3 Estimation of Losses

This section outlines how the initial loss and the continuing loss rate were determined for this study.

10.3.3.1 Initial Loss

Initial loss is important for obtaining a good fit at the commencement of the hydrograph rise. It also affects the time distribution of rainfall excess and hence the hydrograph peak. Initial loss is not a model parameter, it is a characteristic of each storm, and should not be used in fitting an observed hydrograph (I.E.Aust., 1987).

Initial loss was estimated in real-time from the 'rainfall to the start of hydrograph rise' as defined in Chapter 7. Estimating the initial loss through soil moisture indices was also carried out in Chapter 7, however these relationships cannot be applied here because the relationships were derived using the three storms forecasted in the remainder of this chapter. Relationships could have also been derived using all but the storms that were forecasted in this chapter, however this would have reduced the number of events in the correlation, which as discussed in Chapter 7 was perhaps a significant reason why poor relationships were developed.

The 'rainfall to the start of hydrograph' rise for the storms on the 8/8/81, 24/5/88 and 30/8/92 were 20, 48 and 21 mm respectively. As discussed in Section 7.2, there is very little difference between the initial loss estimated in this manner and that used by Hill (1993) for the RORB model calibration.

10.3.3.2 Continuing Losses

Estimating continuing loss is more difficult than estimating initial loss at the start of an event, and to date, no accurate method has been developed, despite a recent attempt by Loy et al. (1996).

In real-time forecasting it may be necessary to change the continuing loss over the duration of the forecasted event due to temporal variations in rainfall and other factors (Loy et al., 1996), this however is difficult unless physical measurements are made. As it is difficult to predict continuing loss at the commencement of a storm and as a storm progresses, continuing loss is commonly fixed, based on averaging the continuing losses of historically modelled storms (Malone, 1994b).

The continuing losses used by Hill (1993) for modelling the storms on 8/8/81, 24/5/88 and 30/8/92 were 0.32, 4.55 and 1.27 mm/hour respectively. The average continuing loss of the 12 storms used in the calibration of the RORB model by Hill (1993) was 1.5 mm/hour.

10.3.4 Forecasting Rainfall

The performance of a RORB model is very sensitive to rainfall input, in fact 30 percent differences in k_c have been observed by just using different numbers of pluviographs (Dyer, 1994, pers. comm.).

RORB modelling for design requires two fundamental aspects of rainfall data:

- An estimation of the rainfall hyetographs for each sub-catchment; and
- The total rainfall depth over each sub-catchment.

The biggest problem with using RORB for real-time forecasting, is that for an accurate runoff forecast, rainfall must also be forecasted. For example, if at a given forecast time t, a 5 hour hydrograph forecast is required, the hyetograph at each pluviometer must also be forecasted for the next 5 hours.

In a design situation, when the total rainfall depth over each sub-catchment is required, a spatial rainfall pattern over the entire catchment is made using isohyetal maps or by assigning each sub-catchment to the nearest pluviograph. Isohyetal mapping usually provides the most accurate spatial representation within the catchment, but is difficult for real-time forecasting. It was therefore decided that each sub-catchment be assigned the observed rainfall up to the forecast time, plus a forecasted component from the nearest pluviograph. An alternative method to forecast the total rainfall could have used radar images from the Bureau of Meteorology so that the previous movement of the storm could have been traced, combined with rainfall from ground stations, therefore the storm rainfall could have been projected ahead.

To estimate the future hyetograph at each pluviometer, a number of hypothetical scenarios with constant intensity were used. The same rainfall scenario was given to all pluviographs within the catchment at each forecast time. The selection of the smallest rainfall forecast was dependant on the continuing loss chosen. A forecasted hyetograph with an intensity greater than the continuing loss is required for any rainfall excess to be modelled, therefore a future rainfall intensity less than or equal to the continuing loss is analogous to a 'no more' rain case (zero intensity).

Another hypothetical scenario was used, which assumed that the future hyetograph was the same as the observed hyetograph which in a real-time situation, is of course not possible. This was the most accurate forecasted rainfall scenario possible, and its performance was compared to the constant intensity rainfall scenarios.

10.3.5 Commencement of the Forecast Procedure

In operational flood forecasting, the commencement of the hydrograph rise is the point where a forecaster often begins the task of predicting the next stage of the hydrograph. For this part of the study, forecasts commenced at this point in time.

For an off-line forecast (as performed in this study) with access to the shape of the complete hydrograph, as shown in Figure 10.2a, it is a relatively easy task to determine where the hydrograph begins to rise. In an operational real-time situation where the complete hydrograph is unavailable to the forecaster, as shown in Figure 10.2b, judgement must be used as to whether a small increase in the hydrograph will lead to a continual rise in the hydrograph. This uncertainty can be minimised because the forecaster may have available a combination of forecasted rainfall and upstream flow gauges that have a quicker response due to a smaller catchment area in which to assist in determining whether the hydrograph at a specific location downstream will continue to rise. This was discussed in Section 3.3.1 and forms the basis of many flood forecasting systems.

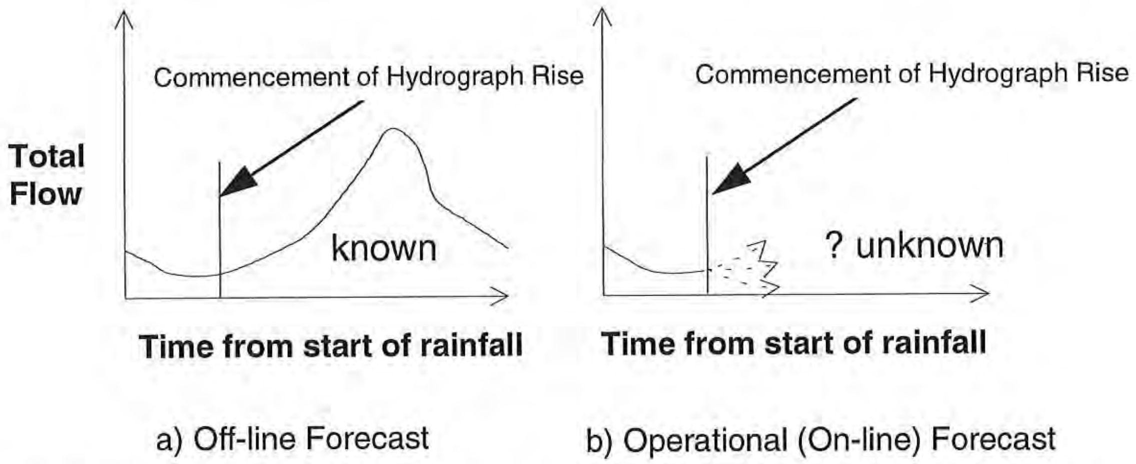


Figure 10.2 Difference between predicting the commencement of the rising limb of the hydrograph for an off-line and on-line forecast

10.3.6 Estimation of the Surface Runoff Hydrograph

The operation of RORB usually results in the estimation of a surface runoff hydrograph. In this study, a constant baseflow was removed from the total hydrograph, equal to the stream flow value when the first rapid rise of the hydrograph began as discussed in Chapter 7. This was adopted by Avery (1989) and is probably the most commonly used approach for this type of forecasting (Wright, pers. comm., 1995). However in this situation, ignoring baseflow would have little effect on the outcome since the proportion of baseflow compared with the peak hydrograph flow is very low for the Onkaparinga River catchment.

In the RORB input file, the surface runoff hydrograph for time increments prior to the start of the first forecast, were assigned a magnitude of zero. The corresponding observed hyetograph records from the commencement of rainfall were used in the RORB input file.

10.4 Real-Time Updating

A question often asked, is whether the model parameters (k_c and m) and/or losses need to be adjusted in real-time at the different forecast times, and if so, how ? Relatively few studies have used RORB with objective updating of losses and/or the model parameters; k_c and m.

In some instances, average k_c and m values are found from historically calibrated storms and fixed throughout the forecasting process. Avery (1989) used RORB in real-time with an initial loss-continuing loss model and the model parameters k_c and m were fixed at 23 and 0.8 respectively by averaging only five historical storms. The continuing loss was updated by matching the currently known and forecasted flow rates at the time of the forecast. Problems with this procedure were sometimes encountered, and the loss algorithm was at times manually adjusted. Avery found that diminishing continuing losses occurred with increased wetting of the catchment and concluded that further research should continue in refining the hydrograph by adjusting the continuing loss rate. But for this situation, because of poor spatial distribution of pluviometers within the catchment, the losses used were probably not representative of the actual physical processes occurring. An alternative method was suggested involving matching the calculated and observed volumes of surface runoff. Avery also used average continuing loss rates with little success.

Dyer et al. (1994) recently concluded that values of k_c are very much storm dependent, therefore different values are needed to forecast different storms. Kuczera (1990) also found that the model parameters from RORB modelling of different storms were statistically incompatible. Kuczera stated that these observations may be caused by a combination of the errors encountered when estimating catchment rainfall as well as the runoff-routing models approximating the runoff process through spatial and temporal simplifications. This would suggest that averaging model parameters is a weakness in real-time forecasting. If a historical data base contains an extremely large number of calibrated storms, it may be possible to divide the storms into groups with similar characteristics, and hence similar model parameters and loss values. However in most instances, especially for this study, not enough recorded events were available to do this.

Another question is; What would be the result of keeping the continuing loss fixed and updating the model parameters k_c and m in time by a comparison of the predicted and observed hydrograph flow data ? For each m value, a unique optimum k_c value could be obtained at each forecast time. The biggest problem with updating the model parameters, as discussed in Section 3.5.1.4, is the occurrence of local maxima in the objective function. Dyer et al. (1994) found that local maxima were not a problem when a similar optimisation procedure was performed. This optimisation technique was used for objective automatic design calibration of the RORB model which accounted for timing errors. Certain sections of the hydrograph were weighted to give them more importance. Initial loss and k_c were altered for each m value.

10.5 Real-Time Algorithm

This section outlines the two stages of the real-time algorithm that were developed to update k_c for each m value:

Stage 1 involved updating the RORB model parameter k_c until the hydrograph peak was passed, based on the coefficient of determination (CD). Coefficient of determination was chosen as the objective function for the same reasons as discussed in Section 3.6.

Stage 2 predicted the remainder of the hydrograph after the peak was passed using the optimum k_c parameter determined from the last forecast within Stage 1. The model parameter k_c was not updated after the peak occurred because traditionally it is the rising limb and peak that is most important in flood forecasting, not the falling limb. Passing the rising limb gives the 'all clear' when large areas are inundated.

In an operational real-time environment there would be some subjectivity as to when the hydrograph peak is deemed to have actually passed. This is similar to the problems discussed in Section 10.4.4 for estimating the commencement of the hydrograph rise.

Five hour forecasts were again performed at 5 hour time steps. The algorithm was performed at each forecast time step for each forecasted rainfall scenario.

10.5.1 Stage 1

This stage was split into three levels. The optimisation procedure for each level was different.

Level 1 (Optimisation with 'No more' rainfall case)

This level optimised k_c for a given set of m and loss values (initial loss and continuing loss). A 'no more' rainfall case was used to find the optimum k_c value to produce the best association between the known and predicted hydrographs using the coefficient of determination up to the forecast time. The portion of the hydrograph output considered at this level of the optimisation procedure is shown in Figure 10.3.

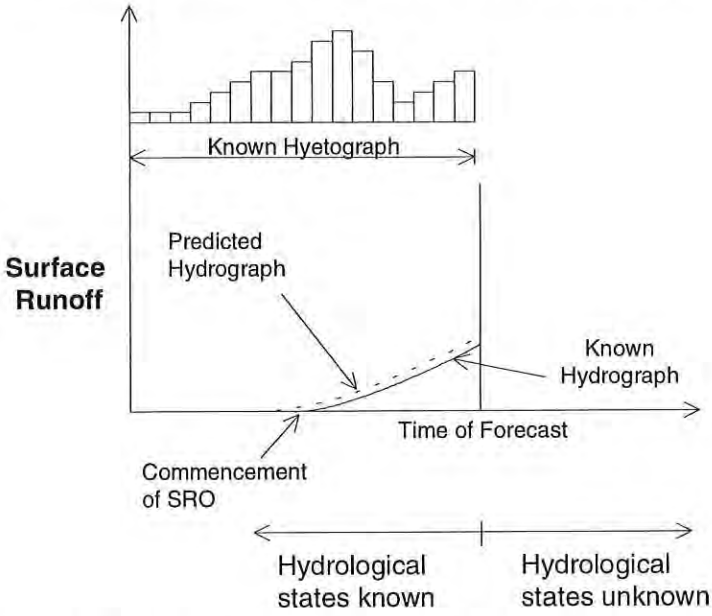


Figure 10.3 The portion of the RORB output considered at Level 1 of the algorithm (up until the forecast time)

(Part A)

The following parameters were arbitrarily chosen as the starting values in the algorithm:

k_c = default (43);

$m = 0.6$;

In *Part A*, the RORB model was run with the above parameters and the output file was generated. The coefficient of determination was only calculated for the predicted and known parts of the hydrograph up to, and including the current forecast time (t).

A translation of the predicted hydrograph was made if required and the coefficient of determination was re-calculated. A translation was determined firstly by calculating the centroids of the areas under the predicted and known portions of the hydrographs up to (and including) the current forecast time (t). The difference between the centroids was calculated and the predicted hydrograph then translated in the direction to yield the best match in the centroids. The actual amount that the predicted hydrograph was translated was rounded off to the nearest hour since RORB can only facilitate integral numbers for translations in Code 4.

(Part B)

The aim of this part was to determine which direction k_c should be iterated. This procedure is a repeat of *Part A* except two different k_c values either side of the default (43) are used; 42 and 44. Despite using a different objective function, Dyer at al. (1994) found that local optima were not a problem at levels of iterating k_c, therefore the coefficient of determination of the predicted and known hydrographs for a k_c of 42 and 44 were compared with that of 43. Whichever value resulted in an improvement in the coefficient of determination compared with that calculated for k_c of 43, was the direction in which k_c was iterated. The translation associated with the optimum k_c value was recorded and used later in *Part C*.

(Part C)

In this part, k_c was incremented in steps of ±5 depending on which direction of iteration gave the best improvement in *Part B*. The same translation calculated in *Part B* was used. This was continued until the maximum CD was passed. Once passed, the direction of iteration was reversed, this time in steps of ±1 until the maximum CD was passed once more.

At this level, three parameters were recorded for each time step and rainfall scenario:

a) optimum k_c ($k_{c\ opt}$)
b) optimum translation ($trans_{opt}$)
c) optimum CD with the translation added (CD_{opt})

Level 2 (Addition of rainfall scenarios)

In this level, the forecast rainfall scenarios were added to the model together with $k_{c\ opt}$ and $trans_{opt}$ and the model re-run. The CD of the unknown hydrologic state component (between time t and t+5) of the hydrograph was calculated and denoted $CD_{forecast}$. The unknown hydrologic state component is shown in Figure 10.4.

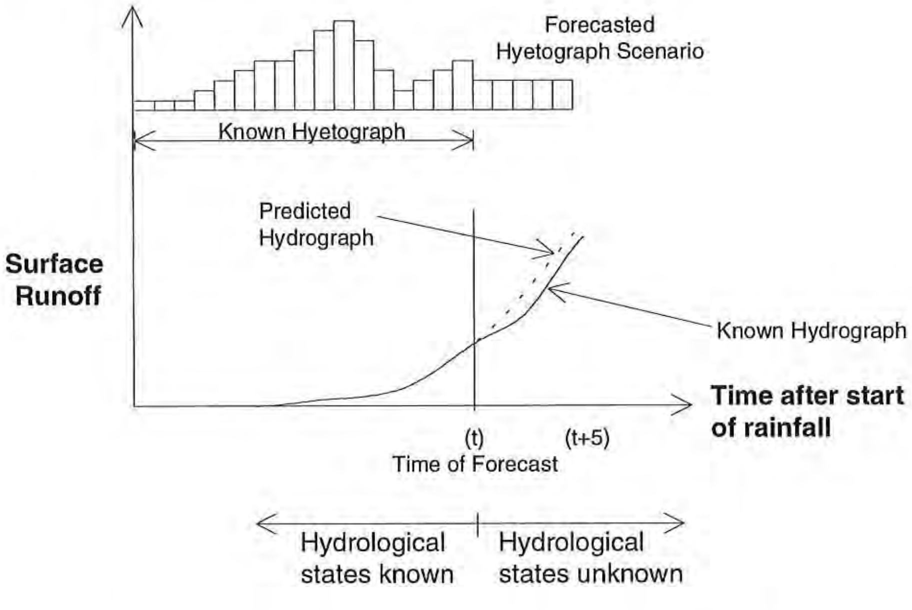


Figure 10.4 The portion of the RORB output considered at Level 2

For an operational forecast, the $CD_{forecast}$ cannot be calculated because the next 5 hours of the hydrograph are unknown. Calculating the $CD_{forecast}$ in this situation was used to compare the different scenarios that were tested.

Level 3

Repeat Levels 1 and 2, this time for a different m, increasing m in steps of 0.1.

Stage 1 was complete once a forecast after the hydrograph peak has been passed. Once Stage 1 was complete, Stage 2 commenced.

10.5.2 Stage 2

The model parameter k_c was not updated within this stage, and therefore contained only Levels 2 and 3 of Stage 1. During Stage 2, the optimum RORB parameters ($k_{c\ opt}$ and $trans_{opt}$) for each m most recently optimised in Stage 1, were used in the remainder of the forecasts.

Figure 10.5 illustrates this process for the hydrograph of a hypothetical flood event. The times when a forecast was made are denoted by forecast times 1, 2, 3, 4 and 5. Stage 1 and hence optimisation, was carried out at forecast times 1, 2 and 3. Stage 2 was performed at forecast times 4 and 5 using $k_{c\ opt}$ and $trans_{opt}$ determined at forecast time 3.

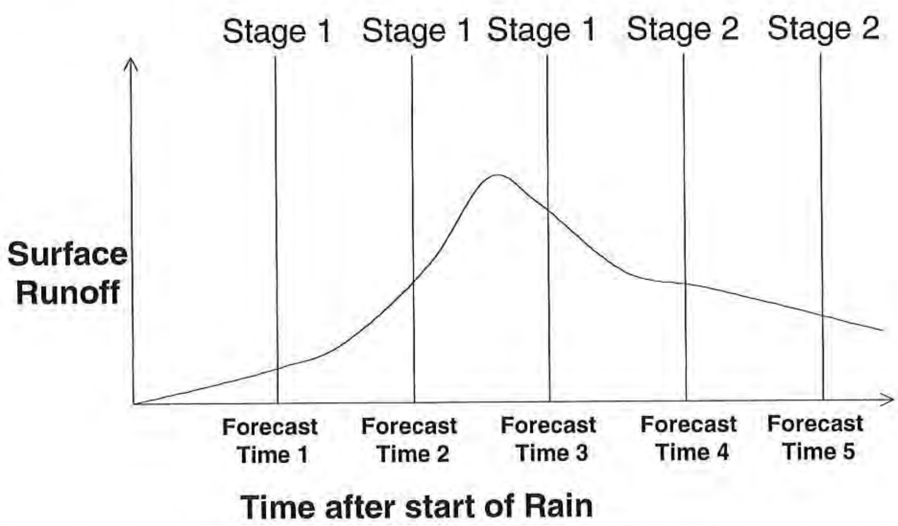


Figure 10.5 An illustration showing the forecast of a hypothetical storm when Stage 1 and Stage 2 optimisation was used. Stage 2 commenced immediately after the Stage 1 forecast that passed the hydrograph peak

A summary of the procedure used for updating the k_c parameter is shown in Figure 10.6.

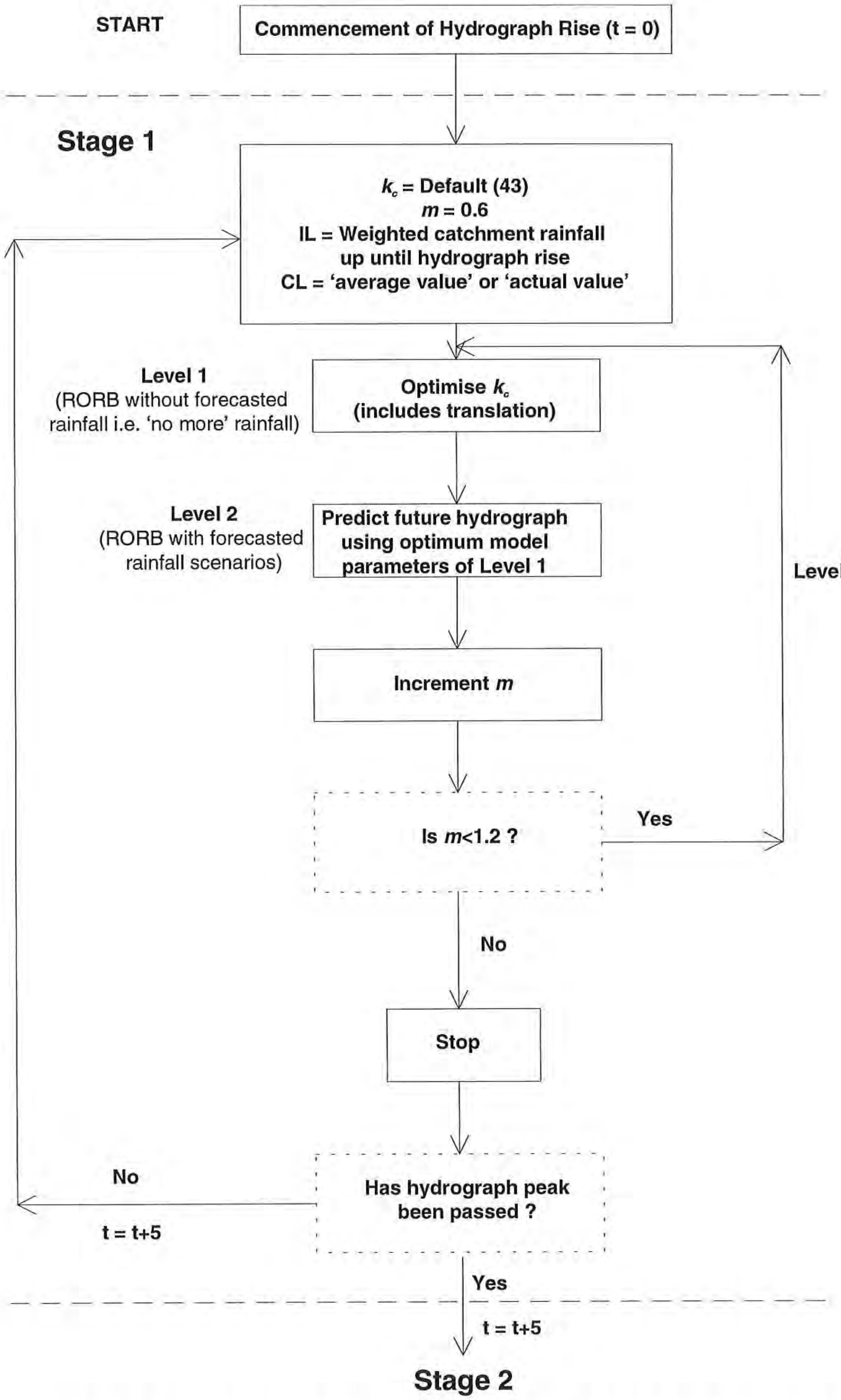


Figure 10.6 Summary of the updating algorithm used with the RORB model

10.6 Automating RORB in Real-Time

The PC version of RORB prompts the user with a multitude of manual inputs including: input file name, output file name, carriage returns, 'yes' or 'no' prompts, k_c, m, type of loss model etc. A number of ways are possible to automate RORB so that it does not require manual input of these parameters. It is not possible to run the PC version of RORB in a batch file mode; i.e. by using the DOS command:

rorbpc.exe < input.dat

The two possible options for operating the PC version of RORB automatically were to: (Haines, 1994, pers. comm.)

- Compile and run the RORB mainframe (version 4.1) source code on a UNIX based system in batch file mode (Dyer et al., 1994). In this way it is relatively easy to interrogate multiple stations and update the data prior to re-running RORB; or

- Combine the PC version of RORB with a keyboard buffer program and a batch file. The keyboard buffer program places the keystrokes required to run RORB into the keyboard buffer so that RORB sees them as if they were typed manually.

The latter technique was envisaged as being easier, and was therefore adopted for this study. A number of keyboard buffer programs were investigated including STUFFIT, KEYFAKE and FAKEY.

To use multiple runs of RORB and the keyboard buffer program, the procedure had to be automated so the whole process could run on its own without user input. This was achieved by writing a PASCAL program. Many of the keyboard buffer programs have limitations in that they can only handle a limited number of characters in the keyboard buffer, otherwise they cannot be used over and over again. The keyboard buffer program chosen for this study was FAKEY which had a buffer capacity of 124 keystrokes, which was ample for the input required into RORB.

Different versions of RORB require different amounts of input. For this study RORBPC v4.03 was used as it has fewer places for key presses.

After each run of FAKEY the keyboard buffer had to be cleared so that new input data could be used. FAKEY has an in-built function capable of 'tossing' out the old faked keystrokes.

The complete real-time algorithm was performed without manual input using the PASCAL program. For each run, a new input file was created based on the type of forecast made. Parts of the input file remained the same, but some components had to change at each forecast time. The channel storage data and sub-catchment data remained constant for each run. Items that changed for each run included translation data (if applicable), storm data and rainfall data. The PASCAL program is not shown due to its cumbersome length, however all the necessary concepts of its operation have been detailed in this thesis.

10.7 Analysis Procedures

Four separate test cases were considered, each using different parameters and hence different degrees of accuracy. These test cases are summarised in Table 10.1. Test Case 1, 2 and 3 all used the algorithm to update k_c.

Table 10.1 The four separate test cases used in the analysis of RORB in real-time

Test Case	$k_{c\,opt}$	Forecast Rainfall	Continuing Loss
1	Algorithm (Level 1)	Constant intensity	Average (Hill, 1993)
2	Algorithm (Level 1)	Constant intensity	Actual (Hill, 1993)
3	Algorithm (Level 1)	Exact	Actual (Hill, 1993)
4	Calibration (Hill, 1993)	Exact	Actual (Hill, 1993)

Test Case 1 was used a constant intensity future hyetograph and the average continuing loss value (1.5 mm/hour).

Test Case 2 was a hypothetical situation with a more accurate continuing loss value, evaluated from the actual continuing loss values used by Hill (1993). A comparison between Test Case 1 and Test Case 2 determines how important the continuing loss component is to the model.

Test Case 3 was another hypothetical situation using the most accurate data possible. It used exact future rainfall and the continuing loss values used by Hill (1993). A comparison between Test Case 2 and Test Case 3 was used to observe how important an accurate rainfall forecast was to the performance of the model.

Test Case 4 did not use the real-time algorithm for optimising the k_c value. It used the k_c values that gave the best fit during the RORB fitting by Hill (1993) and the same rainfall and continuing loss scenarios as in Test Case 3. This case was therefore used as a means of comparing the performance of RORB using k_c values estimated in two different ways; an updated method and a fixed value.

The method which Hill used for RORB fitting to obtain the optimum design values for k_c, were based on subjective visual fitting of the overall hydrograph, in particular the peak and rising limb. This method is therefore theoretically similar to the optimum k_c values calculated at the end of Stage 1 (and then used in Stage 2) of the algorithm.

For Test Case 4, a translation of 3 hours was used based on the average translation of all storms fitted by Hill.

For Test Cases 1 and 2, the future constant intensity hyetograph was chosen based on the continuing losses used in each test case as discussed in Section 10.3.3. Table 10.2 shows the future rainfall intensities arbitrarily chosen for the two forecasted storms for the cases of using both the average and actual continuing loss values.

Table 10.2 The future intensity rainfall scenarios arbitrarily chosen to forecast runoff

Forecasted storm (and CL case)	Future Rainfall Scenarios (mm/hr)
8/8/81, CL_{act}= 0.3 mm/hr	0, 0.5, 1.0, 1.5, 2.0
8/8/81, CL_{av}=1.5 mm/hr	0, 2.0, 3.0
30/8/92, CL_{act}=1.3 mm/hr	0, 2.0, 3.0, 5.0, 8.0
30/8/92, CL_{av}=1.5 mm/hr	0, 2.0, 3.0, 5.0, 8.0

10.8 Results and Observations

The first part of the analysis involved performing Level 1 of the algorithm ('no more' rain case) which gave the optimum model parameters $k_{c\ opt}$ and $trans_{opt}$ at each forecast time, for each m value for the 3 storms tested.

Level 1 of the algorithm was performed first. This was successful for the storms on 30/8/92 and 8/8/81, however for the 24/5/88 storm at the first few forecast times, the algorithm was unable to converge to a suitable solution, hence an optimum k_c value, using the CD objective function. As a result, Test Cases 1, 2 and 3 as defined in Section 10.7, were unable to be performed for the 24/5/88 storm.

Level 2 introduced the different forecasted rainfall scenarios and the two continuing loss cases. Forecasts of the hydrograph were made using each m value at each forecast time for the 8/8/81 and 30/8/92 storms. It was envisaged that all m cases, from 0.6 to 1.2 would be performed. This was possible for the 30/8/92 storm, however for the 8/8/81 storm, m values of 1.0, 1.1 and 1.2, RORB 'crashed'. This could not be explained as the same thing also occurred when the model was run independently of the FAKEY program.

Tables 10.3 and 10.4 show the optimum parameters from Stage 1 of the real-time algorithm using both continuing loss cases for the storms occurring on the 30/8/92 and 8/8/81 respectively. Only m values of 0.6-0.9 are shown because these were the only values common for both storms. At the commencement of Stage 1 (i.e. for 'early' forecasts), optimum k_c values were generally high, especially for the 30/8/92 storm. The accuracy of Stage 1 of the optimisation at each forecast time based on the CD_{opt} was generally good, especially when the actual continuing loss (as used by Hill) was adopted. The optimum translations ($trans_{opt}$) were small prior to the peak, however once the peak was passed, a larger translation was calculated by the algorithm. Since there was very little difference between the actual and average continuing loss values for the 30/8/92 storm, the optimum parameters were quite similar. For the 8/8/81 storm there was a much larger difference between the optimum model parameters for both continuing loss values, and hence the performance of Stage 1 based on the CD_{opt}. This suggests that an accurate continuing loss value is important for this stage of the forecast.

In Tables 10.3 and 10.4, the optimum forecasts are shaded based on the CD_{opt} at each forecast time. The m value that gave the best performance in terms of the CD at the conclusion of the rising limb for the 30/8/82 storm (at t=33 hours) was 0.9, and for the 8/8/81 storm (at t=16 hours) was 0.8. This shows that the optimum m value increased for increasing flood size. When forecasting before the end of the rising limb the optimum m value for both storms varied.

Table 10.5 shows the difference between the optimum k_c values calculated by the algorithm after the hydrograph peak had been passed (at the end of Stage 1), and those used for fitting the RORB model of Hill (1993) for m values from 0.6-0.9. There are reasonable similarities between these values for both storms, however the similarities are not as pronounced when the updating algorithm used the actual continuing loss, particularly for the 8/8/81 storm. In all cases the k_c values calibrated by Hill were generally less than those calculated by the algorithm. The storm on the 30/8/92 was the larger of the two, and therefore gave higher optimum k_c values than the 8/8/81 storm.

Table 10.3 Optimum parameters from Stage 1 ('no more' rain), 30/8/92 storm, for both actual and average continuing loss cases

Forecast Time	m	k_c CL_{act} 1.3 mm/hr	k_c CL_{av} 1.5 mm/hr	$trans_{opt}$ CL_{act} 1.3 mm/hr	$trans_{opt}$ CL_{av} 1.5 mm/hr	CD_{opt} CL_{act} 1.3 mm/hr	CD_{opt} CL_{av} 1.5 mm/hr
t = 8 hrs	0.6	118	105	0	0	0.981	0.981
	0.7	116	103	0	0	0.981	0.981
	0.8	114	102	0	0	0.953	0.953
	0.9	113	100	0	0	0.953	0.953
t = 13 hrs	0.6	59	56	0	0	0.927	0.954
	0.7	38	38	1	1	0.955	0.964
	0.8	30	28	1	1	0.912	0.933
	0.9	22	21	1	1	0.884	0.899
t = 18 hrs	0.6	45	44	2	2	0.744	0.701
	0.7	32	31	2	2	0.797	0.757
	0.8	22	21	2	2	0.824	0.793
	0.9	11	11	2	2	0.726	0.734
t = 23 hrs	0.6	59	57	0	0	0.451	0.403
	0.7	42	41	0	0	0.517	0.472
	0.8	25	25	0	0	0.529	0.506
	0.9	18	17	0	1	0.575	0.646
t = 28 hrs	0.6	47	47	-1	-1	-0.441	-0.105
	0.7	47	21	-1	-1	0.726	0.717
	0.8	28	26	0	0	0.770	0.763
	0.9	18	17	0	0	0.745	0.734
**Peak = 31 hrs* t = 33 hrs	0.6	52	52	1	1	0.615	0.602
	0.7	31	23	2	2	0.757	0.655
	0.8	11	10	3	3	0.755	0.694
	0.9	5	4	4	4	0.838	0.702

Shading denotes the optimum forecasts based on CD_{opt} for each forecast time

Table 10.4 Optimum parameters from Stage 1 ('no more' rain), 8/8/81 storm, for both actual and average continuing loss cases

Forecast Time	m	k_c CL$_{act}$ 0.3 mm/hr	k_c CL$_{av}$ 1.5 mm/hr	$trans_{opt}$ CL$_{act}$ 0.3 mm/hr	$trans_{opt}$ CL$_{av}$ 1.5 mm/hr	CD_{opt} CL$_{act}$ 0.3 mm/hr	CD_{opt} CL$_{av}$ 1.5 mm/hr
t = 6 hours	0.6	65	29	0	0	0.996	0.928
	0.7	65	29	0	0	0.996	0.560
	0.8	70	20	0	0	0.996	0.969
	0.9	79	17	0	0	0.996	0.969
t = 11 hours	0.6	50	37	0	0	0.978	0.891
	0.7	36	26	0	0	0.971	0.910
	0.8	26	14	0	0	0.947	0.730
	0.9	18	10	0	0	0.934	0.800
* *Peak = 14 hours* t = 16 hours	0.6	41	31	1	2	0.898	0.340
	0.7	30	21	1	2	0.918	0.422
	0.8	20	10	1	3	0.934	0.494
	0.9	10	8	1	2	0.829	0.512

Shading denotes the optimum forecasts based on CD_{opt} for each forecast time

Table 10.5 Comparison of the k_c values achieved through the real-time algorithm and those used by Hill (1993) for fitting the rising limb of the hydrograph

m	30/8/92 Storm: Real-time Algorithm (End of Stage 1) CL$_{act}$ 1.3 mm/hr ^{2,3}	30/8/92 Storm: Real-time Algorithm (End of Stage 1) CL$_{av}$ 1.5 mm/hr ^{1}	30/8/92 Storm: Hill (1993) Calibration CL$_{act}$ 1.3 mm/hr ^{4}	8/8/81 Storm: Real-time Algorithm (End of Stage 1) CL$_{act}$ 0.3 mm/hr ^{2,3}	8/8/81 Storm: Real-time Algorithm (End of Stage 1) CL$_{av}$ 1.5 mm/hr ^{1}	8/8/81 Storm: Hill (1993) Calibration CL$_{act}$ 0.3 mm/hr ^{4}
0.6	52	52	39	41	31	26
0.7	31	23	21	30	21	17
0.8	11	10	12	20	10	11
0.9	5	4	6	10	8	7

^{1,2,3,4} : k_c values used in Test case 1, 2, 3 and 4 respectively

Figure 10.7 graphically shows the accuracy of the updating algorithm for one case arbitrarily chosen when forecasting the 30/8/92 storm for a continuing loss of 1.3 mm/hour for *m* values of 0.6 and 0.9 up to the hydrograph peak. The coefficient of determination of each case is also presented. Figure 10.7 also shows that at various forecast times, the algorithm was good at modelling what had previously occurred in the catchment, whilst at other times the performance was not good at modelling the past, particularly the last few hours prior to the forecast being made. Ideally, in a perfect situation the portion of the hydrograph up to the forecast time should be exactly replicated. This is totally dependent on the objective function used. This observation suggests that perhaps the coefficient of determination is limited in this application.

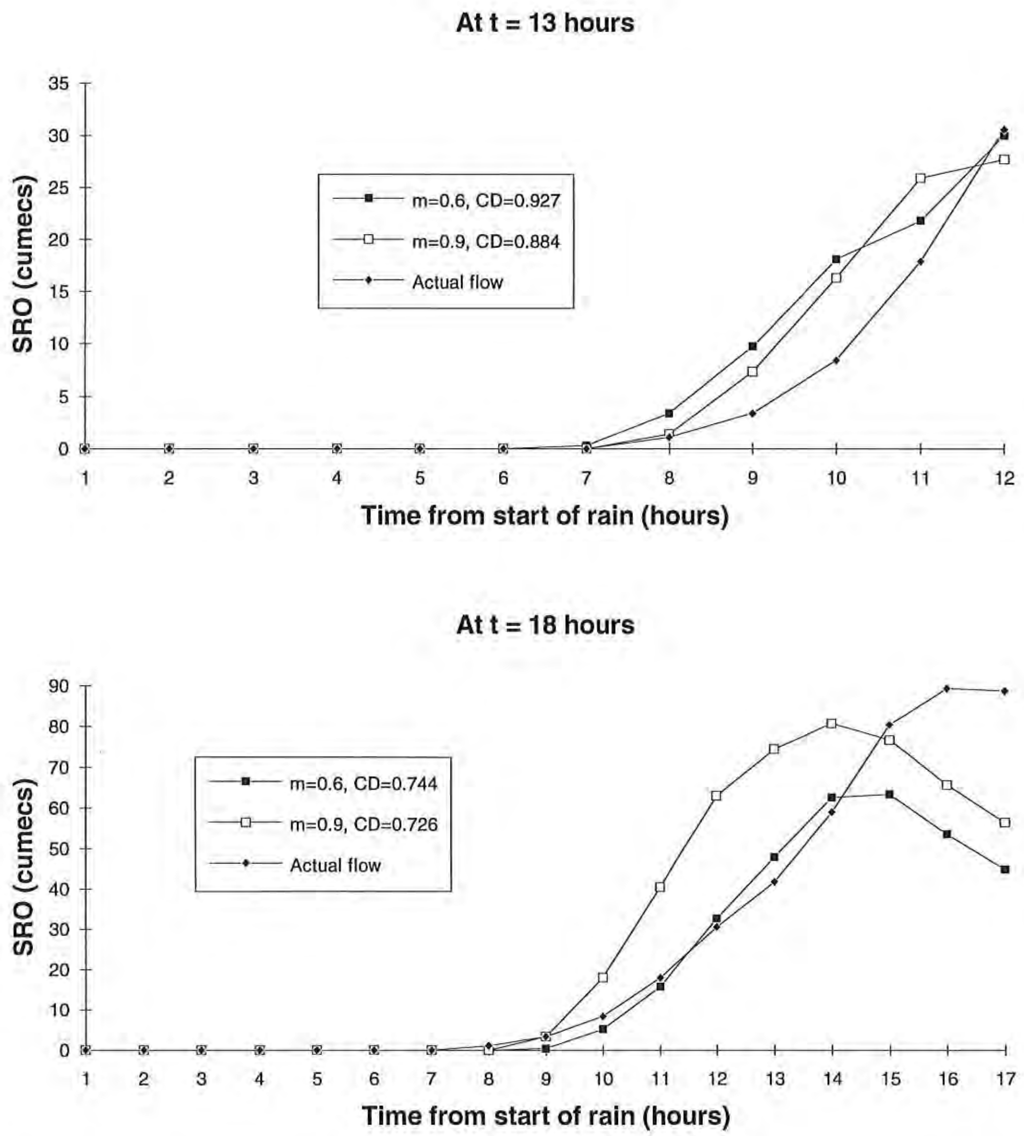


Figure 10.7 The hydrographs generated from Stage 1 ('no more' rain), 30/8/92 storm, CL=1.3 mm/hour for *m*=0.6 and 0.9 with an indication of the CD for each plot

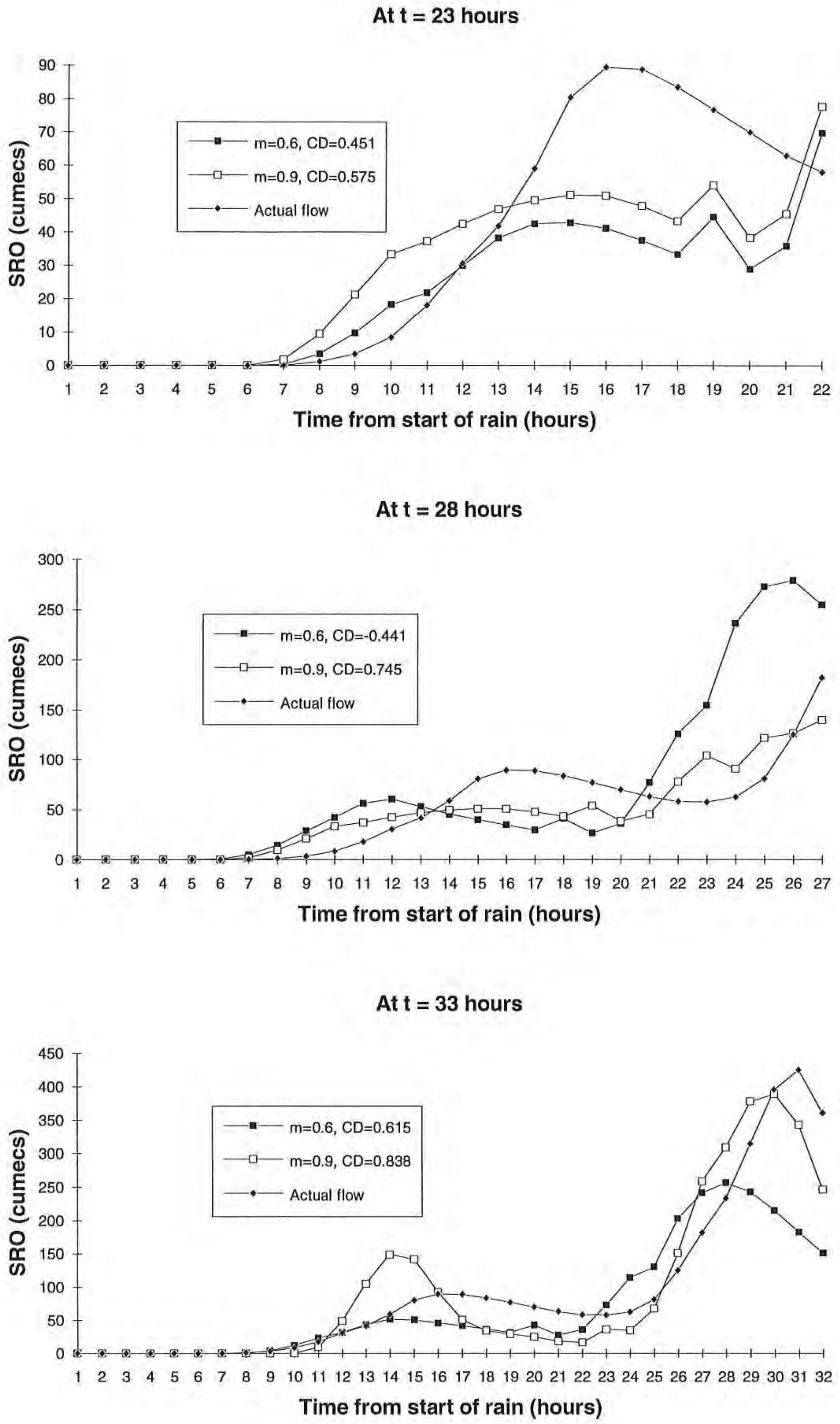


Figure 10.7 (cont.) The hydrographs generated from Stage 1 ('no more' rain), 30/8/92 storm, CL=1.3 mm/hour for m=0.6 and 0.9 with an indication of the CD for each plot

The most important statistical results from the analysis are shown in Tables 10.6 and 10.7 for the storms occurring on 8/8/81 and 30/8/92 respectively. The performance of the four test cases are shown with their associated rainfall scenarios. Larger *m* values, gave a more accurate forecast (i.e. an *m* of 0.9 gave better accuracy than an *m* of 0.6). Within the constant intensity rainfall scenarios (Test Cases 1 and 2), the results which are shaded, indicate those constant intensity rainfall scenarios with a volume similar to the volume of the actual intensity hyetograph over that forecast period. There is considerable difference between the performance of the different rainfall scenarios within Test Cases 1 and 2 based on the $CD_{forecast}$. From these results, the performance of Test Cases 1 and 2 using the rainfall scenarios appears to be poor using both the averaged continuing loss (Test Case 1) and actual continuing loss (Test Case 2). The constant rainfall scenarios most accurately representing the volumes associated with the actual intensity hyetograph, did not necessarily perform better than the other constant intensities. Test Cases 3 and 4 did not perform much better either, in terms of the $CD_{forecast}$.

Figures 10.8, 10.9, 10.10 and 10.11 display the performance of the models for the extreme *m* values of 0.6 and 0.9, summarising the performance of the model more easily. In fact, the results shown in Tables 10.6 and 10.7 perhaps do not give a true representation of the performance of the model. In Tables 10.6 and 10.7 the performance according to the $CD_{forecast}$ was poor, but on visual examination, some of the results are acceptable, certainly from an operational flood forecasting aspect. The general 'shape' of many of the forecasts were quite good, particularly when actual forecasted rainfall was used. Figures 10.8, 10.9, 10.10 and 10.11 show that the model performance was largely dependant on the forecasted rainfall scenarios. The 'no more' rainfall scenario drastically underestimated the forecast, especially on the rising limb of the hydrograph. However, with the inclusion of the exact time distribution of rainfall over the catchment (Test Case 3) an improvement in the model's performance is evident, particularly for the 8/8/81 storm.

Figures 10.8, 10.9, 10.10 and 10.11 suggest that many of the forecasts were not updated correctly. The idea behind updating the forecast was so that at each forecast time t, the model was run in order to replicate accurately what has previously happened in the storm. Therefore, if on the rising limb, the forecast hydrograph should continue increasing with a similar slope to the already known portion of the rising limb as explained in Figure 5.7 of Section 5.8.2.

Figure 10.7 corresponds to Test Case 3 of Figures 10.10 and 10.11. The optimisation of Stage 1 of the algorithm using the coefficient of determination was unable to replicate the known hydrograph up to each forecast time in Figure 10.7. This seems strong evidence that there is some weakness in using the coefficient of determination as the objective function.

Table 10.6 Performance ($CD_{forecast}$) of the four test cases used on the 8/8/81 storm

		Case 1 (mm/hr)			Case 2 (mm/hr)					Case 3	Case 4
Forecast Time	m	0	2.0	3.0	0	0.5	1.0	1.5	2.0	Actual	Actual
	0.6	0.21	-0.30	-7.00	-1.38	-1.02	-0.13	0.58	0.96	0.54	0.55
t = 6 hours[1]	0.7	0.02	0.78	0.20	-2.40	-2.09	-1.30	-0.58	0.03	-1.49	0.61
	0.8	0.19	0.83	0.17	-2.93	-2.64	-1.94	-1.29	-0.71	-2.22	0.72
	0.9	-0.36	0.44	0.88	-3.18	-2.91	-2.26	-1.67	-1.14	-2.58	0.78
	0.6	-38.32	-28.63	-10.77	14.96	-12.51	-6.91	-2.83	-1.06	-0.30	0.44
t = 11 hours[1]	0.7	-35.27	-25.91	-9.90	-14.04	-11.90	-7.02	-3.40	-1.44	-5.53	0.52
	0.8	-36.40	-24.49	-6.97	-14.51	-12.47	-7.94	-4.48	-2.23	-6.22	0.65
	0.9	-33.14	-21.85	-6.31	-14.48	-12.48	-8.15	-4.79	-2.53	-6.28	0.74
	0.6	-13.77	-11.81	-8.82	0.00	0.33	0.40	-1.06	-4.60	0.04	0.92
t = 16 hours[1]	0.7	-13.09	-11.05	-8.14	0.63	0.76	0.43	-1.09	-3.91	0.65	0.88
	0.8	-15.06	-13.57	-11.42	0.85	0.88	0.27	-1.45	-4.41	0.64	0.87
	0.9	-15.22	-12.63	-9.38	0.50	0.76	0.33	-1.83	-5.81	0.66	0.67
	0.6	-83.31	-69.48	-48.48	-9.14	-5.53	-0.76	-6.25	-26.35	-2.28	0.16
t = 21 hours[2]	0.7	-83.52	-68.62	-47.62	-4.24	-1.72	0.19	-6.55	-24.16	-3.96	0.14
	0.8	-93.76	-83.04	-67.99	-2.98	-0.71	0.09	-7.83	-25.71	-2.66	0.19
	0.9	-98.00	-75.92	-53.22	-14.99	-8.57	-0.73	-6.83	-28.27	-14.22	0.12
	0.6	-34.98	-26.99	-21.54	-4.69	-2.73	-2.24	-12.45	-38.34	-1.425	-2.21
t = 26 hour[2]	0.7	-36.96	-27.98	-22.61	-2.38	-0.88	-1.52	-11.57	-33.38	-2.38	-2.73
	0.8	-46.70	-39.71	-34.06	-2.53	-0.79	-1.67	-12.11	-33.85	-2.53	-3.10
	0.9	-49.20	-34.95	-33.68	-14.39	-9.25	-6.04	-19.32	-50.71	-14.39	-3.68
	0.6	-32.06	-22.50	-28.15	-4.39	-2.17	-4.68	-26.89	-78.57	-1.80	-1.36
t = 31 hours[2]	0.7	-35.70	-24.56	-31.21	-3.28	-1.26	-4.82	-26.04	-70.65	-3.28	-2.04
	0.8	-45.85	-37.15	-39.12	-5.09	-2.24	-5.14	-27.29	-71.94	-5.09	-2.68
	0.9	-47.88	-31.03	-57.34	-21.65	-12.99	-10.52	-41.86	-111.3	-2.46	-3.71
	0.6	-25.28	-15.13	-63.28	-1.86	-0.36	-16.24	-78.72	-209.1	-0.49	-3.50
t = 36 hours[2]	0.7	-30.22	-18.06	-72.54	-1.64	-0.17	-17.27	-77.28	-192.6	-1.64	-5.31
	0.8	-40.37	-30.29	-62.96	-5.32	-1.66	-17.24	-79.52	-198.0	-5.32	-7.45
	0.9	-42.46	-26.33	-154.7	-28.10	-14.85	-30.35	-131.7	-330.8	-28.1	-10.2
	0.6	-67.20	-35.29	-418.0	-1.86	-1.69	-113.1	-508.4	-1331	-58.1	0.40
t = 41 hours[2]	0.7	-84.10	-45.13	-484.4	-7.95	-2.06	-116.3	-494.6	-1227	-61.3	0.19
	0.8	-114.8	-80.73	-366.2	-25.79	-7.51	-119.5	-528.1	-1296	-56.7	-0.03
	0.9	-120.2	-88.66	-1093	-90.32	-39.44	-241.9	-1018	-2436	79.2	-0.25

1/2 : Stage 1 or 2 of algorithm

Shading denotes constant rainfall scenarios with a volume similar to actual rainfall volume

Table 10.7 Performance ($CD_{forecast}$) of the four test cases used on the 30/8/92 storm

		Case 1 (mm/hr)					Case 2 (mm/hr)					Case 3	Case 4
Time (hrs)	*m*	0	2.0	3.0	5.0	8.0	0	2.0	3.0	5.0	8.0	Actual	Actual
	0.6	-1.66	-0.84	0.31	-0.83	-16.98	-1.69	-0.63	0.33	-0.84	-14.44	-0.02	0.91
t = 8[1]	0.7	-1.69	-0.92	0.13	-0.23	-8.61	-1.71	-0.71	0.18	-0.34	-8.13	-0.13	-0.19
	0.8	-1.71	-0.69	0.01	-0.06	-5.89	-1.72	-0.77	0.08	-0.18	-5.93	-0.25	-3.43
	0.9	-1.71	-1.01	-0.07	-0.01	-4.25	-1.72	-0.81	0.01	-0.12	-4.85	-0.34	-8.44
	0.6	-16.87	-11.13	-2.04	-11.41	-178.7	-15.64	-8.19	-0.79	-13.78	-174.6	-2.82	-0.18
t = 13[1]	0.7	-12.44	-8.65	-2.73	-2.95	-49.19	-10.71	-5.80	-1.03	-4.65	-58.34	-1.71	-1.75
	0.8	-12.60	-8.97	-3.41	-2.00	-30.48	-12.57	-9.73	-2.98	-2.35	-29.14	-2.56	-4.47
	0.9	-14.00	-10.34	-4.74	-1.54	-18.86	-13.56	-8.79	0.47	-1.69	-19.33	-2.93	-7.18
	0.6	-32.60	-27.81	-19.80	-21.41	-113.2	-27.47	-21.31	-15.10	-22.72	-127.8	-15.66	-14.83
t = 18[1]	0.7	-27.01	-22.49	-15.48	-17.25	-80.96	-21.62	-16.06	-11.01	-17.66	-88.63	-11.65	-14.58
	0.8	-23.17	-18.66	-12.27	-15.15	-69.99	-17.27	-12.09	-7.96	-15.33	-74.67	-8.68	-16.03
	0.9	-28.20	-21.99	-8.77	-21.67	-99.19	-21.88	-14.55	-9.75	-24.13	-113.1	-10.19	-19.55
	0.6	-0.04	0.21	0.45	-0.79	-9.76	0.03	0.28	0.32	-1.41	-11.04	-0.69	0.70
t = 23[1]	0.7	-0.08	0.20	0.60	0.41	-3.29	0.05	0.37	0.63	0.12	-4.09	0.45	0.41
	0.8	-0.04	0.23	0.58	0.39	-2.65	0.09	0.38	0.57	-0.01	-3.73	0.25	-0.03
	0.9	-0.33	-0.08	0.33	0.78	0.45	-0.15	0.18	0.51	0.54	-1.13	0.41	-0.52
	0.6	-15.84	-13.78	-9.34	-2.32	-4.91	-15.45	-12.51	-8.14	-1.70	-6.04	-10.38	-1.88
t = 28[1]	0.7	-11.96	-17.44	-11.36	-2.49	-7.09	-11.22	-9.53	-7.15	-3.24	-1.10	-8.19	-1.75
	0.8	-10.31	-9.32	-7.44	-4.40	-2.38	-9.859	-8.59	-6.88	-4.15	-2.31	-7.40	-1.73
	0.9	-10.93	-9.96	-8.14	-5.18	-2.70	-10.47	-9.20	-7.53	-4.83	-2.56	-8.02	-1.71
	0.6	-1.78	-1.39	-0.81	-1.64	-11.96	-1.92	-1.34	-0.82	-2.26	-15.45	-1.36	-0.99
t = 33[1]	0.7	-4.02	-3.56	-2.79	-2.65	-8.34	-0.23	0.01	0.17	-0.54	-5.13	-0.07	-1.29
	0.8	-6.53	-6.16	-5.50	-4.93	-6.80	-4.46	-4.03	-3.53	-3.24	-5.16	-2.22	-1.79
	0.9	-9.88	-9.70	-9.36	-8.94	-9.03	-6.05	-5.85	-9.44	-5.31	-5.43	-2.59	-2.38
	0.6	-13.50	-9.23	-4.58	-30.90	-239.8	-13.96	-7.94	-5.35	-45.40	-318.8	-9.28	-12.91
t = 38[2]	0.7	-34.37	-28.88	-4.58	-33.17	-171.9	-11.50	-7.59	-5.11	-18.31	-103.3	-5.90	-18.73
	0.8	-51.23	-46.83	-40.41	-44.20	-107.3	-42.65	-37.38	-32.60	-37.85	-94.32	-27.22	-25.60
	0.9	-61.80	-59.99	-57.50	-58.08	-74.34	-54.05	-51.80	-49.56	-49.14	-59.76	-35.42	-32.13
	0.6	-8.53	-5.31	-0.57	-7.13	-92.29	-5.88	-1.93	0.70	-15.43	-135.9	-3.10	-3.57
t = 43[2]	0.7	-7.58	-4.78	-1.11	-7.94	-73.51	-5.49	-2.82	-0.56	-4.60	-40.62	-2.92	-2.80
	0.8	-4.16	-2.42	-0.31	-4.15	-4.78	-1.86	-0.29	0.41	-5.55	-37.21	-1.36	-1.62
	0.9	-3.57	-2.61	-1.21	-0.82	-6.96	-1.31	-0.80	-0.54	-1.92	-9.04	-2.00	-0.75

[1/2] : Stage 1 or 2 of algorithm

Shading denotes constant rainfall scenarios with a volume similar to actual rainfall volume

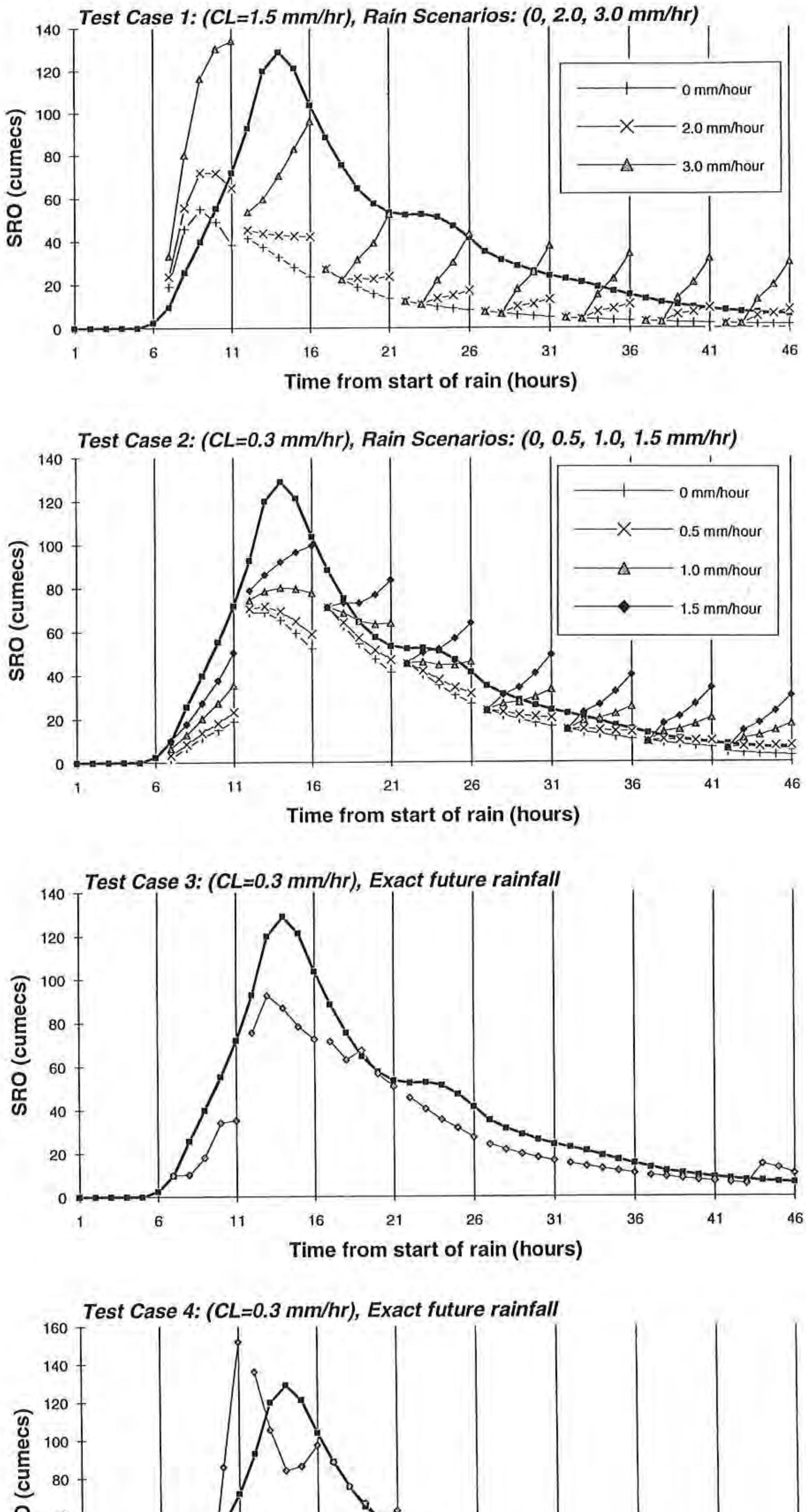
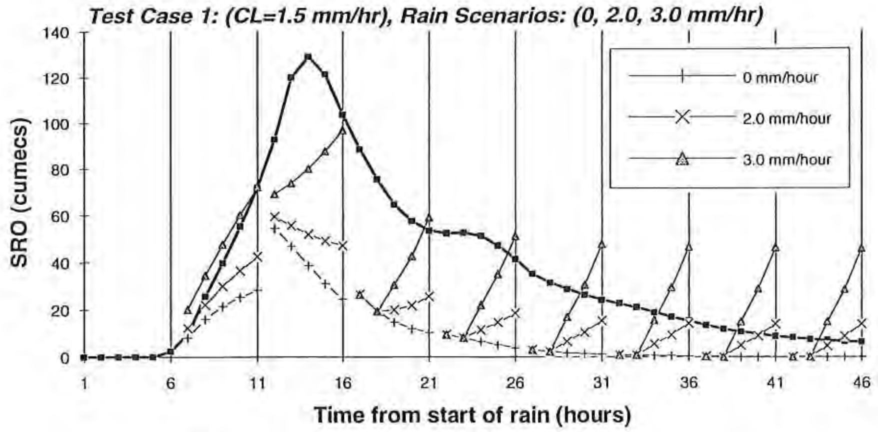
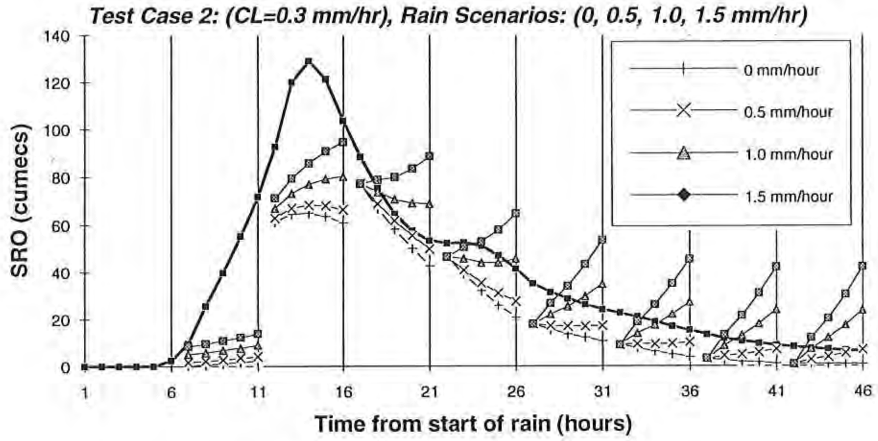
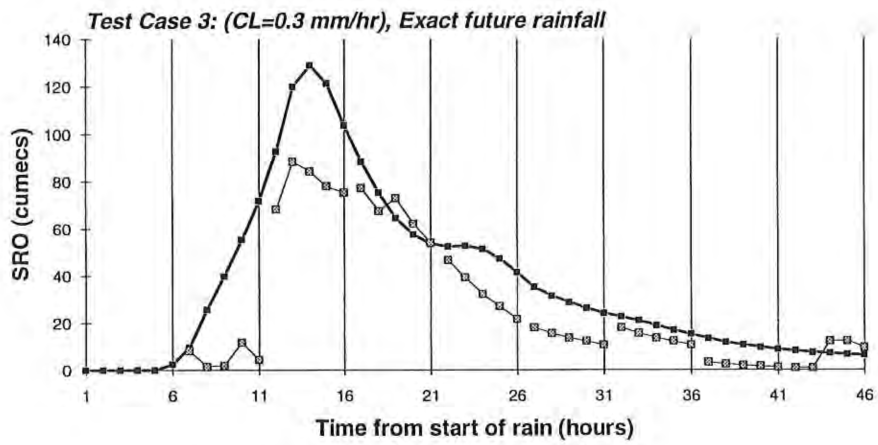


Figure 10.8 Comparison of the four test cases, m=0.6, 8/8/81 storm







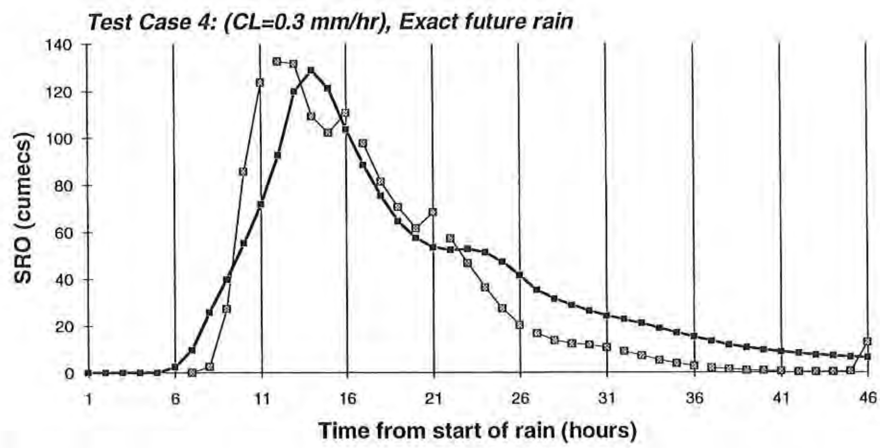


Figure 10.9 Comparison of the four test cases, m=0.9, 8/8/81 storm

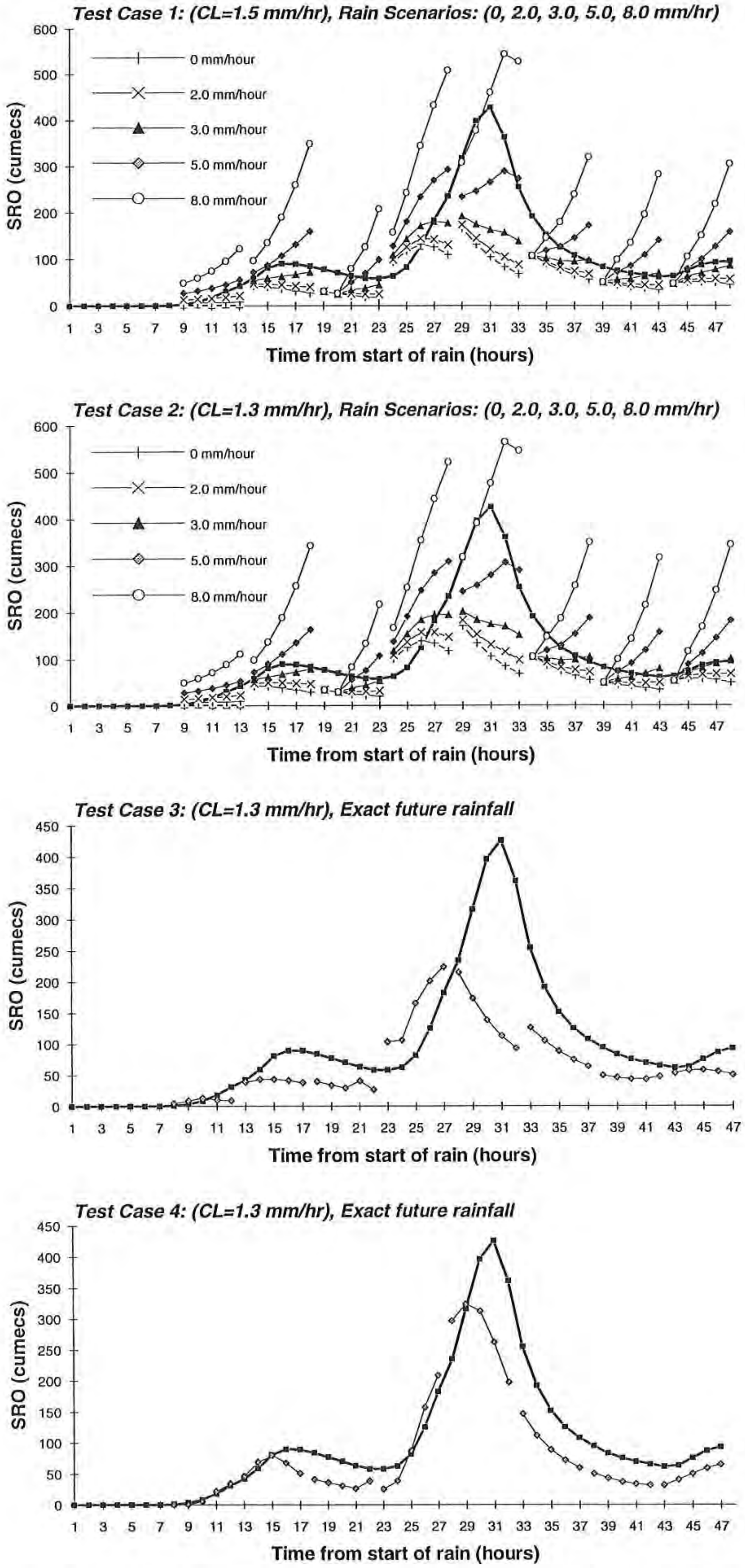


Figure 10.10 Comparison of the four test cases, m=0.6, 30/8/92 storm

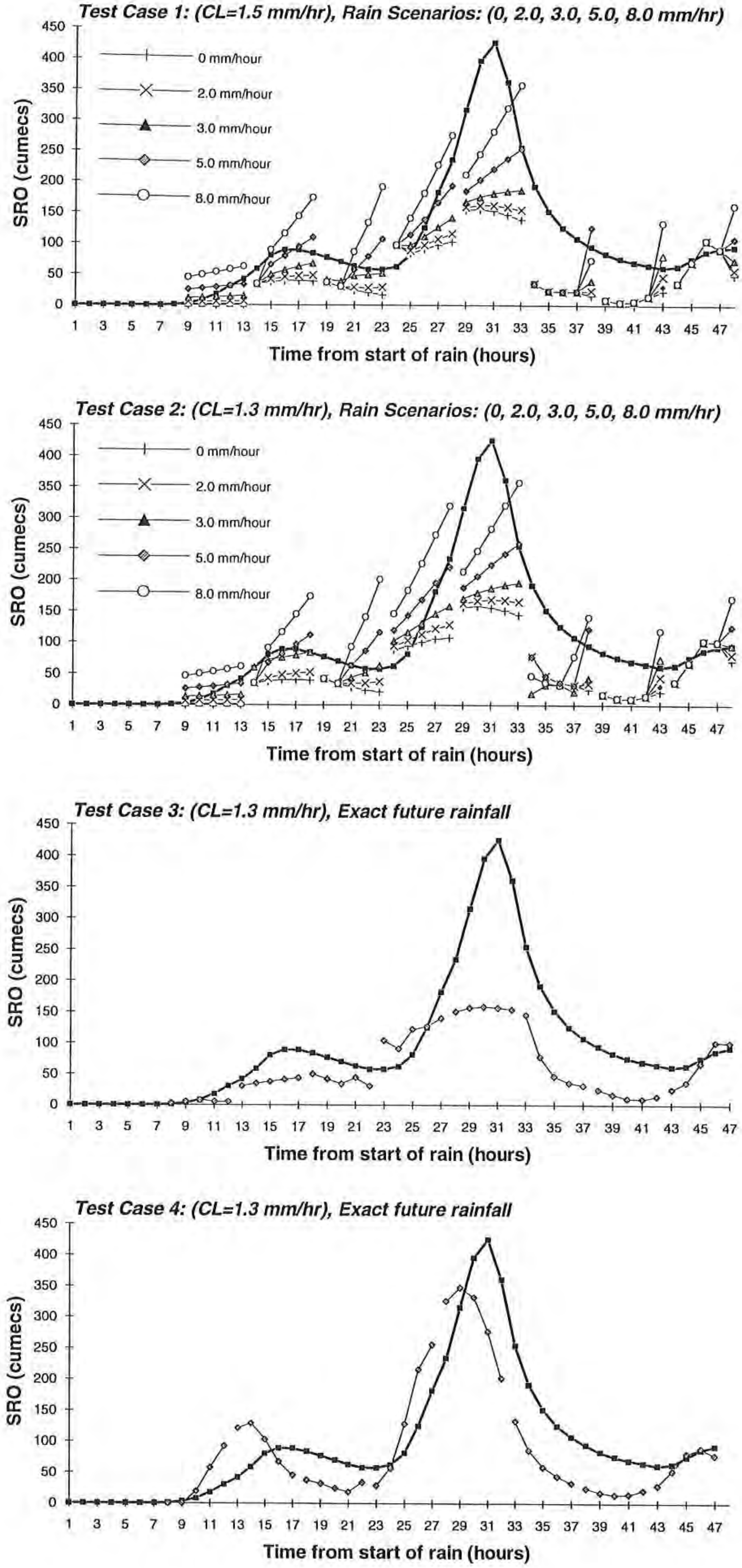


Figure 10.11 Comparison of the four test cases, m=0.9, 30/8/92 storm

10.9 Discussion

Ideally, more storms should have been forecasted to further confirm the performance of the model, and certain pluviometers could have been removed to test the sensitivity of a less accurate spatial representation within the catchment. However, the time taken to set up the models and to forecast the different aspects shown in this chapter was substantial. The time taken to run the algorithm could have been reduced by increasing the iteration interval and perhaps optimising the PASCAL code.

Although the overall 'shape' of some of the forecasts were good, the factor that probably contributed to the poor $CD_{forecast}$ values as suggested by Tables 10.6 and 10.7, was a result of the next hourly forecast Q(t+1), being inaccurate, analogous to an updating problem similar to that discussed in Chapter 9. This was perhaps a function of the accuracy of the continuing loss used. This is of course more obvious for the 8/8/81 storm because the 30/8/92 storm had a similar actual continuing loss to the averaged continuing loss. For the 8/8/81 storm, when the averaged continuing loss was used, the next hourly forecast Q(t+1) was not close to the observed flow, whereas, when the more accurate continuing loss value was used, the next hourly forecast was much closer to the observed value, for all *m* cases.

It was therefore no surprise that for the 8/8/81 storm, lower volumes and a lower hydrograph peak were observed when the average continuing loss (1.5 mm/hr) was used compared with the smaller, but more accurate (0.3 mm/hr) value. The higher continuing loss caused less rainfall excess, therefore less runoff.

Test Case 4 was probably the most accurate of the four cases. It was more accurate than Test Case 3 which used actual rainfall and the optimised algorithm parameters. Test Case 4 was able to predict the rising limb and peak of the hydrographs quite well, however once the peak had passed, the performance of Test Cases 3 and 4 were similar. This result, and the fact that the k_c values shown in Table 10.5 were relatively similar, may suggest that a constant k_c value as used in Test Case 4, can produce a more accurate forecast of the rising limb and the hydrograph peak.

One factor that may account for the discrepancies between the k_c values used from the two different fitting processes, is that Hill based the translation component on differences in hydrograph peaks, whereas the real-time algorithm calculated translations based on differences in the centroids of the observed and forecasted hydrographs at each forecast time. Timing of the hydrograph peak for Test Case 4 was generally a few hours short but had the translation values adopted by Hill (1993) for each storm been used, the hydrograph peak would have been translated forward a few more hours, and a more accurate prediction of the hydrograph peak resulted.

An interesting observation is shown in Tables 10.8 and 10.9 which lists the percentage errors in the hydrograph peak and volume for the two storms tested with Test Case 4, and the average percentage errors from the design calibrations made by Hill (1993). The results of Test Case 4 are shown for m values of 0.6-0.9, whereas the average percentage result from Hill's analysis were calculated from m values of 0.6-1.2. Both methods used an actual forecasted rainfall scenario with an accurate representation of continuing loss. Except for the hydrograph of the 8/8/81 storm, an under estimation in the hydrograph peak and volumes were observed, suggesting the rainfall input in both situations was perhaps far from ideal. This may also be due to the model structure and the associated storages of the RORB model within the catchment.

Table 10.8 Comparison of hydrograph peak and volume errors for Test Case 4 and Hill's design calibration for 30/8/92 storm

	Hydrograph Peak (% Error)	Hydrograph Volume (% Error)
Test Case 4, m=0.6	-24.0	-28.5
Test Case 4, m=0.7	-21.0	-25.5
Test Case 4, m=0.8	-19.5	-23.5
Test Case 4, m=0.9	-18.3	-22.1
Design Calibration, Hill (1993)	-30.5	-16.2

Table 10.9 Comparison of hydrograph peak and volume errors for Test Case 4 and Hill's design calibration for 8/8/81 storm

	Hydrograph Peak (% Error)	Hydrograph Volume (% Error)
Test Case 4, m=0.6	17.7	-12.1
Test Case 4, m=0.7	12.8	-10.7
Test Case 4, m=0.8	6.3	-10.0
Test Case 4, m=0.9	2.8	-9.5
Design Calibration, Hill (1993)	-30.3	-28.4

Applying the same constant intensity rainfall to all pluviographs within the catchment at any one time, is perhaps another weakness. Even in operational forecasting, the forecaster would assign different scenarios to different pluviographs based on the direction in which the storm is moving, elevation and other local factors.

10.10 Conclusions

Three critical factors have been investigated in this chapter using RORB as a real-time forecasting tool; rainfall input, consideration of losses (in particular continuing loss) and updating of the model parameter k_c. The other aspect considered was the ability for the RORB model to interact in an automated real-time forecasting mode.

The results of this chapter again reinforce the fact that the instrumentation used to measure rainfall within the Onkaparinga River catchment is far from ideal. These results along with those in other chapters indicate that rainfall input is a large source of error, in particular the spatial distribution of pluviometers throughout the catchment. In most situations where the actual rainfall intensity was used, particularly for the 30/8/92 storm, the hydrograph peak and volume were under estimated. The question raised is; Why are these under estimations present? It could be due to errors in the hydrograph values, caused by a poor rating curve at Houlgraves Weir, but most likely due to errors in the rainfall input. The spatial distribution of losses is important as the contributing areas to runoff are the wet (or saturated) areas of each catchment.

It was shown that an accurate rainfall forecast is perhaps the most important factor in using the RORB model in real-time forecasting. Even a constant intensity rainfall scenario with a volume similar to the actual intensity was not adequate to produce an accurate forecast. To achieve a more accurate forecast, the correct time distribution of rainfall is also required. By doing so, the shape of the forecasted hydrographs are more accurate and the starting values of the next forecast are also improved.

Fixing the continuing loss, whilst updating k_c using the coefficient of determination as the objective function, did not update the next forecast, Q(t+1) as accurately as initially hoped. In fact, many of the updates were worse than what a trained forecaster could do. Updating k_c was not reliable in producing a good association between the volumes of the observed and forecasted hydrographs. However, when the more accurate continuing loss was used, an improvement in the accuracy of the next forecast Q(t+1) was observed. But when the averaged (less accurate) continuing loss was used, the coefficient of determination should have accounted for this. The poor performance was therefore significantly related to the operation of the objective function used. The problem with using the coefficient of determination as the objective function, is that it does not consider the magnitude of the most recent hydrograph value(s). Although the 'overall' shape (or association) between the observed and forecasted hydrographs might be good, the magnitude of the most recent hydrograph values are not emphasised and therefore, the next values forecasted may not be as accurate as if performed by a trained forecaster, but could in some way be weighted. The convergence difficulties found when forecasting the 24/5/88 storm may have been caused by the coefficient of determination as the objective function. In this situation, another objective function which considers, say just the difference in magnitude of the most recent hydrograph values, as well as using the coefficient of determination, would be more ideal.

This study showed that k_c does not need to be varied within a storm, but certainly should vary between storms. But how then should the k_c value for each storm be estimated ? Given a large historical data base, the storms could be separated into groups with similar hydrologic characteristics, such as antecedent precipitation index. When forecasting a storm, once it is decided which group that storm lies in, the average k_c value from that group for various m values can be calculated. But in most instances, especially for this study, not enough recorded events were available.

The assumption that continuing loss is constant is more than likely a simplification and a more accurate forecast would probably have been achieved if the continuing loss was updated at each forecast time, as suggested by Avery (1989), either by matching the most recent calculated and observed hydrograph values, or matching volumes of surface runoff. However, by adjusting the continuing loss there would be doubts whether the continuing loss values attained would be representative of reality because of the poor spatial representation of rainfall within the catchment. In the future, a more realistic situation would be to use an initial loss-proportional loss model, adjusting the proportional loss rate as the event proceeds. This would be similar to updating the continuing loss in an initial loss-continuing loss model based on differences in the volumes of the predicted and observed hydrographs.

It can be concluded that developing RORB as an on-line operational forecasting model combined with a system to objectively update the model parameters is difficult. RORB in its PC format is a model not designed for this type of modelling situation, especially in a DOS environment. Using RORB on a UNIX based system would therefore be a more suitable proposition for more detailed future studies of this nature.

Chapter 11

Conclusions and Recommendations

11.1 Summary

The literature review revealed how the need and the growing requirement for flood prevention has increased in the last few decades. More specifically there is a growing need for improved real-time flood forecasting techniques, not only in Australia, but in other countries as well, which are experiencing an increase in populated urban areas within river flood plains.

Compared with other developed countries including Japan, the U.S., and those found in Europe, Australian forecasting techniques are generally limited, and display a lack of technology, despite the availability of many overseas systems. Rainfall forecasting techniques in Australia have lagged well behind those in the nations mentioned, except perhaps the techniques implemented for the Brisbane area. Flood forecasting models used in Australia, particularly rainfall-runoff models such as RORB are limited in their use because of their development in the 1960s for design simulation, rather than real-time forecasting. Recently, these models have been modified so that they can be more readily adapted to real-time simulations. Additional models are also now being developed with real-time forecasting specifically in mind.

ALERT and other monitoring systems have recently been developed to assist in flash flood forecasting but need some years of data collection so that flash flood prediction methods can be developed. This was one reason which precipitated the change in this research project from the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment to the Onkaparinga River catchment which has a more comprehensive flood record.

Many of the traditional forecasting models and procedures are very subjective in their operation and rely heavily on the experience and judgement of the forecaster. Very few objective techniques are used in forecasting floods in Australia, probably due to the great variability, and therefore unreliability, of flood phenomena in this country. The different flood characteristics found in Australia, have led to the development of different forecasting strategies, and therefore a lack of collaboration between the forecasting authorities around Australia.

Non-traditional modelling techniques such as artificial neural networks were seen as being well suited to complex problems such as hydrologic forecasting where the relationships between the catchment variables are not well understood. Artificial neural network modelling has relied on training of historical data which previously has required little subjectivity on behalf of the user, because the underlying physical processes do not need to be fully understood.

In addition, a simple, yet often neglected forecasting tool in Australia, is the use of soil moisture indices to improve the efficiency and reliability of a flood forecast.

This study investigated in detail, three different aspects related to real-time flood forecasting, upstream of Houlgraves Weir on the Onkaparinga River catchment, South Australia. The principle objective was to determine whether any substantial improvement in the accuracy of a flood forecast could be achieved by reducing the subjectivity associated with flood forecasts. The first aspect investigated was antecedent soil moisture indices to assist in flood forecasting. The second aspect studied was artificial neural networks as a modelling tool, and finally the RORB rainfall-runoff model was studied in real-time mode.

Throughout the analysis, twelve historical flood events were used, spanning a period from 1981 to 1992. Their hydrologic characteristics and response times were all very different, particularly the event occurring on the 30/8/92, which was estimated to be a 100 year ARI flood event with a flood peak of about twice the second ranked event, and perhaps the largest event of the last century in this catchment.

In Chapter 7, both antecedent precipitation index (API) and pre-storm baseflow (BF) were used to estimate the initial loss (IL) at the commencement of a storm. Exponential relationships were developed using a regression technique, however the derived relationships had poor correlations. Antecedent precipitation index appeared to be a slightly better means of estimating the initial loss than pre-storm baseflow, however the best R^2 value using antecedent precipitation index was only 0.68, which is only a reasonable correlation.

The overall results of Chapter 7 were dependent on what storms were used in the regression analysis, and the methods used to estimate the initial loss. No correlation was established between the length of antecedent rainfall and performance of the derived relationships. Pre-storm baseflow in the Onkaparinga River is very low, often with little variation, which would account for its unsuitability to estimate initial loss, and is therefore not recommended for future use on this catchment. Perhaps the limiting factor was that only twelve storms were used to derive the relationships. Not only was the number of storms in the historical data set small, but the spatial representation of rainfall over the catchment for each storm was variable. Prior to 1990, the spatial representation of rainfall within the catchment, was restricted by the number of operational pluviometers. Obtaining vastly different exponential relationships when certain storms were ignored, indicated just how variable each storm was. Even though antecedent precipitation index varied greatly from event to event, it could still be an important factor in future flood forecasting on the Onkaparinga River.

In Chapter 8, the first application of artificial neural networks was performed, simulating the complete hydrograph of a flood event, in a similar way to a design process. The main input variable to the artificial neural network was rainfall. Antecedent precipitation index was also included as an input as an extra means of enhancing the simulation of the hydrograph. Two rainfall inputs were considered with different spatial representations; firstly a weighted catchment and secondly, a single station hyetograph representation. Different storms were used for training, therefore training sets contained different amounts of data and hydrologic similarity. The inclusion of antecedent precipitation index failed to improve the results, and in fact some results worsened with its inclusion probably because the antecedent precipitation index values were biased through a lack of rainfall data. The type of rainfall input, in particular the spatial variability also affected the performance. It was also noticed that the quality of the data in terms of training set variability, was just as important, if not more important, than the quantity of data used for training.

The accuracy of the artificial neural network as a real-time runoff forecasting tool was investigated in Chapter 9, and the results were not as encouraging as first hoped, especially for five hour forecasts. The model inputs were current and previous rainfall and runoff. Previous runoff was included as an input to assist in updating the forecasted hydrograph. A significant difficulty with the results presented in Chapter 9 was that the actual process to determine the output is not fully understood. A number of explanations can be hypothesised however, based on observation and sensitivity testing.

The variable performance of the different training methods indicated that the forecasts were highly dependent on firstly, how the models were trained, and secondly, on the storms used. The most accurate forecast contained the least amount of hydrologic variability and the least amount of training data, therefore the quality of the training data was perhaps at least as important as the quantity. The performance of the model was improved when the most recently known rainfall-runoff information from the forecasted storm was included in training.

Perhaps the biggest disappointment of the artificial neural network for real-time forecasting, was its failure to correctly update the hydrograph at each forecast using the previous runoff inputs. Through model input sensitivity, it was shown that the artificial neural network was able to numerically differentiate between the rainfall and previous runoff inputs, but it was also shown that the model did not consider the two inputs as having distinct and independent purposes. For example, even with the inclusion of inaccurate rainfall inputs, which was perhaps the case, the previous hydrograph flow inputs, should still have assisted in updating the hydrograph at each forecast. This may also have been caused by poor selection of the network structure, in particular the fully connected aspect of the model. A detailed investigation into redesigning the network's architecture was not possible, due to time constraints. Sensitivity also showed that many of the inputs to the model were not considered important and perhaps unnecessary. By considering only the 'important' inputs, a more efficient and accurate forecast may result.

Chapter 10 investigated the use of RORB, a traditional rainfall-runoff model in an objective real-time forecasting mode. Comparisons were made to more subjective procedures relating to rainfall forecasting and model parameter selection. RORB was automated using a PASCAL program combined with a keystroke 'faker'. This was difficult and time consuming using the PC version since the RORB model has not been developed for this purpose.

An initial loss-continuing loss model was used, combined with an objective updating algorithm that adjusted k_c at each forecast time based on a comparison of the coefficient of determination for the predicted and observed hydrograph. Different rainfall scenarios were also considered. One of the critical parameters was the accuracy of the forecasted rainfall scenario, in particular the rainfall temporal pattern. When the correct time distribution was used, the shape of the hydrograph was more accurately forecasted, especially the starting value of the next forecast Q(t+1). When a constant rainfall intensity was adopted, the performance of the forecast, particularly the rising limb, was more inaccurate. The volumes of the forecasted hydrographs were less than the observed hydrographs when k_c was updated in time which was perhaps a function of the poor spatial representation of rainfall, and may indicate that updating k_c as the storm progresses in time is not ideal in replicating the physical process occurring.

11.2 Conclusions

It seemed certain that by using only twelve historical flood events, there was insufficient data to establish relationships and accurate flood forecasting techniques. Not only was there a lack of flood events, but the floods themselves were extremely variable in all hydrological aspects. The data set was perhaps biased with the inclusion of the 30/8/92 event, with its magnitude being about twice that of the remaining floods, however it is necessary to include extreme floods in the analysis if a greater flood was to occur in the future.

Apart from this weakness, instrumentation within the catchment, especially the number and spatial distribution of pluviometers in pre-1990 floods was a critical factor in the accuracy of this research. This is in agreement with Hill (1993, p 101) who noted that; "*....it was more difficult to obtain satisfactory fits for events that occurred in the early 1980s.*". Until more flood events are recorded, the accuracy of any flood forecasting methodology for the Onkaparinga River catchment will remain questionable, unless flow measuring stations upstream are used.

It was originally thought that in ANN modelling, the underlying physical processes did not need to be fully understood, and since being adapted on training of historical data, they could be considered as a rather objective modelling tool. However, for an investigation of this nature, unless the historical data set is large, ANNs are perhaps indirectly a subjective forecasting tool. Unless the historical data set covers a wide spectrum of flood scenarios, the forecaster must present the model with training sets that have suitable and similar characteristics to the flood which is currently being forecasted. The performance of the ANN model was confined to be within the accuracy of the training data presented, which emphasises the importance of a well maintained and dense data collection network. It was thought that ANNs had an advantage over deterministic approaches in that they require less data. The idea that data collection programs for ANN modelling can be less intensive, time consuming and costly is perhaps not true, especially for rainfall-runoff modelling. From a practical view point, it can be concluded that ANNs cannot cope or adjust to changes in a system when modifications are made to a data collection network, such as the density of rainfall instrumentation, because any relationships derived by training on specific training sets cannot be assumed to apply in the future.

For Australian catchments, particularly the Onkaparinga River catchment, objective flood forecasting will continue to remain an aspect that requires further development. The RORB model was difficult to automate and interact with a DOS environment, and the development of new models specifically designed for real-time forecasting will need to continue. Executing RORB on an alternative operating system such as a UNIX system would be more desirable. Due to the great variability and complex nature of the rainfall-runoff process, particularly in Australia, it will be difficult for a single objective function to represent the accuracy of flood forecasts. By adopting a constant k_c value and constant continuing loss, more accurate forecasts were achieved. To achieve a more accurate forecast, especially in terms of volumes, it is suggested to either adjust continuing loss as the storm proceeds, or use an initial loss-proportional loss model.

The rainfall-runoff process relies on the joint probability of many factors not considered in this research, therefore subjective procedures relying on catchment knowledge and experience, will continue to dominate flood forecasting techniques in this country. Whilst technological developments continue to be made, they must be supplemented with advice and input from forecasters who have a detailed understanding of the particular catchment response. For catchments where there is considerable variation between the response of different rainfall events, an index may be useful in accounting for the variability between storms for historical analysis.

Whether the poor results from this research were due solely to the catchment and the input data used is unclear, but these factors are more than likely the cause. It is however hoped that the techniques used and the observations made from this research, can be extended to other catchments to see whether similar results are obtained elsewhere, especially in adjacent catchments.

11.3 Further Research

It would be appropriate if similar research was carried out on catchments with either a longer historical data set (i.e. eastern states of Australia) or in catchments where rainfall is a more reliable occurrence (i.e. Tropics). The accuracy of any derived relationships and modelling procedures could therefore be viewed with more confidence.

By doing this, the uncertainty of whether calculated parameters such as antecedent precipitation index are biased through a lack of data is removed. Any results can therefore be more confidently used to further substantiate and develop flood forecasting techniques. This would be particularly important to validate the accuracy of ANNs for flood forecasting. Research similar to that presently carried out by the Co-operative Research Centre (CRC) for Catchment Hydrology should continue in similar areas to validate and extend some of the findings of this research.

If with continued research, ANNs are found to be more appropriate for flood forecasting, an investigation should be made into how an ANN model could be linked into an operating system such as the ALERT system for real-time forecasting. This would probably not be a major problem since ANNs have been used in other applications for operational forecasting.

It seems that one of the biggest problems with using ANNs is determining the number of training sets required to maximise the model's performance. A study into establishing the optimum number of training sets for a certain network configuration (i.e. the number of input, hidden and output nodes) would be a useful extension to this study. In addition, if the ANN was used on a catchment with a large amount of data, the training input could be selectively decreased, which would therefore enable the sensitivity of the input to be tested and help determine which aspects of the model are most important.

With more reliable data, the concept of antecedent soil moisture indices appears to be an encouraging method for removing some of the subjectivity associated with flood forecasting, particularly for establishing the initial conditions of the catchment, therefore allowing more accurate initial estimates of model parameters which will require a less intensive updating procedure. The splitting of flood events into groups of similar antecedent characteristics is one method of removing the subjectivity of flood forecasting, and should be further researched.

The development of hydrologic models specifically for real-time flood forecasting should continue, concentrating on their ability to operate on different computer operating systems using different data collection networks. Objective updating techniques also need continued research.

Losses and the way they are considered by rainfall-runoff models need further development and refinement. In relation to the RORB model, analysis using initial loss-proportional loss models should be investigated as this appears to relate more closely to the actual physical processes occurring in a catchment than an initial loss-continuing loss model.

The continued development of new classes of models, similar to the model proposed by Kemp and Daniell (1996) which are more physically correct, must continue. The model by Kemp and Daniell has the ability to take into account all runoff processes as well as storage effects. It considers the different hydrologic processes separately, instead of modelling only surface runoff represented by a series of storages along the watercourses. The proposed model will allow separate modelling of baseflow and make it easier to adjust losses in time, therefore making it more applicable to real-time use.

Although a separate concept, rainfall forecasting methods in Australia must be researched before substantial improvements in forecast accuracy and reduction in lead times occur, as the spatial movement of rainfall affects the resulting flood peak. Comparisons between the accuracy of ground recorded rainfall and radar measured rainfall should be studied.

The sensitivity of how much improvement can be achieved at a downstream location of a catchment by using upstream flow gauging stations also needs further research.

The sensitivity of the number of pluviographs to the performance of a flood forecast is one area that requires urgent research. This is perhaps the most critical factor in producing accurate flood forecasts, but is a weakness that can be overcome with more comprehensive data collection programs.

References

AEMI (1995), "*Flood Warning: an Australian Guide*", Australian Emergency Management Institute, Australian Government Publishing Service, Canberra, 42 pages.

Ahsan M. and O'Connor K.M. (1994), "A Reappraisal of the Kalman Filtering Technique, as applied in River Flow Forecasting", *Journal of Hydrology*, 161, pp 197-226.

Aitken A.P. (1973), "Assessing Systematic Errors in Rainfall-Runoff Models", *Journal of Hydrology*, 20 (2), pp 121-136.

Anderson E.A. (1993), "A Continuous, Incremental Antecedent Precipitation Index (API) Model for use with the National Weather Service River Forecast System", In: *Proceedings of the Conference on Engineering Hydrology, San Fransisco, California, July 25-30*, pp 934-939, American Society of Civil Engineers, New York.

Avery D.R. (1989), "Application of RORB Runoff Routing Model to a Flood Warning System in the Tweed Valley, New South Wales", In: *Proceedings from the International Hydrology and Water Resources Symposium, Christchurch, New Zealand, 23-30 November*, pp 90-94, The Institution of Engineers, Australia.

AWRC (1992), "*Floodplain Management in Australia*", Australian Water Resources Council Water Management, Series No. 21, AGPS, Canberra.

Bae D., Georgakakos K.P. and Nanda S.K. (1995), "Operational Forecasting with Real-Time Databases", *Journal of Hydraulic Engineering*, 121 (1), pp 49-60.

B.C. Tonkin & Associates (1977), "*The Investigation of Flood Storage and Flood Warning for the River Torrens - Working Report No. 2 - Hydrological Modelling*", Prepared for The Engineering and Water Supply Department, South Australia, Adelaide.

B.C. Tonkin & Associates (1986), "*Unit Hydrograph Studies for Ten Adelaide Hills Catchments for the Engineering and Water Supply Department*", Prepared for The Engineering and Water Supply Department, South Australia, Adelaide.

B.C. Tonkin & Associates (1992), "*Revision to the 1978 Stormwater Drainage Investigation*", Prepared for The Corporation of the City of Unley, Adelaide.

Bertoni J.C., Tucci C.E. and Clarke R.T. (1992), "Rainfall-based Real-Time Flood Forecasting", *Journal of Hydrology*, 131, pp 313-339.

Biswas A.K., (1970), "*History of Hydrology*", North Holland Publishing Company, Amsterdam, 336 pages.

BoM (1963a), "*Report on Development of a Flood Forecasting System for the Lower Macleay River Valley, N.S.W, Volume 1 : Development of an Operative Flood Forecasting System*", Bureau of Meteorology.

BoM (1963b), "*Report on Development of a Flood Forecasting System for the Lower Macleay River Valley, N.S.W, Volume 2 : Research Leading to the Flood Forecasting Procedures*", Bureau of Meteorology.

BoM (1983), "Bureau of Meteorology Flood Forecasting and Warning Service", Department of Science and Technology, Bureau of Meteorology, 50 pages.

Boyd M.J., Bates B.C., Cordery I. and Pilgrim D.H. (1989), "PC Programs for Flooding and Stormwater Drainage", In: *Proceedings from WATERCOMP '89, The First Australian Conference on Technical Computing in the Water Industry, Melbourne, Australia, 30 May-1 June,* pp 99-103, The Institution of Engineers, Australia.

Brath A. and Rosso R. (1993), "Adaptive Calibration of a Conceptual Model for Flash Flood Forecasting", *Water Resources Research*, 29 (8), pp 2561-2572.

Browning K.A., Collier C.G., Larke P.R., Menmuir P., Monk G.A. and Owens R.G. (1982), "On the Forecasting of Frontal Rain using a Weather Radar Network", *Monthly Weather Review*, 110, pp 534-552.

Burlando P., Rosso R., Cadavid L.G. and Salas J.D. (1993), "Forecasting of Short-Term Rainfall using ARMA Models", *Journal of Hydrology*, 144, pp 193-211.

Burnash R.J.C. (1984), "The Meaning and Challenge of Real-Time Data and Analysis Systems to Future Public Service Programs", *Bulletin of the American Meteorological Society*, 65 (4), pp 338-342.

Carroll D.G. (1993), "PROPHET - The Brisbane City Council Creek Flood Monitoring and Forecasting System", In: *Proceedings of 7th National Local Government Engineering Conference, Adelaide, 30 August - 3 September*, pp 1-7, The Institution of Engineers, Australia.

Carroll D.G. (1994), "Aspects of the URBS Runoff Routing Model", In: *Proceedings of Water Down Under '94, Adelaide, November 21-25*, Volume 3, pp 169-176, The Institution of Engineers, Australia.

Chander S. and Shanker H. (1984), "Unit Hydrograph Based Forecast Model", *Hydrological Sciences Journal*, 29 (3), pp 279-291.

Chow K.C.A., Watt W.E. and Watts D.G. (1983), "A Stochastic-Dynamic Model for Real-Time Flood Forecasting", *Water Resources Research*, 19 (3), pp 746-752.

Collier C.G. (1985), "Remote Sensing for Hydrological Forecasting", In: *Facets of Hydrology Volume II*, Chapter 1, pp 1-19, J.C. Rodda, John Wiley & Sons, Chichester, England.

Cordery I. (1970a), "Initial Loss for Flood Estimation and Forecasting", *Journal of the Hydraulics Division*, Proceedings of the American Society of Civil Engineers, 96 (12), pp 2447-2466.

Cordery I. (1970b), "Antecedent Wetness for Design Flood Estimation", *Civil Engineering Transactions*, The Institute of Engineers, Australia, October, pp 181-184.

Crapper G.C.A. (1989), "Development of a Real-Time Reservoir Routing Flood Warning Procedure using the RORB Model", In: *Proceedings from the International Hydrology and Water Resources Symposium, Christchurch, NZ, November 23-30*, pp 86-89, The Institution of Engineers, Australia.

Crapper G.C.A. (pers. comm., 1994), telephone call in September 1994.

CRC (1994), "Annual Report 1993-1994", *Cooperative Research Centre for Catchment Hydrology*, Melbourne.

Daniell T.M. (1991), "Neural Networks - Applications in Hydrology and Water Resources Engineering", In: *Proceedings from the International Hydrology and Water Resources Symposium, Perth, October 2-4*, pp 797-802, The Institution of Engineers, Australia.

Daniell T.M. and Hill P.I. (1993), "*Flood Hydrology Study of the Onkaparinga River*", (Report for the Onkaparinga Flood Study Steering Committee), Department of Civil and Environmental Engineering, The University of Adelaide, Adelaide.

Daniell T.M. and Wundke A.D. (1993), "Neural Networks - Assisting in Water Quality Modelling", In: *Proceedings from Watercomp, Melbourne, Australia, March 30-April 1*, pp 51-57.

Dooge J.C.I. (1959), "A General Theory of the Unit Hydrograph", *Journal of Geophysical Research*, 64 (2), pp 241-256.

Doswell C.A., Brooks H.E. and Maddox R.A. (1995), "Flash Flood Forecasting: An Ingredients-Based Methodology", In: *Preprints of 5th Workshop on Operational Meteorology AES/CMOS, Edmonton, Alberta, 28 February-3 March*, 8 pages.

Dotson H.W. and Peters J.C. (1990), "Hydrological Aspects of Flood Warning - Preparedness Programs", *Technical Paper No. 131*, U.S. Army Corp of Engineers, Hydrologic Engineering Centre, 7 Pages.

DWRP (1977), "Dee Weather Radar and Real-Time Hydrological Forecasting Project", *Steering Committee, Central Water Planning Unit*, Reading, England, 172 pages.

Dyer B.G. (pers. comm., 1994), E-mail in May 1994.

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", *Report 94/1, Cooperative Research Centre for Catchment Hydrology*, Melbourne, 93 pages.

Evans R. (1994), "Run River Run", *Geographical-The Royal Geographical Society Magazine*, pp 17-20, Royal Geographical Society, Centurion Publications Ltd., London, England.

Feldman A.D. (1994), "Assessment of Forecast Technology for Flood Control Operation", In: *Coping with Floods*, (Ed: Rossi G., Harmancioglu N. and Yevjevich V.), Chapter 20, pp 445-458, Kluwer Academic Publishers, Dordrect, Netherlands.

Fleming N.S. (1994), "Comparison of Water Consumption Forecasting Methods including Artificial Neural Networks", In: *Proceedings from Water Down Under '94, Adelaide, Australia, November 21-25*, Volume 3, pp 115-120, The Institution of Engineers, Australia..

Flood I. and Kartam N. (1994a), "Neural Networks in Civil Engineering I: Principles and Understanding", *Journal of Computing in Civil Engineering*, 8 (2), April, pp 131-148.

Flood I. and Kartam N. (1994b), "Neural Networks in Civil Engineering II: Systems and Application", *Journal of Computing in Civil Engineering*, 8 (2), April, pp 149-162.

Foley B.A. and Brown P.R. (1993), "Artificial Neural Networks-Their Application to Hydrologic Modelling in a Small Catchment in the Adelaide Hills", *Final Year Undergraduate Research Project*, Department of Civil and Environmental Engineering, The University of Adelaide.

French M.N., Krajewski W.F. and Cuykendall R.R (1992), "Rainfall Forecasting in Space and Time using a Neural Network", *Journal of Hydrology*, 137, pp 1-31.

French M.N. and Krajewski W.F. (1994), "A Model for Real-Time Quantitative Rainfall Forecasting using Remote Sensing, 1. Formulation", *Water Resources Research*, 30 (4), pp 1075-1083.

French M.N., Andrieu H. and Krajewski W.F. (1994), "A Model for Real-Time Quantitative Rainfall Forecasting using Remote Sensing, 2. Case Studies", *Water Resources Research*, 30 (4), pp 1085-1097.

Fujita M. and Zhu M.L. (1992), "An Application of Fuzzy Theory to Runoff Prediction", In: *Proceedings of the Sixth IAHR International Symposium on Stochastic Hydraulics, Taiwan*, pp 727-743.

Fuyi Z. (1993), "Application of the Flood Forecasting System for the Huaihe River in the Great Floods, 1991", In: *Proceedings of XXV Congress of International Association for Hydraulic Research, Tokyo, Japan, 30 August-3 September,* Volume 1, pp 225-232.

Giesemann M. (1986), "Melbourne's Flood Warning System", In: *Flood Warning in Australia*, (Ed: Smith D.I. and Handmer J.W.), Chapter 11, pp 153-173, Centre for Resources and Environmental Studies, Canberra.

Georgakakos K.P. (1986a), "A Generalised Stochastic Hydrometeorological Model for Flood and Flash-Flood Forecasting, 1. Formulation", *Water Resources Research*, 22 (13), pp 2083-2095.

Georgakakos K.P. (1986b), "A Generalised Stochastic Hydrometeorological Model for Flood and Flash-Flood Forecasting, 2. Case Studies", *Water Resources Research*, 22 (13), pp 2096-2106.

Georgakakos K.P. (1987), "Real-Time Flash Flood Prediction", *Journal of Geophysical Research*, 92 (D8), pp 9615-9629.

Georgakakos K.P. and Bras R.L. (1982), "Real-time Statistically Linearized Adaptive Flood Routing", *Water Resources Research*, 20 (11), pp 513-524.

Georgakakos K.P. and Hudlow M.D. (1984), "Quantitative Precipitation Forecast Techniques for use in Hydrologic Forecasting", *Bulletin of the American Meteorological Society*, 65 (11), pp 1186-1200.

Grijsen J.G., Snoeker X.C. and Vermeulen C.J. (1993), "An Information System for Flood Early Warning", Report No. 479, *Presented at the 3rd International Conference on Floods and Flood Management, Florence, Italy, November 24-26,* Delft Hydraulics.

Haines A. (pers. comm., 1994), E-mail in May 1994.

Halff A.H. and Halff H.M. (1993), "Predicting Runoff from Rainfall using Neural Networks", In: *Proceedings of the Conference on Engineering Hydrology, San Fransisco, California, July 25-30*, pp 760-765, American Society of Civil Engineers, New York.

Hall A.J. and Elliot J.F. (1986), "New Technologies for Flood Forecasting", In: *Flood Warning in Australia*, (Ed: Smith D.I. and Handmer J.W.), Chapter 10, pp 135-152, Centre for Resources and Environmental Studies, Canberra.

Hill P.I. (1993), "*Extreme Flood Estimation for the Onkaparinga River Catchment*", Thesis for the Degree of Master of Engineering Science, Department of Civil and Environmental Engineering, The University of Adelaide.

Hill P.I. (1994), "*Estimation of Design Losses from the Empirical Analysis of Data*", unpublished, 9 pages.

Hjelmfelt A.T. and Wang M. (1993a), "Artificial Neural Networks as Unit Hydrograph Applications", In: *Proceedings of the Conference on Engineering Hydrology, San Fransisco, California, July 25-30*, pp 754-759, American Society of Civil Engineers, New York.

Hjelmfelt A.T. and Wang M. (1993b), "Runoff Simulation using Artificial Neural Networks", In: *Proceedings of XXV Congress of International Association for Hydraulic Research, Volume 2, Tokyo, Japan, 30 August-3 September*, pp 517-522.

Hudlow M.D. (1988), "Technological Developments in Real-Time Operational Hydrologic Forecasting in the United States", *Journal of Hydrology*, 102, pp 69-92.

Hudlow M.D. (1994), "Hydrometeorological Advances in Flood Forecasting in view of Lessons Learned from The Great Mississippi Basin Flood of 1993", In: *Proceedings from Water Down Under '94, Adelaide, Australia, November 21-25*, The Institute of Engineers, Australia.

HYDSYS Pty. Ltd. (1994), HYDSYS/TS User Manual, Release 5.0, HYDSYS Pty. Ltd., Canberra.

I.E.Aust (1987), "*Australian Rainfall and Runoff - A Guide to Flood Estimation*", Volume 1, (Ed: Pilgrim D.H.), The Institution of Engineers, Australia, 374 Pages.

Johnstone P.R. and Pilgrim D.H. (1976), "Parameter Optimization for Watershed Models", *Water Resources Research*, 12 (3), pp 477-486.

Karunanithi N., Grenney W.J., Whitley D. and Bovee K. (1994), "Neural Networks for River Flow Prediction", *Journal of Computing in Civil Engineering*, Vol 8, No 2, pp 201-220.

Kemp D.J. and Daniell T.M. (1996), "A Proposal for a Rainfall-Runoff-Routing (RRR) Model", In: *Proceedings from 23rd Hydrology and Water Resources Symposium-Water and the Environment, Hobart, May 21-24*, Volume 1, pp 15-21, The Institution of Engineers, Australia.

Kitanidis P.K. and Bras R.L. (1978), "Real Time Flood Forecasting of River Flows", Department of Civil Engineering, Cambridge, Report No. 235, Massachusetts Institute of Technology.

Kitanidis P.K. and Bras R.L. (1980a), "Real-Time Forecasting with a Conceptual Hydrologic Model, 1. Analysis of Uncertainty", *Water Resources Research*, 16 (6), pp 1025-1033.

Kitanidis P.K. and Bras R.L. (1980b), "Real-Time Forecasting with a Conceptual Hydrologic Model, 2. Applications and Results", *Water Resources Research*, 16 (6), pp 1034-1044.

Klatt P. and Schultz G.A. (1983), "Flood Forecasting on the Basis of Radar Rainfall Measurement and Rainfall Forecasting", In: *Proceedings of Symposium on Hydrological Applications of Remote Sensing and Remote Data Transmission, Hamburg, Germany, August 1983*, IAHS International Committee on Remote Sensing and Data Transmission, Publication No. 145, pp 307-315.

Knee R.M. and Falkland A.C. (1989), "Lake Burley Griffen Flood Forecasting Model", In: *Proceedings from the International Hydrology and Water Resources Symposium, Christchurch, N.Z, 23-30 November*, pp 81-85, The Institution of Engineers, Australia.

Kotwicki V. (1984), "Mt Bold Reservoir Flood Routing", *Water Resources Branch*, Engineering and Water Supply Department, South Australia.

Kouwen N. and Soulis E.D. (1993), "Remote Sensing Inputs for Flash Flood Forecasting in Urban Areas", In: *New Techniques for Modelling the Management of Stormwater Quality Impacts*, (Ed: James W.), Proceedings of the Stormwater and Water Quality Management Modelling Conference, Toronto, Ontario, February 26-27, 1992, Chapter 8, pp 177-200, Lewis Publishers, U.S.A.

Kuczera G. (1990), "Estimation of Runoff-Routing Model Parameters using Incompatible Storm Data", *Journal of Hydrology*, 114, pp 47-60.

Lachtermacher G. and Fuller J.D. (1994), "Backpropagation in Hydrological Time Series Forecasting", In: *Stochastic and Statistical Methods in Hydrology and Environmental Engineering, Volume 3, Time Series Analysis in Hydrology and Environmental Engineering*, (Ed: Hipel K.W., McLeod A.I., Panu U.S. and Singh V.P.), pp 229-242, Kluwer Academic Publishers, Dordrecht, Netherlands.

Lange Dames and Campbell Australia Pty. Ltd. (1990), "*Report on the Feasibility of a Flood Inundation Study for the Onkaparinga River below Mount Bold Dam*", Engineering and Water Supply Department, Adelaide.

Lardet P. and Obled C. (1994), "Real-Time Flood Forecasting using a Stochastic Rainfall Generator", *Journal of Hydrology*, 162, pp 341-408.

Laurenson E.M. and Mein R.G. (1990), "*RORB-Version 4, Runoff Routing Program User Manual*", Monash University, Department of Civil Engineering.

Laurenson E.M. and Pilgrim D.H. (1963), "Loss Rates for Australian Catchments and their Significance", *Journal of the Institution of Engineers*, Australia, Jan-Feb, pp 9-24.

Linsley R.K., Kohler M.A. and Paulhus J.L.H. (1949), "*Applied Hydrology*", McGraw-Hill, New York.

Loy A., Ayre R.A. and Ruffini J.L. (1996), "Regional Loss Model Relationships for Catchments in South East Queensland", In: *Proceedings from 23rd Hydrology and Water Resources Symposium-Water and the Environment, Hobart, May 21-24*, Volume 1, pp 133-140, The Institution of Engineers, Australia.

Mag V.S. and Mein R.G. (1994), "A Flood Forecasting Procedure which combines the RORB and TOPOG Models", In: *Proceedings from Water Down Under '94, Adelaide, November 21-25*, Volume 3, pp 217-222, The Institution of Engineers, Australia.

Maguire J.C. (1986), "Flood Forecasting : the South Australian Experience", In: *Flood Warning in Australia,* (Ed: Smith D.I. and Handmer J.W), Chapter 6, pp 79-90, Centre for Resources and Environmental Studies, Canberra.

Maguire J.C., Kotwicki V., Purton C. and Schalk K.S. (1986), "Estimation of the RORB Parameter k_c for Small South Australian Catchments", Water Resources Branch, Engineering and Water Supply Department, Adelaide.

Maier H.R. (1995), "A Review of Artificial Neural Networks", *Departmental Research Report, No. R 131,* Department of Civil and Environmental Engineering, The University of Adelaide.

Maier H.R. and Dandy G.C. (1993), "Use of Artificial Neural Networks for Forecasting Water Quality", In: *Preprints of Stochastic and Statistical Methods in Hydrology and Environmental Engineering: An International Conference in Honour of Professor T.E. Unny, University of Waterloo, Ontario, Canada, June 21-25*, pp 509-511.

Maier H.R. and Dandy G.C. (1995a), "Modelling Cyanobacteria (Blue-Green Algae) in the River Murray Using Artificial Neural Networks", In: *Proceedings of Modsim '95 - International Congress on Modelling and Simulation, Newcastle, Australia, November 27-30*, Volume 3, pp 268-275, Modelling and Simulation Society of Australia Inc., Australia.

Maier H.R. and Dandy G.C. (1995b), "Effect of Internal Parameters and Geometry on the Performance of Backpropagation Networks", *Departmental Research Report No. 132*, Department of Civil and Environmental Engineering, The University of Adelaide.

Maier H.R. and Dandy G.C. (1996), "The use of Artificial Neural Networks for the Prediction of Water Quality Parameters", *Water Resources Research,* 32 (4), pp 1013-1022.

Malone T. (1994a), "*Modelling Floods in QNX*", unpublished, 8 pages.

Malone T. (1994b), "Forecasting Mary River Floods", In: *Proceedings from Water Down Under '94, Adelaide, November 21-25*, Volume 3, pp 223-228, The Institution of Engineers, Australia.

Mandeville A.N., O'Connell P.E., Sutcliff J.V. and Nash J.E. (1970), "River Flow Forecasting through Conceptual Models, Part III. The Ray Catchment at Frendon Underwood", *Journal of Hydrology*, 11, pp 109-128.

Masahiko H., Hino M. and Hoshi K. (1989), "Flood Forecasting by the Filter Separation AR Method and Comparison with Modeling Efficiencies by some Rainfall-Runoff Models", *Journal of Hydrology*, 110, pp 107-136.

Mein R.G. and O'Loughlin E.M. (1991), "A New Approach for Flood Forecasting", In: *Proceedings from the International Hydrology and Water Resources Symposium, Perth, October 2-4*, pp 219-224, The Institution of Engineers, Australia.

Mein R.G., Nandakumer N. and Siriwardena L. (1995), "Estimation of Initial Loss from Soil Moisture Indices (Pilot Study)", *Working Document 95/1, Cooperative Research Centre for Catchment Hydrology*, Melbourne, 59 pages.

MFP Australia (1995), "*Revised Initial Patawalonga Catchment Management Plan*", Consultation Draft, Prepared for the Patawalonga Catchment Water Management Board in Association with B.C. Tonkin & Associates, South Australia, Australia, 58 pages.

Michaud J.D. and Sorooshian S. (1994), "Effect of Rainfall-Sampling Errors on Simulations of Desert Flash Floods", *Water Resources Research*, 30 (10), pp 2765-2775.

Milne A. (1986), "*Floodshock-The Drowning of Planet Earth*", Alan Sutton Publishing, Gloucester.

Mimikou M.A., Baltas E.A. and Borga M. (1993), "Flash-Flood Forecasting by using the HEC1F Model", In: *Proceedings of the Conference on Engineering Hydrology, San Fransisco, California, July 25-30*, pp 85-90, American Society of Civil Engineers, New York.

Moore R.J. (1995), "*Developments in Real-Time Flood Forecasting and Weather Radar*", Seminar at Bureau of Meteorology, October 27, Melbourne, Australia.

Moriyama T. and Hirano M. (1990), "Short-Term Forecasting for Water Level of a Flood by Precipitation Radar", *Journal of Hydroscience and Hydraulic Engineering*, 8 (1), pp 1-7.

Nash J.E. (1957), "The Form of the Instantaneous Unit Hydrograph", *Intl. Assoc. Sc. Hydrol.*, Publication No. 45, pp 114-121.

Nash J.E. and Sutcliffe J.V. (1970), "River Flow Forecasting through Conceptual Models, Part 1 - A Discussion of Principles", *Journal of Hydrology*, 10, pp 282-290.

Nemec J. (1986), "Design and Operation of Forecasting Operational Real-Time Hydrological Systems (FORTH)", In: *River Flow Modelling and Forecasting*, (Ed: Kraijenhoff D.A. and Moll J.R.), Chapter 12, pp 299-328, D.Reidel Publishing Company, Dordrecht, Holland.

NeuralWare Inc. (1991), "*Neural Computing, NeuralWorks Professional II/Plus and NeuralWorks Explorer*", NeuralWare, Inc., Pittsburg, U.S, 360 pages.

North J.M. (1986), "Flood Forecasting Methods in New South Wales", In: *Flood Warning in Australia,* (Ed: Smith D.I. and Handmer J.W.), Chapter 12, pp 175-179, Centre for Resources and Environmental Studies, Canberra.

O'Loughlin E.M. (1986), "Prediction of Surface Saturation Zones in Natural Catchments by Topographic Analysis", *Water Resources Research*, 22 (5), pp 794-804.

Peart M.R. and Jayawardena A.W. (1993), "Flood Forecasting and Warning in Hong Kong", In: *Proceedings of XXV Congress of International Association for Hydraulic Research, Tokyo, Japan, 30 August-3 September,* Volume 1, pp 241-248.

Peddie A.J. and Ball J.E. (1993), "Real-Time Flood Forecasting for the Upper Parramatta River", In: *Proceedings from the International Hydrology and Water Resources Symposium, Newcastle, June 30-July* 2, pp 405-410, The Institution of Engineers, Australia.

Penning-Rowsell E.C. (1986), "The Development of Integrated Flood Warning Systems", In: *Flood Warning in Australia,* (Ed: Smith D.I. and Handmer J.W), Chapter 2, pp 15-36, Centre for Resources and Environmental Studies, Canberra.

Pilgrim D.H. (1986), "Bridging the Gap between Flood Research and Design Practice", *Water Resources Research*, 22 (9), pp 165-176.

Pilgrim D.H. (1990), "Can we avert another Flood Disaster", In: *The Journal of the Institution of Engineers Australia*, May 18, pp 32-34, The Institution of Engineers, Canberra, Australia.

Polkinghorne A.A. (1993), "*Modelling Brownhill Creek Catchment for Flood Forecasting - Stage II*", Prepared for the City of Mitcham, Adelaide.

Polkinghorne A.A. (1994), "*Hydrological Study - Brownhill, Glen Osmond, Parklands and Keswick Creeks*", Bureau of Meteorology, Hydrology Section, Adelaide.

Puente C.E. and Bras R.L. (1987), "Application of Non-linear Filtering in the Real Time Forecasting of River Flows", *Water Resources Research*, 23 (4), pp 675-682.

Raudkivi A.J. (1979), "*Hydrology-An Advanced Introduction to Hydrological Processes and Modelling*", Pergamon Press, Oxford, England, 473 pages.

Rossi G. (1994), "Historical Development of Flood Analysis Methods", In: *Coping with Floods*, (Ed: Rossi G., Harmancioglu N. and Yevjevich V.), Chapter 2, pp 11-34, Kluwer Academic Publishers, Dordrect, Netherlands.

Saxton K.E. and Lenz A.T. (1967), "Antecedent Retention Indexes Predict Soil Moisture", *Journal of the Hydraulics Division*, Proceedings of the American Society of Civil Engineers, Volume 93, No. HY4, pp 223-241.

Schultz G.A. and Klatt P. (1980), "Use of the Data from Remote Sensing Sources for Hydrological Forecasting", In: *Proceedings of the Symposium on Hydrological Forecasting, Oxford*, IAHS, Publication No. 129, pp 75-82.

Seo D.J. and Smith J.A. (1992), "Radar-based Short Term Rainfall Prediction", *Journal of Hydrology*, 131, pp 341-367.

Serban P. and Askew A.J. (1991), "Hydrological Forecasting and Updating Procedures", Hydrology for the Water Management of Large River Basins, In: *Proceedings of the General Assembly of the International Union of Geodesy and Geophysics*, I.A.H.S. Publ. No. 201, Vienna, Austria, pp 357-369.

Sherman L.K. (1932), "Streamflow from Rainfall by Unit-Graph Method", *Eng. News Record*, 108, pp 501-505.

Shiiba M., Hoshi K., Tanakamaru H., Moriyama T. and Fujita M. (1993), "Runoff Forecasting", In: *Research and Practice of Hydraulic Engineering in Japan*, Chapter 9, pp 195-218, Journal of Hydroscience and Hydraulic Engineering, No. SI-3 Hydrology, Committee on Hydraulics, Japan Society of Civil Engineers.

Shitawara M. (1992), "Runoff Analysis based on Neural Network", *National Symposium on AI for Hydrology and Water Resources Engineering*, pp 47-52.

Singh K. and Mandakinee M. (1994), "A Modified Two-Level Estimator for Real-Time Forecasting", *Hydrological Sciences Journal*, 38 (5), pp 417-430.

Sittner W.T., Schauss C.E. and Monro J.C. (1969), "Continuous Hydrograph Synthesis with an API-Type Hydrologic Model", *Water Resources Research*, 5 (5), pp 1007-1022.

Smith D.I. and Handmer J.W. (1986), "Flooding in Australia : the Background to Flood Warnings", In: *Flood Warning in Australia,* (Ed: Smith D.I. and Handmer J.W.), Chapter 1, pp 3-13, Centre for Resources and Environmental Studies, Canberra.

Soste L., Elliot J. and Cawood M. (1994), "Effective Flood Warning Systems: The Issue of User Response", In: *Proceedings from Water Down Under '94, Adelaide, Australia, November 21-25*, Volume 1, pp 253-258.

Srikanthan R., Elliot J.F. and Adams G.A. (1994), "A Review of Real-Time Flood Forecasting Methods", *Report 94/2, Cooperative Research Centre for Catchment Hydrology*, Melbourne, 120 pages.

Takasao T., Shiiba M. and Nakakita E. (1994), "A Real-Time Estimation of the Accuracy of Short-Term Rainfall Prediction using Radar", In: *Stochastic and Statistical Methods in Hydrology and Environmental Engineering,* (Ed: Hipel K.W., McLeod A.I., Panu U.S. and Singh V.P.), Volume 3, Time Series Analysis in Hydrology and Environmental Engineering, pp 339-351, Kluwer Academic Publishers, Dordrecht, Netherlands.

Tucci C.E.M. and Clarke R.T. (1993), "Adaptive Forecasting with a Conceptual Rainfall-Runoff Model. Hydrologic Forecasting", In: *Proceedings of Oxford Symposium, April 1980*, IAHS-AISH, Dorking, Publication No. 129, pp 445-454.

United Nations (1990), "Forecasting, Preparedness and other Operational Measures for Water-related Natural Disaster Reduction in Asia and the Pacific", *Water Resources Series No. 69*, Economic and Social Commission for Asia and the Pacific, Bangkok, Thailand.

Wang R. and Ikebuchi S. (1994), "Application of the Manifold Cell Model in Rainfall-Runoff Analysis of a Hydrologic System", *Bulletin of the Disaster Prevention Research Institute*, 44 (2), pp 92-121.

WBCM Consultants (1984), "*Stormwater Drainage Study - South Eastern Suburbs of Adelaide - Brownhill, Glen Osmond, Parklands and Keswick Creeks, Volume 1, Main Report*", Woods Bromley Carruthers and Mitchell Pty. Ltd., 225 pages.

Williams B.J. and Field W.G. (1985), "Real-Time Flood Forecasting using Non-Linear Conceptual Rainfall-Runoff Models", In: *Proceedings of 21st IAHR Congress, Melbourne, Australia, 19-23 August*, pp 505-509.

Williams R. (1992), “Modelling Brownhill Creek Catchment for Flood Forecasting”, Bureau of Meteorology, Hydrology Section, Adelaide, 22 pages.

WMO (1981), "Flash Flood Forecasting", *Operational Hydrology Report No. 18*, Secretariat of the World Meteorological Organisation, Geneva, Switzerland, 38 pages.

WMO (1992), "Simulated Real-Time Intercomparison of Hydrological Models", *Operational Hydrology Report No. 38*, Secretariat of the World Meteorological Organisation, Geneva, Switzerland, 99 pages.

WMO (1994), "Guide to Hydrological Practices - Data Acquisition and Processing, Analysis, Forecasting and other Applications", *WMO No. 168*.

Won K.K, Hwan K.J, Young P.C. and Jae H.K (1993), "Evaluation of Hydrologic Forecasting System based on Neural Network Model", In: *Proceedings of XXV Congress of International Association for Hydraulic Research, Tokyo, Japan, August 30-September 3,* Volume 1, pp 257-264.

Wright C.J. (pers. comm., 1994), informal discussion at Kent Town, BoM in April 1994.

Wright C.J. (pers. comm., 1995), telephone call in October 1995.

Wright C.J. (1994a), "Advances in Flash Flood Warning in South Australia", *Poster Paper in Water Down Under '94, Adelaide, Australia, November 21-25*, Volume 3, pp 499-503.

Wright C.J. (1994b), "Flood Warning and the Weather Bureau", *Hydrological Newsletter*, The Hydrological Society of South Australia, Water Resources Group, D.E.N.R., Adelaide, April, pp 9.

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 pages.

Yevjevich V. (1994), "Technology for Coping with Floods in the 21st Century", In: *Coping with Floods*, (Ed: Rossi G., Harmancioglu N. and Yevjevich V.), Chapter 3, pp 35-43, Kluwer Academic Publishers, Dordrect, Netherlands.

Yoshino F., Onodera N., Masukura K., Hukami K., Yoo A. and Nakakita E. (1993), "Rainfall Observation by Radar", In: *Research and Practice of Hydraulic Engineering in Japan*, Chapter 1, pp 1-25, Journal of Hydroscience and Hydraulic Engineering, No. SI-3 Hydrology, Committee on Hydraulics, Japan Society of Civil Engineers.

Zawadzki I. (1987), "Fractal Structure and Exponential Decorrelation in Rain", *Journal of Geophysical Research*, 92 (D8), pp 9586-9590.

Zhu M.L. and Fujita M. (1993), "Application of Neural Networks to Runoff Forecast", In: *Preprints from Stochastic and Statistical Methods in Hydrology and Environmental Engineering: An International Conference in Honour of Professor T.E. Unny, University of Waterloo, Ontario, Canada, June 21-25*, pp 516-517.

Zhu M.L. and Fujita M. (1994a), "Long Lead Time Forecast of Runoff using Fuzzy Reasoning Method", *Journal of Japan Society of Hydrology and Water Resources*, 7 (2), 1994.

Zhu M.L. and Fujita M. (1994b), "Comparisons Between Fuzzy Reasoning and Neural Network Methods to Forecast Runoff Discharge", *Journal of Hydroscience and Hydraulic Engineering*, 12 (2), pp 131-141.

Zhu M.L., Fujita M. and Hashimoto N. (1994), "Application of Neural Networks to Runoff Prediction", In: *Stochastic and Statistical Methods in Hydrology and Environmental Engineering*, (Ed: Hipel K.W., McLeod A.I., Panu U.S. and Singh V.P.), Volume 3, Time Series Analysis in Hydrology and Environmental Engineering, pp 205-216, Kluwer Academic Publishers, Dordrecht, Netherlands.

Zhu Z., Li W., Feng G. and Nan J. (1993), "The Prediction Method of Many Patterns of Fuzzy Clustering on Floods in China's North Area", In: *Proceedings of XXV Congress of International Association for Hydraulic Research, Tokyo, Japan, August 30-September 3*, Volume 1, pp 280-287.

Appendix A

Brownhill, Glen Osmond, Parklands and Keswick Creek Catchment : A Summary

A.1 Catchment Description

The Brownhill, Glen Osmond, Parklands and Keswick Creek catchment is part of the Patawalonga Basin. The Patawalonga Basin has an overall catchment area of about 235 km^2. The catchment area of the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment is approximately 73 km^2, and very diverse in its land use and drainage characteristics. Its drainage area comprises seven local councils including Stirling, Burnside, Mitcham, Unley, Adelaide, West Torrens and Glenelg. Its location relative to the city of Adelaide and surrounding catchments is shown in Figure A.1.

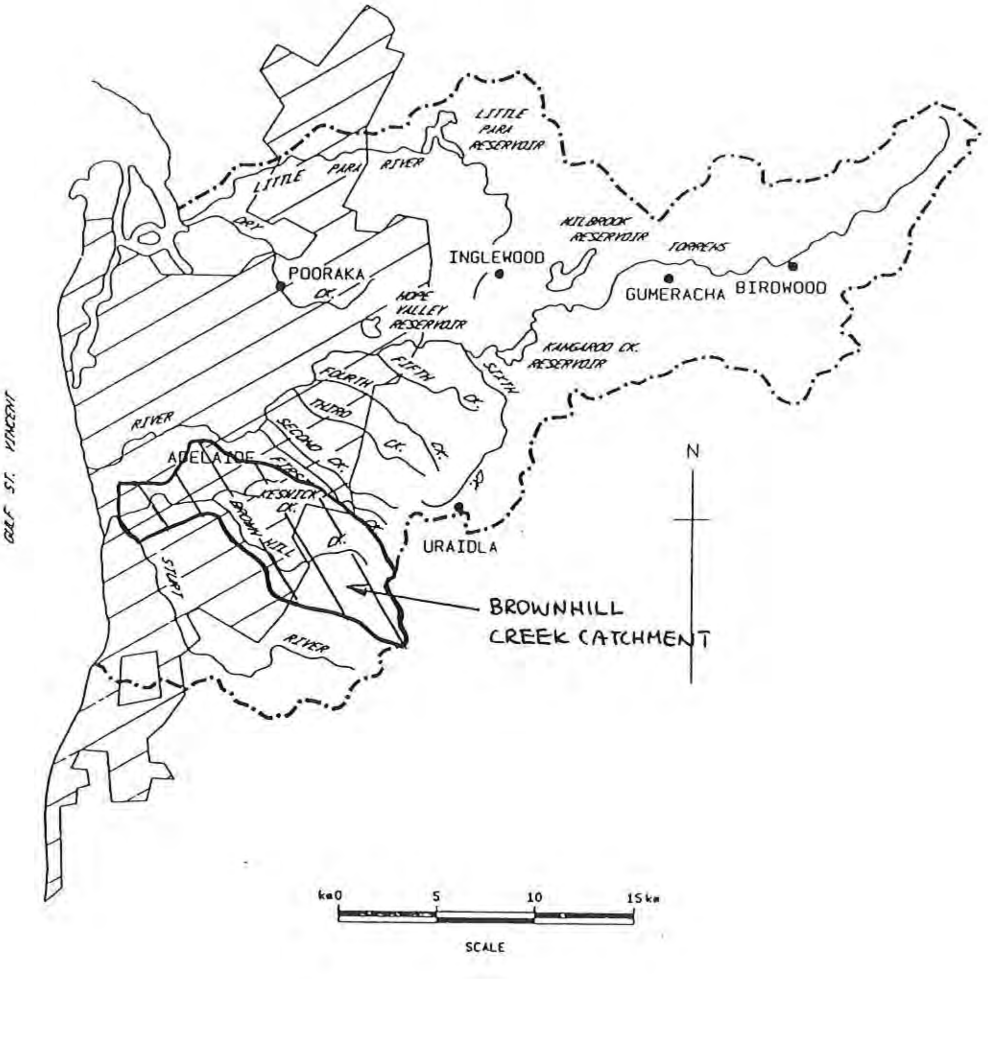


Figure A.1 Approximate location of the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment relative to Adelaide and adjacent catchments (Source: Maguire, 1986)

Brownhill Creek is the largest of the four creek systems within the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment, with an area of approximately 36 km^2. Brownhill Creek commences in the Mount Lofty Ranges near Stirling at the top of the Adelaide Hills Face escarpment, extending westwards, eventually feeding into Keswick Creek, east of the Adelaide Airport.

The upper reaches of the Brownhill Creek catchment are steep and relatively free from urban development, containing native vegetation and land cleared for grazing. This accounts for approximately 50 percent of the Brownhill Creek catchment. Within this part, the creek is naturally formed. In the urban part of the catchment, the creek is defined by a man-made stormwater drainage system. The man-made channel does not lie in any defined valley.

Glen Osmond Creek drains an area much smaller than that of the Brownhill Creek catchment, but is similar in land use, and in the way that the creek changes from being naturally formed in its upper reaches, to either stone or concrete lined in its downstream urban portions, without following a defined valley. Its catchment area is about 10 km^2 and only about 4 km^2 is rural or contains native vegetation.

Parklands Creek receives its inflow from a major stormwater drainage system extending from the eastern suburbs of Adelaide in the Burnside City Council, draining westwards towards the South Parklands. A portion of the city of Adelaide also contributes runoff to Parklands Creek. This catchment has an area of about 11 km^2 and much of this watercourse is an open earth lined channel.

Keswick Creek commences at the confluence of Glen Osmond and Parklands Creeks at Wayville. It is predominantly a concrete lined channel which continues to accept flow from urban drainage systems until it reaches the Adelaide Airport. It then becomes an earth lined channel, following the boundaries of the Adelaide Airport, joining with Brownhill Creek before discharging into the Patawalonga Basin. The area downstream from the confluence of the Parklands and Glen Osmond Creek catchment that contributes runoff to Keswick Creek is approximately 15 km^2.

The Adelaide Airport has a catchment area of approximately 6.5 km^2 and drains into Keswick Creek immediately before entering the Patawalonga Basin via an open channel.

A.2 Why Develop a Flood Warning System for the Brownhill, Glen Osmond, Parklands and Keswick Creek Catchment ?

A detailed survey leading to a report on the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment was made in the early 1980s (WBCM Consultants, 1984). This report primarily investigated the existing hydraulic capacities of the drainage network throughout the catchment. Using RORB, ILLUDAS and HEC-2, it was found that a very large variation in flood capacities in terms of overspill, existed within these systems. Parts of Brownhill, Glen Osmond and Keswick Creeks were found to have a capacity of up to 200 years ARI, but some areas of these systems were deemed to have a capacity of only a 3 year ARI. The Parklands Creek has the lowest capacity, of 2-16 years ARI throughout its length, which explains why it is often seen overflowing through the south Parklands area. The extent of flooding that could be expected throughout the catchment is quite alarming, and for different ARI events a flood plain map was produced by WBCM Consultants.

In general, damage would vary from fast flowing localised inundation in the upper reaches, to extensive slower moving water inundating properties in regions near the Adelaide Airport.

WBCM Consultants estimated the cost of damage during particular events. Damages were calculated in 1980 and transformed into December 1983 values using the Adelaide Consumer Price Index without bridge and utility damages. During a 10 year ARI event, the damage was estimated to be about $5.8M for a 100 year event $40M, and for a 200 year event, $60M. The average long term annual damage bill was estimated to be about $2M.

Most of the damage would be located in the Keswick Creek catchment. Of the $60M estimated for a 200 year ARI flood, it was estimated that $38M (or 63 percent) would occur in this catchment.

In the last few decades, no major flooding has been recorded throughout the catchment. The worst flooding in the catchment when any form of instrumentation was operational, occurred on 2/7/81 with peak discharges into the Patawalonga Basin of only about 20 m^3/s. More recently on the 14/12/93, a large rainfall event passed through the western portion of the catchment producing a peak flow at Adelaide Airport of about 31m^3/s, despite little rainfall being recorded in the upper reaches of the catchment.

The big question is, when will a large event occur on this catchment ? According to the best information available, it will occur one day, the question is when ? The greatest concern is the small catchment size combined with an increased degree of urbanisation will create a very quick catchment response, with little warning time (Wright, pers. comm., 1994).

In the late 1980s a flood warning plan was established for the catchment and a flash flood monitoring network was established in the form of ALERT stations.

A.3 Flood Warning on the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment

Presently an ALERT (Automatic Local Evaluation in Real-Time) system is used to monitor rainfall and water levels at stations within the catchment. Data is automatically telemetered from field stations to a base station at the Bureau of Meteorology, Kent Town using VHF radio signals. Signals are sent at regular six hour intervals or when either 1 mm of rain falls or when there is a 10 mm change in water level.

Prior to 1993, the ALERT system was located only in the rural component of the Brownhill Creek catchment. Rainfall stations were situated at Scotch College, Belair, Eagle on the Hill and at the summit of Brown Hill. Water level was measured at Scotch College at the bottom of the rural component of the catchment. The station at Brown Hill has since been vandalised and stolen, and is presently inoperational. Since the station at Brown Hill was in a high and exposed position, its ability to accurately record rainfall was affected by frequently strong winds.

Since 1993, more ALERT stations have been added throughout the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment. Rainfall stations have been placed at Crafers and Hawthorn (Brownhill Creek catchment); Ridge Park and Charles Street (Glen Osmond Creek catchment); Glenside, Beaumont (Parklands Creek catchment); Keswick Army Barracks and Adelaide Airport (Keswick Creek catchment). Additional water level stations have been placed at Hawthorn, Ridge Park, Keswick Army Barracks, Adelaide Airport, Charles Street, Victoria Park and Roberts Street. Recently a new base station was set up at Mitcham S.E.S.

The advantage of an ALERT system over POLLED systems is that an ALERT system responds immediately to an event. A POLLED system requires an operator to call up individual stations to obtain current water level and rainfall information.

Once data is transmitted to the base station, a computer stores and processes all information. It can display data from each catchment in tabular and graphical form. The computer monitors the water levels and rainfall, and sends an alarm if thresholds are exceeded. The ALERT software must run on a QNX operating system, rather than DOS.

The alarm is sent via Modem to a Pager to the forecasting officer at the Bureau of Meteorology, who must then go to the base station, evaluate the information and determine whether other authorities should be alerted for further action. Presently the trigger for a rainfall alarm is 12 mm within 3 hours, and for water levels the trigger is about the peak discharge for the 1 year ARI storm.

A typical alarm message would be: (Wright, 1994a, p 500)

"ALERT Alarm for Scotch College, Rainfall exceeded 12 mm in 3 hours (current total 35 mm) Message from Kent Town"

Details of the ALERT stations can be found in Table A.1 giving reference to the station names and what they record.

Table A.1 Details of ALERT stations in the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment

Station No.	Station Name	Station Type
BM523101	Hawthorn	Rain/River
BM523100	Ridge Park	Rain/River
BM023874	Eagle on the Hill	Rain
BM023873	Crafers	Rain
BM023847*	Brown Hill	Rain
BM023846	Belair	Rain
BM023119	Roberts Street	River
BM023118	Charles Street	Rain/River
BM023115	Keswick Army Barracks	Rain/River
BM023114	Beaumont	Rain
BM023105	Scotch College	Rain
BM023034	Adelaide Airport	Rain/River
AW504901	Scotch College	River
AW504906	Glenside	Rain
AW504907	Victoria Park	River

* currently inoperational

The location of the ALERT stations are shown in the map provided in Figure A.2. It is evident that instrumentation is now more evenly distributed throughout the catchment.

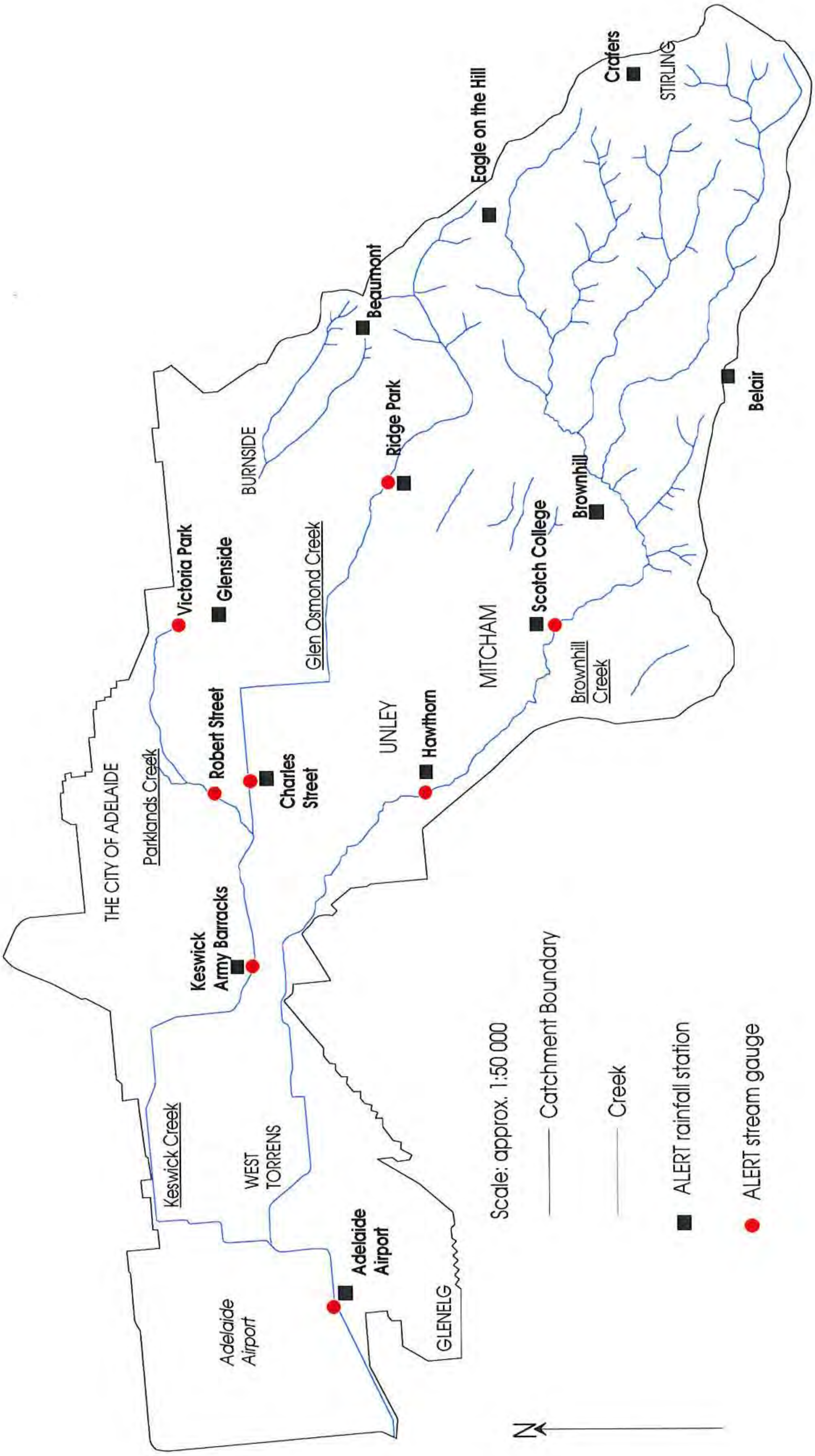


Figure A.2 Location of the ALERT stations in the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment

A.4 Flood Events Since the Establishment of the ALERT Stations

Since the establishment of the first ALERT stations, the magnitude of flood events that have occurred in the catchment have been very small.

When the only operational ALERT stations were located in the rural part of the Brownhill Creek (upstream of Scotch College), only five small events occurred. The first two occurred on 10/9/91 and 18/9/91, with peak flows of 2 m^3/s and 5 m^3/s respectively at the Scotch College ALERT station. The other three coincided with the large damaging floods that occurred in the Cudlee Creek region of the Torrens River catchment and other locations in the Mount Lofty Ranges. These events occurred on 30/8/92, 24/9/92 and 8/10/92 having peak flows of 3.9, 2.6 and 3.3 m^3/s respectively at the Scotch College ALERT station.

Since the introduction of extra ALERT stations to the remainder of the catchment, very few flood events have occurred. A significant rainfall event hit Adelaide on 14/12/92, but only passed over the western portion of the catchment. Had it passed over the remainder of the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment, much larger flows would have been observed. The peak flow at Scotch College was less than 1 m^3 but at Adelaide Airport the peak flow was about 31 m^3/s.

Using design intensity-frequency-duration rainfall curves following the procedures outlined in I.E.Aust (1987), the ARI of the rainfall events associated with these events were calculated. All except the 14/12/93 event had an ARI of no greater than 2 years, however the 14/12/93 event had an ARI of about 20 years over part of the catchment.

One reason why the catchment has not experienced significant flooding, is because of its small size and slender shape (as shown in Figure A.2) leading up to the Adelaide Hills. The catchment shape requires a slow moving storm cell to move in a specific direction down the catchment to maximise its impact. The 14/12/93 event was an example of a large rainfall occurrence that did not move in such a direction.

More recently on 23/7/95, during the final stages of this study, another smaller event occurred with a peak flow at Scotch College of about 3 m^3/s.

A.5 Recent Analysis on Events Prior to the Commencement of this Study based on ALERT Data

Only a limited amount of analysis has been performed on the events that have occurred so far on the catchment using ALERT data. A report was written by Williams (1992) on the storms occurring on 10/9/91 and 18/9/91; one by Polkinghorne (1993) on the events of 30/8/92, 24/9/92 and 8/10/92 and most recently by Polkinghorne (1994) on the event of 14/12/93. Only the report by Polkinghorne (1994) looked at the whole Brownhill, Glen Osmond, Parklands and Keswick Creek Catchment. The other reports looked only at the rural catchment, upstream of Scotch College.

These reports were written to gain some idea of the hydrologic characteristics and rainfall-runoff response of the catchment, and to build a database of the catchment so that in later years, more rigorous flood warning strategies and criteria can be implemented.

The report by Williams (1992) used the unit hydrograph method to model the two earliest storms where a number of observations were made. It was suggested that a mitigation effect from farm dams affected the modelling. Very low initial loss values were also used in the model calibration (< 5 mm) with continuing losses of 5-6 mm/hr.

Polkinghorne (1993) used the unit hydrograph method and RORB model to calibrate the storms occurring on 30/8/92, 24/9/92 and 8/10/92 up to Scotch College. Again it was concluded that low initial losses were appropriate for these events, in fact values of 0 mm were found to be most appropriate.

Polkinghorne (1994) used the RORB model set up by WBCM Consultants (1984) to calibrate the event of 14/12/93 on the whole Brownhill, Glen Osmond, Parklands and Keswick Creek catchment. Interestingly, the RORB model used by Polkinghorne (1993) was slightly different to that by Polkinghorne (1994) upstream of Scotch College. Low initial loss values were again used for much of the catchment.

Although low initial loss values were used upstream of Scotch College in these recent reports, calculation of API values indicated that the value should have been higher. Infact, the study by WBCM Consultants (1984) suggested that initial loss values should be in the range of 10-25 mm and continuing losses in the range of 2.5-4.0 mm/hr. Williams suggested that very low initial losses for the rural part of Brownhill Creek catchment, were because the catchment is relatively small and quite steep, meaning runoff rates are therefore high creating little chance for infiltration. This may be a result of localised geological and soil formations within the catchment.

A.6 Future Work and Recommendations

A number of problems exist with the modelling strategy of these previous studies, even though most are unavoidable because of the lack of available data. Analysis has been confined to very small events, which are not similar in any way to a large event which would cause major flooding in the catchment. Therefore the results, including the derived parameters from these studies, should be viewed with caution.

Instrumentation within the catchment is new and problems have occurred with their operation. Rating tables for water level recorders are far from accurate, and until large events occur, their accuracy remains questionable.

Even though it was decided early on not to perform any detailed work on the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment (because of a lack of data), a number of suggestions and a limited amount of analysis within this study was undertaken to assist in the future development of real-time flood warning and modelling on this catchment.

1. The RORB models used by Polkinghorne (1993 and 1994) assumed that no major changes had been made to the drainage system within the catchment since the last study performed by WBCM Consultants (1984). A detailed investigation of the drainage characteristics of the catchment was made to validate this.

   A survey of the catchment was carried out with reference to the latest drainage maps supplied by the local councils, with minor changes found.

   The most up to date hydraulic information, in particular the main trunk drainage, was added to 1:10,000 scale maps. Minor adjustments to the RORB sub-catchment boundaries were also made.

   Each RORB sub-catchment was digitised using ARC-INFO at The Department of Geography, The University of Adelaide. Both the PC and UNIX version were used as each had different limitations and capabilities. ARC-INFO enabled conversion of map co-ordinates into real world grid co-ordinates so that the catchment could be manipulated at a later date. The file format of the final digitised pictures were .DXF (Data Exchange File). The initial digitised coverage was created as a Line coverage and then later converted into a Polygon coverage which enabled accurate calculation of a number of parameters.

The parameters obtained from ARC-INFO included the sub-catchment areas, creek reach lengths and centroids of the sub-catchments. These parameters were checked using manual techniques such as using a planimeter, plumb line method and manual length measuring.

Perhaps the biggest changes have occurred in the Unley Council, who have recently revised their stormwater drainage systems (B.C. Tonkin & Associates, 1992), the Burnside Council and parts of Mitcham Council.

The digitised components of the catchment are shown in Figure A.3. As yet, no substantial RORB modelling has been undertaken using the digitised format of the catchment or the most up to date hydraulic information. The only limitation with such a model is during a major flood, the flows will be outside the defined flood channel in the lower part of the catchment.

Table A.2 shows the areas of each sub-catchment and the centroids in real world co-ordinates as calculated by ARC-INFO.

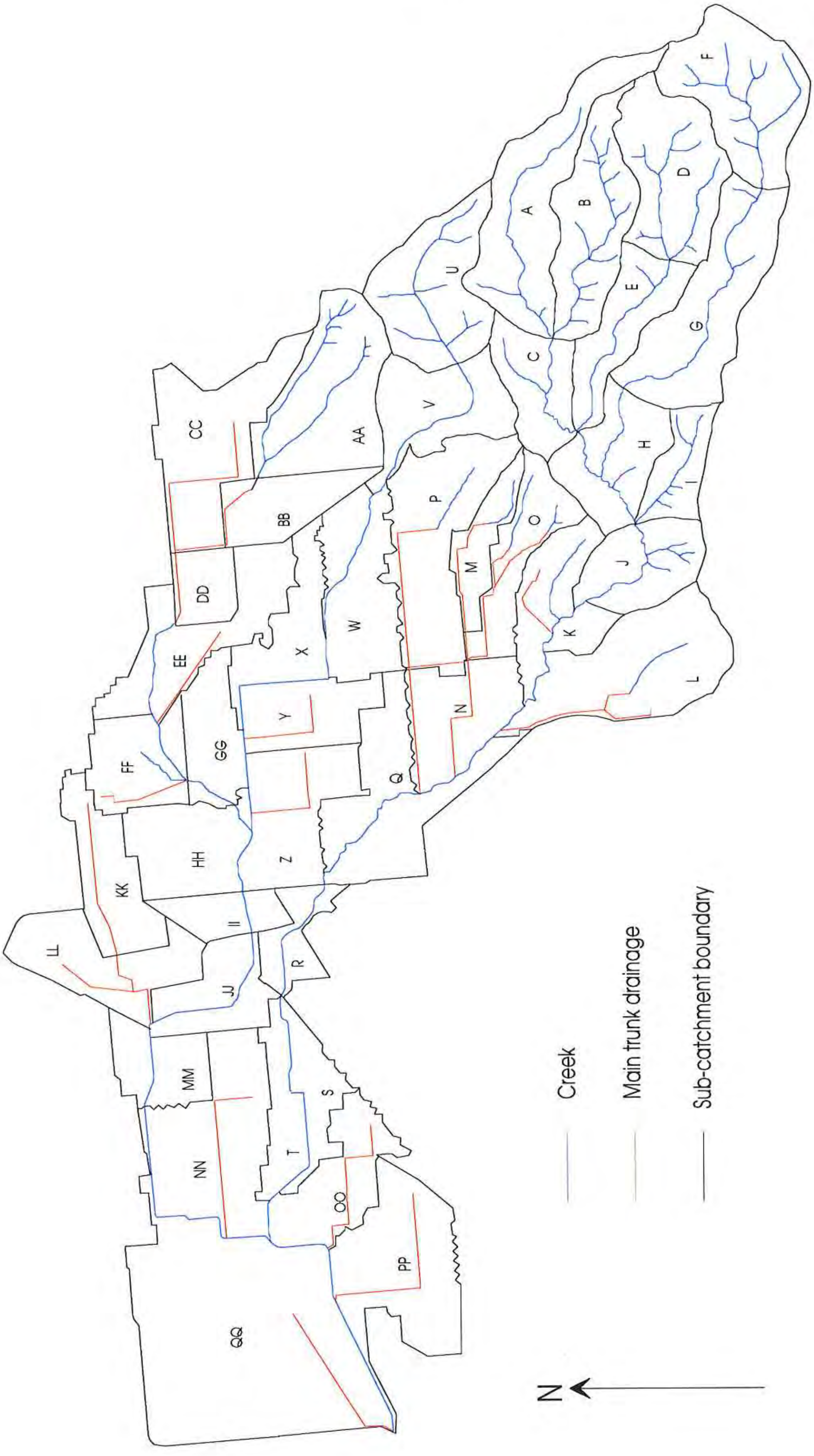


Figure A.3 Digitised RORB model of the Brownhill, Glen Osmond, Parklands and Keswick Creek catchment

Table A.2 Sub-catchment areas and centroids of the RORB model shown in Figure A.3

		Sub-catchment Centroid (Real World Co-ordinates)	
RORB Sub-catchment	Area (km^2)	X (Eastings)	Y (Northings)
A	2.58	87595.2	26381.0
B	1.96	87745.5	25799.0
C	1.17	85645.1	26555.0
D	2.13	88196.1	24861.0
E	1.32	86402.5	25607.0
F	2.32	89239.1	24147.0
G	2.53	86609.1	24358.0
H	1.51	84921.3	25621.0
I	0.79	84811.1	24828.0
J	1.30	83581.0	25290.0
K	1.42	83305.4	26266.0
L	2.56	82410.5	25356.0
M	0.77	83869.6	27116.0
N	1.72	81753.0	27350.0
O	1.26	83522.4	26791.0
P	2.52	83678.9	27712.0
Q	2.12	80892.3	28384.0
R	0.71	79225.7	29432.0
S	0.79	77221.2	29252.0
T	0.84	77212.1	29609.0
U	2.09	86849.7	27655.0
V	1.63	85501.2	27651.0
W	1.84	83399.8	28632.0
X	1.20	82806.3	29402.0
Y	1.23	81854.2	29214.0
Z	1.79	80600.9	29473.0
AA	2.45	85690.3	29099.0
BB	2.32	84770.3	30332.0
CC	1.07	84307.5	29512.0
DD	0.65	83366.6	30503.0
EE	1.92	82613.0	30603.0
FF	1.28	81284.5	31321.0

Table A.2 (cont.) Sub-catchment areas and centroids of the RORB model shown in Figure A.3

GG	1.09	81668.2	30389.0
HH	1.51	80222.2	30717.0
II	0.69	79439.4	30351.0
JJ	1.21	78614.0	30394.0
KK	1.37	79814.6	31601.0
LL	1.68	78999.5	31946.0
MM	1.00	77585.9	31061.0
NN	2.64	76837.7	30244.0
OO	1.46	76516.3	28765.0
PP	2.50	75346.7	28123.0
QQ	6.34	74401.4	30183.0
Total	*73.27*		

2. Another concern relates to the rural part of the Brownhill Creek catchment upstream of Scotch College, in particular the spatial representation of rainfall in this area. This part of the catchment is relatively small, but the topography is extremely variable being quite steep and undulating in many parts. As shown in Figure A.2, the outer perimeter is where the pluviometers are located, but it is this region that is highest and steepest, therefore the rainfall occurring in the centre of the catchment which is generally lower in elevation, is not well represented. Therefore in RORB modelling, assigning pluviometers to sub-catchments in the middle of this part of the catchment, means they are perhaps being assigned a higher amount than reality. An averaged hyetograph calculated for unit hydrograph modelling is also perhaps over estimated.

   Based on this, it would be recommended that more gauging stations be located in the central part of the catchment upstream of Scotch College ALERT, or the rainfall adjusted according to the elevation of the topography.

   When the storms of 30/8/92, 24/9/92 and 8/10/92 were modelled by Polkinghorne (1993) using RORB, the ALERT rainfall station at Crafers (BM023873) was not operational. Therefore the model was calibrated without a recording station in the upper most portion of the catchment, which is probably the highest rainfall zone of the catchment. The isoheytal plots as constructed by Polkinghorne (1993) are probably inaccurate. With the addition of another nearby pluviometer, not necessarily an ALERT station, such as Mt. Lofty (AW504552) a better spatial rainfall distribution could been achieved.

Table A.3 shows the elevation of rainfall stations within this part of the catchment. Figure A.4 shows lines of best fit of elevation versus the total rainfall for the events of 8/10/92, 24/9/92/ 30/8/92 and 14/12/93. In Figure A.4, Mt. Lofty (AW504552) was included, being the highest station and Scotch College (BM023105) being the lowest station. Except for the 30/8/92 storm, it is quite evident that as elevation increases, the total rainfall also increases.

Table A.3 Elevation of the rainfall stations of the rural part of the Brownhill Creek catchment

Station	Scotch College	Belair	Eagle on the Hill	Brownhill	Crafers	Mt. Lofty
Elevation (m)	92	380	345	300	580	700

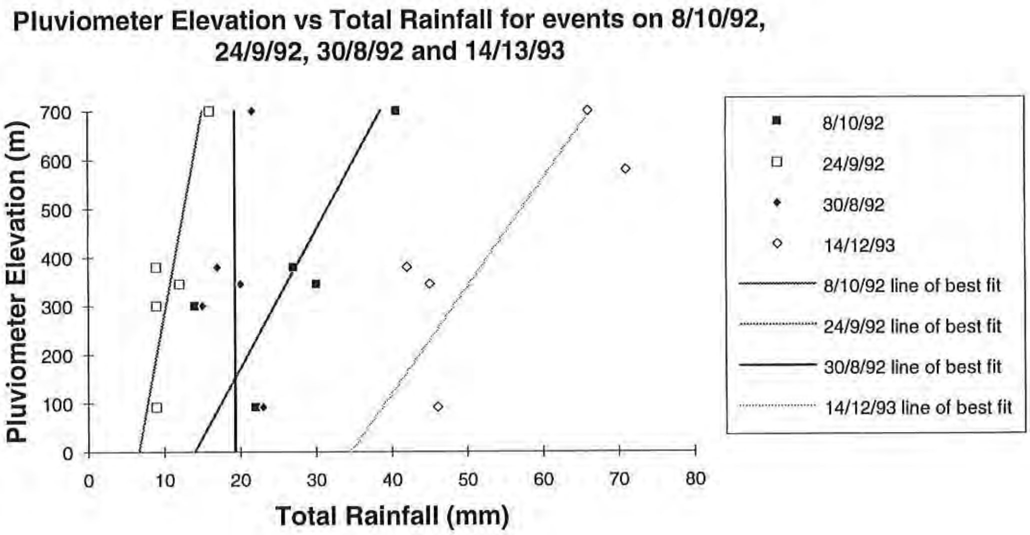


Figure A.4 Straight line elevation-total rainfall relationship for rainfall stations of the rural part of the Brownhill Creek catchment

3. Another problem exists with creating isoheytal plots of the catchment. Polkinghorne generated isoheytal plots of the total storm rainfall by manually drawing lines and visually interpolating to determine the rainfall at the centroids of different sub-catchments. An alternative and perhaps more accurate method, especially when more gauging stations become available is to use a software package such as SURFER. The use of SURFER is discussed by Hill (1993) and different interpolation methods are available.

The biggest problem with using a software package like SURFER is that accurate boundary conditions around the outside of the catchment are needed, otherwise the package may interpolate incorrectly. This is particularly important when the number of stations inside the catchment are low.

4. Since the rainfall-runoff response of the catchment is relatively rapid, it is important that the timing of an event is accurately predicted. In historical modelling for the calibration of parameters, it will be important to select a time interval that will depict a realistic response within the catchment. The rainfall-runoff time delay for a large event would be only a few hours at most, and perhaps less to Scotch College, therefore selecting an hourly interval in historical modelling would not be recommended. An interval as low as 5-15 minutes may be necessary, which is often difficult to correctly model because of the 'spiky' nature of the hydrographs.

   In using larger time intervals during modelling, one must be careful in selecting what type of flow to adopt. For example, HYDSYS allows for either mean, maximum and instantaneous flows. Large variations in the hydrograph would be expected between these different flow representations. However, the effect of this becomes less when smaller time intervals are modelled.

5. MFP Australia (1995) identified a number of flood mitigation options including flood control dams and wetlands to reduce the impact of flooding. The sites identified are located at Brownhill Creek (Recreation Reserve), Glen Osmond Creek (near Mt. Osmond) and Parklands Creek (Glenside Hospital and South Parklands).

   A large detention basin was recently constructed in 1993 in the West Parklands draining much of the city of Adelaide into the north-western part of the catchment. This has also not been considered in any of the modelling so far.

   Other structures have also been proposed by MFP Australia, not only for flood control, but for water quality improvements in the form of wetlands and stormwater retention basins throughout the catchment, in view of the recent publicity the catchment has gained regarding improvements in environmental and water quality aspects of the basin.

   The effect of these options, especially those of flood control dams would significantly alter the hydrologic characteristics of the catchment and therefore the structure of any model developed so far within the catchment.

6. Antecedent precipitation index (API) values were calculated for the storms occurring on 30/8/92, 24/9/92, 8/10/92 and 14/12/93 for the pluviometers operational at that time. API values for 60, 30, 14 and 7 day antecedent periods were calculated in the same manner as in Chapter 7 and shown in Tables A.4, A.5, A.6 and A.7. An overall catchment API was not calculated. The recession factor (K) arbitrarily chosen for the winter-spring storms was 0.90, and for the 14/12/93 storm, 0.85 was adopted because the catchment was drier.

Table A.4 60 day API at the pluviograph stations shown

Storm	BM023874	BM023846	BM023105	BM023873
30/8/92	50.4	42.1	35.0	-
24/9/92	58.0	53.6	41.3	-
8/10/92	50.2	42.9	42.9	-
14/12/93	15.0	15.0	14.2	20.7

Table A.5 30 day API at the pluviograph stations shown

Storm	BM023874	BM023846	BM023105	BM023873
30/8/92	50.6	42.9	35.6	-
24/9/92	57.7	53.7	41.4	-
8/10/92	48.5	41.6	30.3	-
14/12/93	15.1	14.4	14.4	16.2

Table A.6 14 day API at the pluviograph stations shown

Storm	BM023874	BM023846	BM023105	BM023873
30/8/92	45.2	40.3	33.9	-
24/9/92	52.3	50.0	38.3	-
8/10/92	43.8	37.5	28.8	-
14/12/93	18.3	18.3	17.5	23.8

Table A.7 7 day API at the pluviograph stations shown

Storm	BM023874	BM023846	BM023105	BM023873
30/8/92	44.2	42.3	34.9	-
24/9/92	34.7	33.3	29.0	-
8/10/92	35.4	33.5	30.3	-
14/12/93	25.8	25.8	24.9	30.9

Appendix B

Recent Accounts of Flooding in the Adelaide Region described in *The Advertiser*

The Advertiser **6/9/1979**

Torrential rain closes Hills road

Torrential rain caused police to close the Mount Barker Road last night.

The storm caused landslides on other roads and flooding in metropolitan homes.

About 1.5 metres of water covered the road near the Old Toll Gate and several cars were trapped in the flooding.

Mud and rocks were washed on to the road making it extremely dangerous to traffic.

Police guided traffic through the section between the Toll Gate and Devil's Elbow for several hours before both up and down tracks were closed at 9.30 p.m.

Traffic was diverted to other routes and a Highways Department sweeper cleared the road, which was reopened to one lane on the up-track and one lane on the down-track 40 minutes later.

Cars were trapped in floodwaters near the junction of the Mount Barker and the Strathalbyn roads at Aldgate.

The road was closed when more than a metre of water covered it.

Landslides were reported on the Strathalbyn road between Aldgate and Mylor, and on the Gorge Road near Kangaroo Creek dam.

The Brownhill Creek broke its banks and several houses in the Mitcham area were flooded. Houses at Malvern, Wayville and Dulwich were also flooded.

Volunteers from the Burnside State Emergency Service helped clean up.

Flooding on the Mount Barker Road is believed to have caused flooding on several other main roads in the eastern suburbs.

Dozens of cars were reported stalled on flooded sections of Cross, Portrush and Unley Roads.

Many Royal Adelaide Show visitors, who last night parked their cars in backyards of houses in the Wayville area, found the vehicles bogged.

Meanwhile Adelaide's cold and gusty weather is likely to continue for another 48 hours, according to the Bureau of Meteorology.

● Contd. Page 3.

The Advertiser **27/6/1981**

Widespread Hills flooding

City likely still to be lashed by heavy rain

Heavy rains which have pounded Adelaide for three days are likely to continue.

Flooded creeks have damaged more than 100 houses in the Adelaide Hills and foothills.

The Onkaparinga River broke its banks near Balhannah yesterday and about eight houses at Balhannah and two at Oakbank had to be evacuated.

In the metropolitan area, water from Third and Fourth creeks swept into houses at Rostrevor, Magill and Payneham.

The swollen creeks and sodden ground are vulnerable to further flooding, and damage already believed to cost more than $1m. may increase if the forecast rain is heavy.

A Bureau of Meteorology forecaster said last night the recent weather had been caused by "an unstable, moist, westerly airstream associated with complex lows south of the continent."

Late yesterday Telecom technicians were battling to restore extensive damage which had caused thousands of telephones throughout the metropolitan and inner country areas to be cut off.

A spokesman said services might not be fully restored until next week if bad weather continued to hamper repair work, and further breakdowns could occur during the weekend.

A record demand for electricity was caused by the wet and cold weather.

The demand on Tuesday was 15 p.c. more than the peak demand last year. Full report, Page 4.

Racecourse 'devastated'

By GRAHAM ROGERS

Raging floodwaters caused wholesale devastation at the historic Oakbank racecourse yesterday.

The Onkaparinga River, which flows at the back of the grandstand area of the course, flooded its banks early yesterday afternoon.

The chairman of the Onkaparinga Racing Club, Mr Philip Neek, said last night the grandstand was "awash".

"There was nothing we could do except stand back and watch the jockey boxes, horse and pedestrian bridges, horse stalls, fences and railings float away out of sight," he said.

"At one stage the flood level had crossed the track, reached the flat tote and was two-thirds of a metre deep in the secretary's office and grandstand bar area.

"Judging by the debris which is strewn along the safety fence in the straight, it appears as if a big percentage of the course improvements have been demolished.

"It is impossible to estimate the damage accurately at this stage, but the whole business is heart-breaking.

"Fortunately, all the improvements are insured for replacement value.

"But I'm starting to feel that I may be a Jonah to the club.

"I have only been chairman for this season. Part of the grandstand burnt down during the summer, and now this has happened."

Creeks rip through houses in foothills

Third and Fourth Creeks, no more than a trickle in summer, ripped through several suburbs in the metropolitan area yesterday in raging torrents.

Anguished householders stood amazed and helpless as the flooded creeks sent water gushing through houses, damaging or destroying furniture, cars, fences and gardens.

Third Creek, which begins in Horsnell Gully, and Fourth Creek, which starts in the Morialta Conservation Park, wreaked havoc in Magill, Campbelltown, Rostrevor, Erie and Payneham.

Damage also was caused in Rostrevor by Morialta Creek.

Flooding was reported at Flagstaff Hill, where angry residents cited the council's poor drainage as the main cause.

But the most widespread damage was in the Magill and Campbelltown areas.

Pulford Grove and Melory Crescent, Magill, were awash as residents tried to stem the flow with hundreds of sandbags.

Many people were at work when the creeks began their paths of destruction and returned to find their houses partially under water.

At a split-level house in Pulford Grove, windows had to be opened to let water escape.

More than 1.5 metres of water covered a Peugeot car in the downstairs garage.

People in the house next door donned wet-suits while working to prevent the water entering their house.

An enthusiastic postman waded cautiously in the streets delivering mail as water cascaded over stone-front fences.

Such was the suddenness of the flooding in Magill that a woman who had put the kettle on before visiting a neighbor across the road was unable to return minutes later to turn it off when the creek burst its banks and flooded the road.

Flooded again

Mrs Hawkins, of Greer Place, Magill, who was flooded on Wednesday and complained bitterly about action taken by the Campbelltown Council, was flooded again yesterday.

Residents in Campbelltown also were critical of action taken by the Campbelltown Council.

A storm drain put in Sycamore Terrace to stop flooding by Third Creek quickly became choked with debris and by 12.30 p.m. parts of Sycamore Terrace and neighboring James Street and Vincent Court were under water.

Mr Owen Ferreira, of Vincent Court, seemed to be the most severely affected in the Campbelltown area.

His house suffered extensive water damage, his fence was destroyed and a toolshed in his backyard was washed away and deposited upside down in a neighbor's yard.

Complaints in this area also were levelled at insurance companies which, residents said, would not insure people living near creeks, except by imposing prohibitive premiums.

People living on the side of James Street unaffected by the swollen waters watched and prayed that no more rain would fall.

The Campbelltown Council garbage collection truck delivered sandbags.

It was estimated that Third Creek was more than six metres deep at this point.

The water had started to subside in Campbelltown and Magill yesterday afternoon, but people were reluctant to begin cleaning up while doubt existed over whether there would be more rain.

Everyone in both areas did agree they would just have to continue to live with the danger of future flooding because it would be impossible to sell after yesterday's damage.

Seven rescued

State Emergency Service volunteers rescued seven people and a dog from floodbound houses in Seabrook Drive, Rostrevor.

Most of the flooding in the Rostrevor, Magill and Payneham areas was due to Third and Fourth creeks overflowing.

About 90 soldiers from the Woodside Army camp were called in about noon to help volunteers in the threatened Oakbank-Balhannah areas.

Members of 3 Bn RAR and the 16 Air Defence Regiment filled more than 4000 sandbags to stem the rising floodwaters.

A further 7000 sandbags were being held in reserve overnight.

The Army provided a further 2000 sandbags for the metropolitan area.

The soldiers were withdrawn from the Oakbank-Balhannah area about 5 p.m., but were told to listen to radio station 5AD for any possible fresh call-up.

Heavy damage was caused to the Oakbank racecourse by the floodwaters.

Woodside and Hahndorf were cut off from the freeway by the flooding.

Metropolitan reservoirs increased their holdings from 41 p.c. to 49 p.c. of their capacity after the run-offs of yesterday's rain.

Yesterday's increased intake amounted to 15,030 megalitres.

The downpour yesterday morning caused a heavy demand on the RAA road service and more than 1672 calls were received from stranded motorists from midnight on Thursday.

The Morialta Conservation Park will be closed until further notice because of flooding.

The trail leading to the Morialta Falls and two bridges had been washed away. Damage to the park was reported as high as $250,000.

Water leaked through the roof of the SA Museum and on to valuable Aboriginal bark paintings stored in cartons, but they were not damaged.

Last night the Premier, Mr Tonkin, said the State Emergency Service had advised against declaring a state of emergency at this stage.

A spokesman for the Minister of Water Resources, Mr Arnold, said last night responsibility for the flooding of creeks and rivers in the metropolitan area rested with local government.

The Commissioner of Highways, Mr A. K. Johinke, said last night the old Norton Summit Road was closed from Magill to the top of the hill after rock and land slides.

Heavy rain was affecting one kilometre of the Duke's Highway under reconstruction at Ki-Ki, 15 kilometres north of Coonalpyn.

PAGE 26 — Hills flood report.

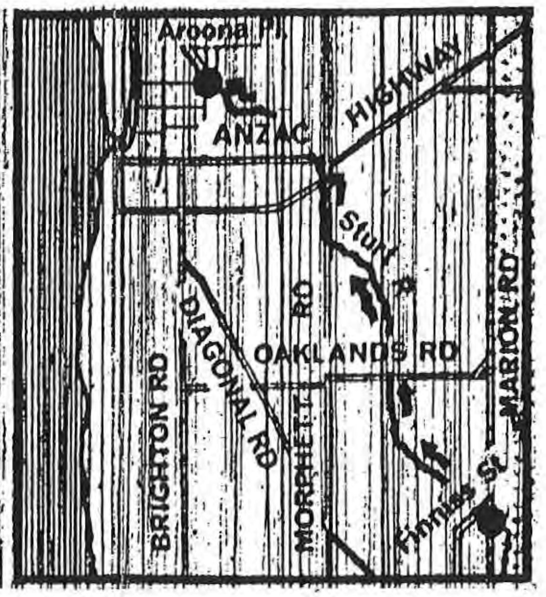
The Advertiser 3/7/1981

Youth swept down flooded river

35 minutes of icy terror

Thirteen-year-old Scott [illegible] was swept on a terrifying 35-minute, eight-kilometre ride down the Sturt River yesterday — and escaped with swollen and torn hands.

[illegible]



Floods, hail again — and storms are looming

[illegible]

... and the threat of further flooding, for the time being, was over.

The heaviest fall recorded in the 24 hours to 9 a.m. yesterday was 70 millimetres at Stirling. A further 19 millimetres fell in the six hours to 3 p.m.

At Stirling and Crafers about six buildings and houses were damaged after their roofs were covered with hailstones up to 10 centimetres deep and water came through the ceilings.

At Hawthorn, the lower level of a Denning Street house was flooded by water about a metre deep from Brownhill Creek. Two houses at Coromandel Valley and Hawthorndene were threatened by creeks.

Rain over the past two days has resulted in a huge intake into metropolitan reservoirs.

A spokesman for the Minister of Water Resources, Mr Arnold, said total holdings had increased from 62.1 p.c. to 63.2 p.c.

From 8.30 a.m. until 3.15 p.m. yesterday the level of Mount Bold Reservoir had risen by a metre with an intake of 2500 megalitres. (A megalitre is 1m. litres.)

The Deputy Commissioner of Highways, Mr M. J. Knight, said yesterday the Birdsville Track from Clifton Hills to Birdsville was passable only to four-wheel-drive vehicles following heavy rains near Pandie station.

The Advertiser 23/7/1995

FLOODS, STORMS LASH STATE

By PETER HARAN

Hundreds of exhausted emergency services workers are bracing for the aftermath of huge storm and flood chaos which triggered evacuations, road closures and property damage in the Adelaide Hills and outer metropolitan areas yesterday.

A week of downpours, storms and heavy rains has caused damage from the State's West Coast to the lower north and through many hills towns.

Telstra was forced to fly in technicians from interstate and country regions as Adelaide's phone system buckled under the barrage of bad weather and some phone users could be without services for a week.

Winter storms and winds saw a mini-tornado wreck homes at Tarlee, crop damage in some parts of the state, sporting fixtures cancelled and golf courses closed.

In a concentrated 72-hour burst the hills town of Hahndorf was hit by a 100mm deluge – four inches in the old scale.

Hahndorf was just one of the hills centres under threat as emergency services – including the CFS, SES and police – closed roads north-east of the Mt Barker Freeway from Verdun to Birdwood and Gumeracha to Williamstown.

A Bureau of Meteorology spokesman said Adelaide had recorded 12mm, pushing the July total to 89mm compared with the monthly average of 75mm.

A map of the worst-hit flood areas

Reservoir holdings have soared from just 38 per cent capacity a week ago to 50 per cent at the last reading for the week on Friday.

Although heavy rains will ease later today, yesterday and last night's downpours are concerning emergency services workers in the hills, with some rivers already bursting their banks.

During the day police appealed for motorists to stay out of the worst flood zones and expressed anger at hordes of people who attempted to push through roads covered with sheets of water.

Country Fire Services chief, Mr Russell Grear, at the centre of flooding near Kersbrook, said late yesterday: "Drivers must keep out of the hills, we have flooding everywhere and anything in excess of 25mm could lead to a very serious situation."

● More reports Pages 4 and 5

Raging torrent damages homes

By CRAIG CLARKE

HOMES were flooded and others evacuated as the worst floods in three years swept the Adelaide Hills yesterday.

Mt Pleasant and Birdwood bore the brunt of the damage with rising waters leaving three retirement units and a house under flood.

At its peak, almost a dozen homes were sandbagged or evacuated while eight Hills roads were cut as the River Torrens burst its banks along a 2km stretch.

Damage was minor and there were no reports of injuries. Farmers moved their stock to higher ground to prevent them from being swept away in the rapidly-flowing waters.

Almost 100mm of rain has deluged the Hills in the past 72 hours.

And residents are bracing for more flooding today when overnight rain flows into the Torrens, threatening more homes.

The weather bureau expects the rain to ease today.

Almost 100 exhausted Country Fire Service volunteers have worked virtually non-stop since Friday night answering scores of calls for help.

The Mt Pleasant CFS captain, Mr Colin Fawcett, said: "It's been terrible up here and I don't think it's going to get any easier".

Late yesterday he ordered the sandbagging of the Springton dam which looked likely to burst and flood homes.

"We haven't see it like this since the 1992 floods," Mr Fawcett said.

In 1992 floods caused widespread damage in the Adelaide Hills.

The worst-hit area was Cudlee Creek, where a flash flood wrecked the local caravan park resulting in one person drowning.

In Birdwood yesterday, Lynette and Ian Thorley – who have been flooded five times before – were preparing to meet the new danger head on.

"We've taken up the carpets and put all the electrical gear on tables – it's just a matter of waiting now to see what happens," said a grim-faced Mrs Thorley.

"Other people along the river have done what we have, I just hope it goes down

"I think our biggest fear is waking up in the morning in a pool of water."

The CFS regional commander, Mr Rob Sandford, appealed for calm, saying the flooding would soon subside.

"I think we're over the worst of it, it just depends on how the weather holds up overnight," he said.

Police and CFS crews set up checkpoints on Hills roads, turning back sightseers

Reservoir boost in Hills deluge

HAHNDORF in the Adelaide Hills has been deluged with about 100mm of rain – four inches under the old scale – in the past 72 hours.

And other Hills towns including Lobethal, Lenswood, Meadows and Mt Barker have had well over 50mm.

A Bureau of Meteorolgy spokesman said Adelaide had had 12mm, pushing the July total to 89mm compared with the monthly average of 75mm.

Reservoir holdings have soared from just 38 per cent capacity a week ago to 50 per cent at the last reading for the week on Friday.

Downpours in Hills catchments on Friday night and Saturday morning will further boosted holdings.

SA Water operations engineer Mr Andrew Jessup said Hills reservoirs had had some excellent intakes over the past week, with holdings rising more than 1 per cent a day.

Yesterday a number of metropolitan golf courses including Patawalonga and Glenelg were closed following the rains.

Glenelg course manager Mr Rob Lewis said some sections of fairways were under water while the rest of the course was very soft.

"We would have done a lot of damage if we had allowed play this weekend," he said.

He said the position would be reviewed on Monday morning.

The City of Adelaide south course and par 3 course were also closed, but the north course remained open.

A spokesman said the north course was likely to stay open today unless there was further heavy rain.

Kooyonga was also closed yesterday and a decision on when to re-open the course would be made this morning.

Belair Park course spokesman Mr Mike Sprengel said the Hills course would be open today "but we don't suggest people play because there is too much water lying around".

He said a number of parts of the course had been roped off.

The Flagstaff Hill course was open yesterday and a decision on whether to open today will be made this morning.

The heavy rains have caused minor problems for farmers in the South-East but elsewhere in the State the falls have been welcomed, says the SA Farmers Federation.

"There has been some minor crop damage in the South-East as a result of surface water in low-lying areas," said the Federation's chief executive Mr Michael Deare.

He said areas affected included the Keith, Kingston and Padthaway regions.

Livestock could also be affected by footrot when there was a lot of surface water on pastures.

"But I haven't had any complaints from other areas of the State, and the West Coast can take a lot more rain," he said.

"The last thing I would say is that we want the tap turned off." - ANDY WILLIAMS

Floodwaters surge over a road in Birdwood in the Adelaide Hills

Floods and drivers keep police busy

POLICE had their hands full diverting motorists in the Adelaide Hills during yesterday's more than 12 hours of heavy rain.

Road closures began before noon at Kersbrook and Mt Pleasant.

Roads along the Onkaparinga Valley were later closed, followed by flooding and road closures at Verdun, Hahndorf and north at One Tree Hill and Elizabeth. Worst hit were the Birdwood to Williamstown Rd and Birdwood to Gumeracha.

In the Kersbrook area five roads were shut and floods threatened six Mt Pleasant homes where a retirement village was evacuated.

Police monitored Cudlee Creek where floods resulted in a death in 1992 and CFS crews cleared drains and sandbagged homes at Springton, Gumeracha and Birdswood.

Black Top Rd at One Tree Hill, Main North Rd at Smithfield and Midway Rd at Elizabeth were flooded and two Strathalbyn roads were closed.

Appendix C

The Recent Concern for the Flood Potential in Adelaide as highlighted in *The Advertiser*

The Advertiser 27/1/1996

flood

would adelaide go under?

STORY: COLIN JAMES
ART WORK: KARL HORVAT
PICTURES: MORTLOCK LIBRARY

View from the tram crossing at Morphettville Racecourse, towards Novar Gardens, 1931.
Mortlock Library, B53255.

IT is a statistical and scientific certainty that Adelaide will be hit by a flood of devastating proportions. The flood is expected to start in any one of the number of rivers and creeks which feed into the metropolitan area. It will have the capacity to kill hundreds of people, destroy thousands of homes, inundate hospitals, schools and churches, put tens of thousands of South Australians temporarily out of work and cripple industry, transport and telecommunications for weeks, if not months. The damage bill could run into the millions and, possibly, the billions. Detailed studies have resulted in millions being spent in the past decade to protect Adelaide from the flood which scientists, meteorologists and engineers say will definitely come. Maps have been prepared to show the areas most at risk. Emergency plans have been drawn up to evacuate thousands of people from their homes. Experts have calculated how deep the water will be, what services will be affected and how long it will take to restore the city to normal. Every detail of the flood and its impact has been plotted.

The only thing the experts have not been able to determine is when it will happen. They just hope enough has been done to save the city.

The Torrens Linear Park has been designed to help floodwaters to flow through to Gulf St Vincent. Along with the space the park has created along much of the Torrens, exotic vegetation has been removed from the river; its channels have been widened and realigned; its banks have been reshaped to provide greater slopes; and existing levees, or stopbanks, have been made higher and wider, while other, new banks have been created.

Farther upstream, the Kangaroo Creek Dam, near Cudlee Creek, has been extensively modified to provide more capacity to trap the water officially identified 16 years ago as the biggest source of a potential flood. The dam's wall has been raised and reinforced, and its storage level dropped to make more room. Its spillway has been modified to control the sustained heavy rain which engineers expect will last for at least 24 to 48 hours, turning usually tranquil creeks and drains in the Adelaide Hills into torrents.

Records have been used to calculate that a major flood will happen in Adelaide, on average, every 100 years. This is known as the 100-year flood. A worse flood is expected every 200 years and another, even more extreme deluge, every 500 years. The last major flood to swamp Adelaide was in 1931, when farmland and swamps which have since become the western suburbs disappeared under a sea of water. Before that, the city was inundated in 1923, 1917, 1898, 1889 and throughout the 1840s.

Authorities believe any floodwaters from the rural catchment of the Torrens will be successfully trapped by the Kangaroo Creek Dam. However, there is a remote chance that if the dam fills to maximum capacity, water will flow over the top of its earth wall. This will send thousands of millions of litres of water and debris into the River Torrens, swamping Adelaide and causing damage worth an estimated $6 billion.

The risk of the dam overflowing or breaching – and the expected damage bill – was assessed by the former Engineering and Water Supply Department in 1980 as part of an investigation into the flooding of the Torrens. Engineers reported the dam's spillway would not cope with a flood of the biggest size they could calculate and the top of the dam wall certainly would erode. This would cause "considerable loss of life and catastrophic property damage", they said. It was estimated at least 100 people would lose their lives.

The results of the dam breaching were incorporated by the E&WS into a four-volume report produced in December, 1980, on how the risks of the Torrens flooding could be reduced.

The Tonkin government ordered the report after an Adelaide engineering consultancy, B.C. Tonkin and Associates, completed a preliminary study of the Torrens flooding risk.

The investigation found little had been done to reduce the risk of flooding since the 1930s, when a number of official reports culminated in the construction of a "breakout creek" and "outlet structure" for the Torrens at Henley Beach South.

B.C. Tonkin and Associates conducted detailed studies of the flows of the Torrens river system under severe storm conditions using historical data, meterological information and computer models. Results were transferred on to "flood maps", which were attached to the report. These showed the areas, or "flood plains", which would be affected by flooding.

When the report was published 12 months later, its findings sent shockwaves through Adelaide's water and engineering bureaucracy. It confirmed a long-held belief that the "pressure for land for the creation of housing lots, industrial complexes and community facilities" in Adelaide had led "to the present situation of intense development" along the Torrens "from the foothills to the sea with little regard to the consequences of a major flood.".

The Tonkin report found:

FLOODING would occur at various locations over the Torrens flood plain, particularly at Campbelltown, adjacent to Lower Main North East Rd.

● Continued Insight 2

The Advertiser **27/1/1996 (cont.)**

WILL ADELAIDE SURVIVE THE BIG FLOOD?

● From Insight 1

THE TORRENS channel would be "surcharged", or breached, immediately east of South Rd. Flooding would occur in the north-west and south-west of the city in a fan shape. The report said the effects of significant overflows would be "disastrous" to adjacent built-up areas.

COMPUTER modelling showed the flood would be similar to that experienced in 1889, when large parts of Adelaide were inundated.

NOTHING would change if only minor river straightening and debris removal was undertaken.

The report found the first location of flooding, or "Flood Zone 1", consisted of the river widening to a width of 500m over land in the north-eastern suburbs. "Significant areas" of this flood plain had been developed for residential purposes, it said.

The second location lay between Port and Holbrooks roads. The report said embankments built in the 1920s meant the river was expected to "overtop", or run over its banks, immediately west of the Port Rd. The problem would become less severe downstream.

HOWEVER, the flood would spread, or "fan", to the north-west and south-west of Adelaide over "extensive areas of residential development". The third location, Flood Zone 3, lay below Holbrooks Rd. The report said any "overflows from the river below Port Rd could not re-enter the river but would flow through the residential streets to finally enter the Port River to the north and the Patawalonga to the south". A flood depth in excess of 1m was "possible in some localities".

The Tonkin report recommended:

FURTHER investigation of the damage of a flood to buildings, public utilities, roadways, sewers and private dwellings. It advised studying the cost to the community of 50, 100 and 500-year floods.

SURVEYING the flood plains and areas expected to be flooded "to determine the extent of flooding, the route and effects of overflows".

INTRODUCING a flood warning system, which would include facilities and co-ordinated plans to help evacuate people living in areas "officially designated as potential areas of inundation".

CARRYING out limited maintenance of the River Torrens channel to remove debris and dead trees which could damage or flood structures within or spanning the river. The report contained a direct warning: "It is stressed the likelihood of major flooding is real and can be expected at any time based on the premise that the events discussed in the report are chance events and therefore have a certain probability of occurring." The Bureau of Meteorology studied rainfall records and reported that "extreme rainfall for short durations" which could result in severe flooding would "be produced by an intense and almost stationary thunderstorm". Such a thunderstorm was most likely to occur in "summer or early autumn", it said.

The Tonkin report said an "extreme event" would be a storm of about double the severity recorded in 1889, when 220mm of rain fell at Cudlee Creek, at the top of the Torrens, over five days. The report said "little imagination" was "required to conjure up a picture of extensive devastation related to such an event".

Imagination does not need to be used. Reports from *The Observer* newspaper in April, 1889, detailed the biggest flood in South Australia's urban history. The paper reported the River Torrens had "never been so high" and a flood above the Hope Valley and Thorndon Park reservoirs "was of tremendous volume".

"The water ran along the Torrens channel to the extraordinary depth of nine feet above the weir," said the newspaper. "At midnight, without any warning, an immense volume of water came down the bed of the usually small stream.

"Past Walkerville and East Adelaide, the banks of the stream were exceedingly high and, between them, the water rushed at a great rate. At the Torrens Lake, great damage was done. The water came down like a tidal wave." *The Observer* reported that whenever "a flood comes down from the Hills, the low-lying land between Hindmarsh, Thebarton and Henley Beach, broadly known as the Reedbeds, is always flooded".

The day after the Torrens flooded, water had "rushed over all this country, inundating it to an extent hitherto unknown to the oldest inhabitant".

"From the Henley Beach road past the Findon road, and down through the reedbeds to the sandhills, an immense inland sea or rushing water carried everything movable before it. The water was from two to five feet deep, and of course flooded all the houses in the depressed country over which it ran," said *The Observer*. The Tonkin report was given to the E&WS which, in turn, was directed by the then minister for public works, Mr Peter Arnold, to accelerate an investigation into the extent of the flood risk to Adelaide.

The findings of its 10-month investigation were grim. The E&WS produced a detailed report which recommended urgent action to reduce the risk of flooding in Adelaide.

The E&WS formulated a strategy to contain, within the River Torrens channel, floods with return periods of 200 years or less. The terms "return period" and "recurrence interval" of a flood refer to the number of years, on average, within which a given flood peak will be equalled or exceeded once. In a sobering chapter, the department said that, if no action was taken, a flood of the extent experienced every 200 years would inundate over 13,000 properties and cause damage estimated at $215 million. It said the cost needed to be measured by the damage inflicted by the flood and the time it took the city to restore itself afterwards.

The report said the "do nothing approach" would see floodwaters sweep down the Torrens, causing damage in Adelaide's eastern suburbs before bursting over the banks at Port Rd and spreading across the western suburbs.

Official figures estimated 6000 State students, 800 private school pupils, 355 preschool children and 2000 tertiary students would be affected by the 200-year flood. Underground telecommunication cables and telephone installations in basements would be destroyed.

Damage would be greatest in the low-lying western suburbs. The E&WS predicted seven private hospitals and nursing homes would have to be evacuated while access to the Queen Elizabeth Hospital would be disrupted.

Two "meals on wheels" kitchens would be inundated. Doctor's surgeries, child health clinics, an intellectually disabled day centre and a sheltered workshop would be flooded. Almost 50 churches would be hit. Sports clubs, bowling greens, drive-in theatres, scout halls, football ovals, tennis clubs and public swimming pools would disappear under water.

All major roads west of Adelaide running north to south and several running east to west would be cut. Eight bridges would be damaged or destroyed. An estimated 335,000 daily trips in private vehicles would have to be abandoned or re-routed for one to two days. Another 29,200 daily trips by commercial vehicles would be affected for three days. Bus services would be severely affected. Even shallow water would seriously disrupt brakes and the ability of passengers to board or disembark. Six bus routes would be cut off for up to three days.

THE Adelaide Airport would be inundated, with floodwaters not expected to subside for about four days. All runways would be affected and the terminals would be flooded. Once the flood subsided, another 10 days would be needed to dry the runways and repair undermined sections. Only emergency flights could land and take-off. Normal passenger traffic would not resume for three months. If federal authorities intervened, this could be reduced to one month. Navigation aids could have to be replaced.

Light aircraft would be diverted to Parafield Airport, while normal passenger flights could land at Edinburgh Airfield, 25km north of Adelaide. The runways and navigation equipment at Edinburgh could cope with aircraft such as Boeing 727s, although fuelling facilities would be stretched and temporary terminal facilities would have to be built. If Edinburgh was also hit by floodwaters from the Gawler River and nearby drains, air transport to Adelaide would "effectively cease" for several months.

A total of 37,950 jobs would be affected by the flood, with widespread disruption inside and outside the flood plains. Full-time employment would be affected as factories, shops and offices were cleaned up and dried out. People would be unable to reach workplaces inside the flooded areas and many would have to take time off to repair their own homes.

Many industrial, commercial and government enterprises would sustain serious damage to plant, equipment and stock. Repair and replacement could take weeks or months to enable operations to start again. Heritage buildings and areas would be affected.

The E&WS recommended spending $3.9 million on works which included the Kangaroo Creek Dam modifications, cleaning up the Torrens, widening its channels, changing the slope of its banks and modifying some bridges. The E&WS said the flood mitigation works would complement the Torrens Linear Park proposal, which had then been recently-released by the government. The Tonkin government, through Mr Arnold, moved promptly and work on the park and the flood measures began soon after the report was released.

One of two hydrology engineers responsible for issuing flood warnings, Mr Chris Wright, has told *The Advertiser* virtually all of the recommended flood mitigation measures has now been completed. He believes they will be enough to save Adelaide from a 100-year flood caused by rainfall above the Kangaroo Creek Dam in the Torrens rural catchment.

Mr Wright, from the Bureau of Meteorology, is a member of the Flood Warning Consultative Committee, a co-ordinating body which meets twice a year to discuss flood-warning measures, the latest research and the funding of monitoring programs, including instruments which measure rainfall and waterflows.

The committee has representatives from SA Water (formerly the E&WS), the Department of Environment and Natural Resources, River Torrens Water Catchment Management Board, SA Police, State Emergency Service, Local Government Association and the Department of Road Transport. The State Disaster Centre, which will control emergency action should a flood occur, is also actively involved.

The centre will largely rely on the existing flood maps to evacuate people and put in place its detailed contingency plans should a flood strike Adelaide. The most recent flood was late last month, when large areas from Edinburgh across to Enfield were inundated. The most recent fatalities from flooding were in August, 1992, when two people drowned after the Torrens overflowed at Cudlee Creek.

Mr Wright and another Bureau of Meteorology hydrologist are using data from both floods to help revise the 1980 flood maps for Adelaide as part of a detailed study into the current flood risk being faced by the city.

MR Wright says he believes the Linear Park development and the flood mitigation measures introduced by the E&WS have significantly reduced the risk of flood damage to Adelaide by a 100-year flood. He believes the next flood of this size will be "contained within the banks" of the River Torrens. However, he acknowledges any flood bigger than this will be a different proposition.

"When the last maps came out in 1980, they caused a considerable stir within the government and E&WS because until they were produced, people didn't actually realise the extent to which flooding could affect the city," says Mr Wright.

"As a result of that, the government put a lot of money into rehabilitation and flood mitigation work along the Torrens, which has just been completed. It has substantially reduced the risk of flooding of the extent and depth in areas which were shown in the 1980 maps.

"As far as I can gather, the one-in-100 year flood will be fully contained within the banks of the river. I think there will be an overflow from a 200-year flood but we won't know, until these maps are produced, where that it is going to take place."

Mr Wright fears a greater threat is posed to Adelaide by urban development alongside the various creeks in the Adelaide foothills which feed into the Torrens below the Kangaroo Creek Dam. Housing has dramatically changed the nature of the catchment. Stormwater now rushed off roofs and across concrete driveways which were once open areas. The stormwater collects in drains and the potential for flooding is enormous.

Mr Wright says it is "many years" since flooding has been experienced in settled hillside areas such as Waterfall Gully — and inexperienced residents will be caught unawares as they try to get out.

As to the spectre of the Torrens breaking its banks again, Mr Wright says, "Nobody but God knows the perfect answer but, according to the best engineering calculations, that shouldn't happen. The risk has been certainly reduced. One day, our flood will occur in the Torrens. The only thing we don't know is when."

Expert's grim warning

Adelaide's flooding deathtrap

SPECIAL REPORT

By Chief Reporter
COLIN JAMES

Residential areas near creeks in the Adelaide foothills will become deathtraps when the city is hit by its next big flood, experts have warned.

The Bureau of Meteorology, which issues flood warnings, says people in areas such as Waterfall Gully could have less than an hour to escape floodwaters.

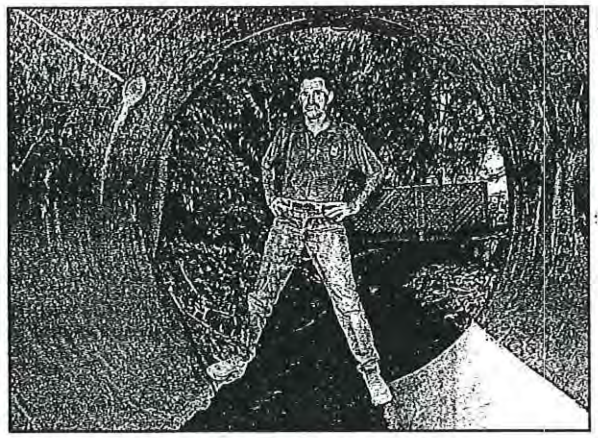
The bureau, which is conducting the biggest review of Adelaide's flood risk since 1980, believes millions of dollars spent in the past decade will save the city from flooding of the River Torrens in its upper rural catchment.

However, hydrologist Mr Chris Wright, who is a member of an official flood committee, says a new and bigger risk is posed by residential development in the Adelaide foothills alongside several creeks which feed into the Torrens.

While modifications to the Kangaroo Creek Dam, north-east of the city, are expected to contain any floodwaters at the top of the River Torrens, stormwater from the foothills will flood into Adelaide because previous open spaces have been developed.

Mr Wright and the Torrens Water Management Catchment Board have told *The Advertiser* stormwater pouring off concrete driveways, roofs and bitumen paths would flood into stormwater drains and creeks.

Mr Wright and the board's general manager, Mr Alan Ockendon, said debris would become trapped under private bridges, creating floods and



IN THE DANGER ZONE

Chris Meulengraaf lives in Waterfall Gully, an area identified as a potential death trap. The idyllic creek winding past his house could become a dangerous torrent. Full story, Page 2.

people would drown if they tried to escape in their motor vehicles or by foot. Waterfall Gully was one of the biggest risk areas because it only had one access road alongside its creek and concrete ramps had been built at many points.

Mr Wright said people with no experience of flooding would have less than an hour to get out before floodwaters made escape impossible.

"It's a real danger that when the flood occurs in an area like Waterfall Gully, residents, perhaps women and children getting into cars and trying to drive out alongside the creek, will be trapped in a potential bottleneck as the crossings become flooded," he said.

"We believe the risk of people drowning is quite high in that area. Safety will be much more readily found by climbing the sides of hills and waiting for waters to recede."

Mr Wright said it was "many years" since there had been flooding in Waterfall Gully and, statistically, another flood was inevitable.

"People who live in that area now are probably not aware there is any risk," he said.

"It means when the flood occurs, which is certain to happen but we don't know when, it is going to be unexpected.

"There will be little warning and no awareness by the people who are going to be affected that the flood is coming or what to do about it. That is going to be a big problem."

● Continued Page 2

● Insight: Flood – Will Adelaide Go Under?

● PAGE 18: Editorial

Foothills flood deathtrap

● From Page 1

Mr Wright said work had started on new maps showing the areas of Adelaide expected to flood. These were expected to be completed late this year and will replace the last maps drawn in 1980.

The new flood maps are part of a major review being conducted by the Flood Warning Consultative Committee of the flood risk facing Adelaide.

Mr Wright said he believed flood mitigation work through the 1980s worth more than $4 million, which included the establishment of the Torrens Linear Park and the modifications to the Kangaroo Creek Dam, would contain a flood of the magnitude of a deluge expected once every 100 years within "the banks of the river".

Exotic vegetation in the Torrens had been cleaned out, its banks have been sloped, its levees adjusted in height and width, and its channels broadened and widened to get stormwater through to the sea quicker and more efficiently. Mr Wright said the measures had "significantly" reduced the risk of flooding in the Adelaide urban area from the Torrens but the First, Second, Third, Fourth and Fifth creeks, which feed into the Torrens, posed considerable danger to the eastern suburbs.

The three major rivers with the potential to cause most damage – the Torrens, Onkaparinga and Gawler – have reservoirs which can trap stormwater while only creeks in the Campbelltown City Council area have had any flood mitigation work.

Mr Wright said the flooding from the creeks near the metropolitan area "may be as serious a problem as the floods in the rural area."

Mr Ockendon repeated the warning, saying people in residential areas near creeks were "complacent" about the risk of flooding. He said "flash" flooding was inevitable because of housing in areas which were flood plains.

Sandy Terry ... concerned about First Creek. Picture: LEON MEAD

EDITORIAL OPINION

Saturday, January 27, 1996

Banking against the big flood

"The water came down like a tidal wave." Not a description of some downpour in the tropics, but of a flood in the normally meek and well mannered Torrens waterway.

That was 107 years ago, when a rush of water brought unprecedented devastation to the young city. It remains the most damaging flood recorded in Adelaide – so far.

Newspaper reports of the day described an "inland sea", submerging houses and killing stock and crops in a shock wave of destruction.

But as with all natural disasters, there are no calendars. The most detailed engineering calculations can literally float out the window in the face of such a downpour, and along a catchment area now brimming with suburban population.

The possibility of a future flood disaster is investigated in this newspaper today. It is not meant to be alarmist. It deals with the facts – and carefully assessed predictions – covering the city's ability to cope with a flood emergency.

As the experts say, it is not a matter of if, but rather when, the next catastrophic rainfall tests the system which feeds water into Kangaroo Creek dam, and then across the flat plains of Adelaide to the sea.

The danger of widespread flooding from the River Torrens has, to some extent, been replaced by a new menace along the creek network in the foothills.

The concerns are not new. A 1980 report recommended action to reduce potential flood damage, including reinforcement of the Kangaroo Creek dam wall, and widening of what is now the Torrens linear park to cope with a great rush of water.

This work has progressed but it has not met all of the concerns raised by the experts.

Most importantly, there is no guarantee that, under sufficient weight of backed-up water, the top of the Kangaroo Creek dam wall will not crumble. A breach would send thousands of millions of litres of water and debris crashing down into the Torrens – swamping houses and causing an estimated $6 billion damage. A remote possibility, perhaps, but still a risk, and one which should be at the centre of any assessment of current and future dangers facing the city.

The entire flood scenario is examined regularly by a co-ordinating group involving SA Water, emergency services, police and road transport.

New flood maps are being prepared based on the latest statistics. Those figures highlight the fact that Adelaide has not suffered severe flooding for many years. And that, say the experts, brings the prospect of a major flood much closer.

In these days of computer modelling, of converting the records into a vision past, present and future, we have expertise on our side.

What must not be left to chance is any engineering work which will lessen the likelihood of damage.

Luck has been with Adelaide for decades. It has given us precious time, and knowledge, to best handle a disaster.

Appendix D

A Recent Example of the Increased Awareness and Publicity given to Artificial Neural Networks for Forecasting as shown in *The Advertiser*

The Advertiser 13/9/1995

Student who tells firms their fortune

By ROBERT MATTHEWS
in London

Anyone thinking of investing in, or joining, a new company might be well advised to have a quiet word with Yurt Alici, a PhD student at Exeter University in southwestern England. He claims to have found a way of predicting which companies will go bust in the next five years.

Forecasting the future is big business in the financial sector. Many City firms secretly recruit so-called "rocket scientists" — brilliant ex-mathematicians and physicists — to develop sophisticated statistical methods for forecasting share prices or currency changes.

Now Mr Alici says he can do the same for entire companies, spotting which ones will go under up to five years before it happens.

His breakthrough is based on a radically new technology known as "neural computing" — a way of programming computers to mimic the human ability to learn from experience.

Mr Alici began by taking the complete financial records of dozens of companies listed on the London Stock Exchange, and divided them into those that had failed and those that were still trading.

Their records contain huge numbers of financial ratios, such as profits to sales or net income to total liabilities, which, in theory, tell something about the health of the companies. Mr Alici found that a relatively small number captured most of the information.

He then took these ratios and fed them into a neural network, an ordinary computer programmed to learn the complex relationships lurking in complex data. For each set of ratios the computer was told whether the company succeeded or failed — allowing the computer to associate failure with certain ratio patterns.

Mr Alici then tested the computer's fortune-telling abilities by giving it the financial ratios of a company it had not previously seen, and asking it to predict the company's fate.

The computer correctly forecast the outcome after one year in 84 per cent of the cases, and even five years into the future almost two-thirds of its predictions were correct. Mr Alici says the technique can even take missing or faulty data in its stride — including any "creative accounting" by companies attempting to mask impending disaster. "This method will still find them out," said Mr Alici.

His research is already arousing interest among potential users.

"We tend to be suspicious of things that claim to predict the future, but we would look very closely at this," said a spokeswoman for ProShare, the company set up by the Stock Exchange to promote wider share ownership.

Mr Alici hopes to turn his research into a product that could be used by everyone from professional investors to people thinking of changing jobs: it only needs an ordinary computer, and the ratio information you need is available in published records, he said.

"If I'm offered a job by a company, I shall probably use it to check them out too."

— The Telegraph Plc

Appendix E

The Location of Pluviometers in the Onkaparinga River Catchment

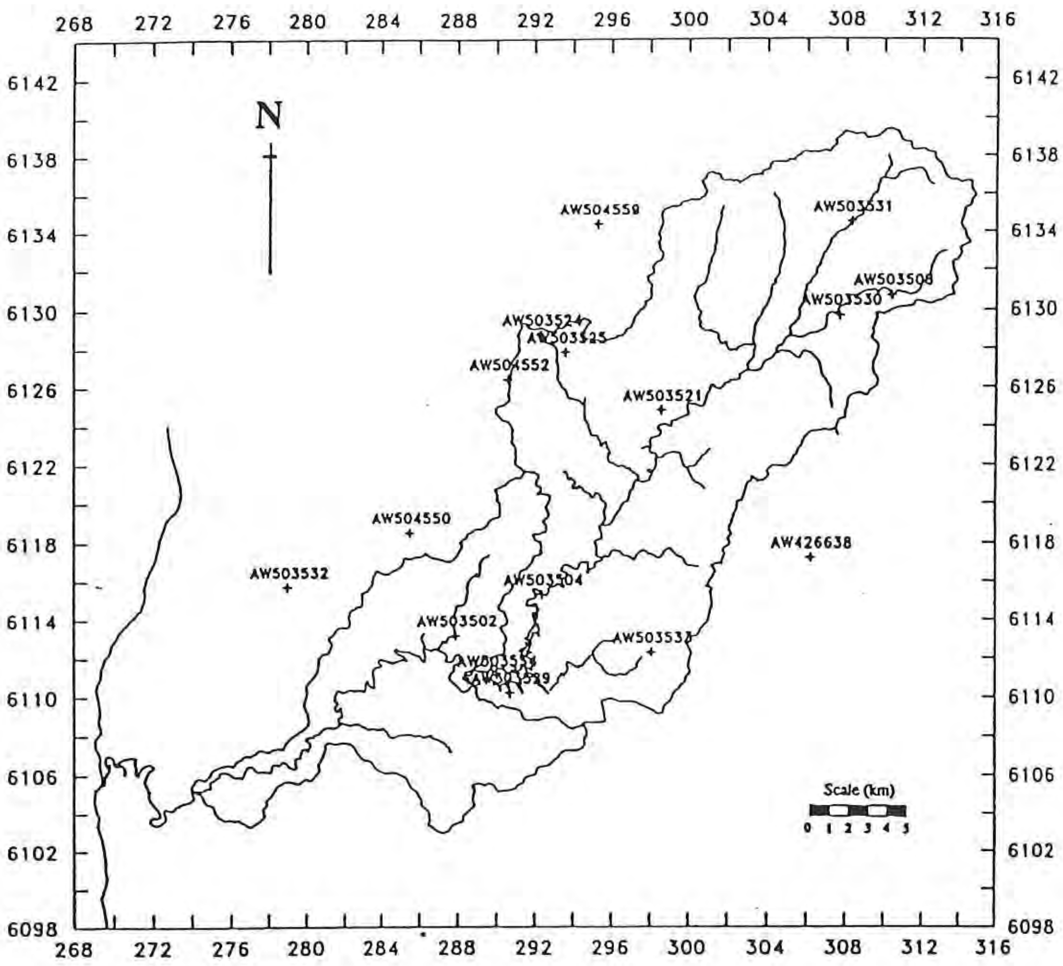


Figure E.1 Location of E&WS pluviometers in the Onkaparinga River catchment (Source: Hill, 1993)

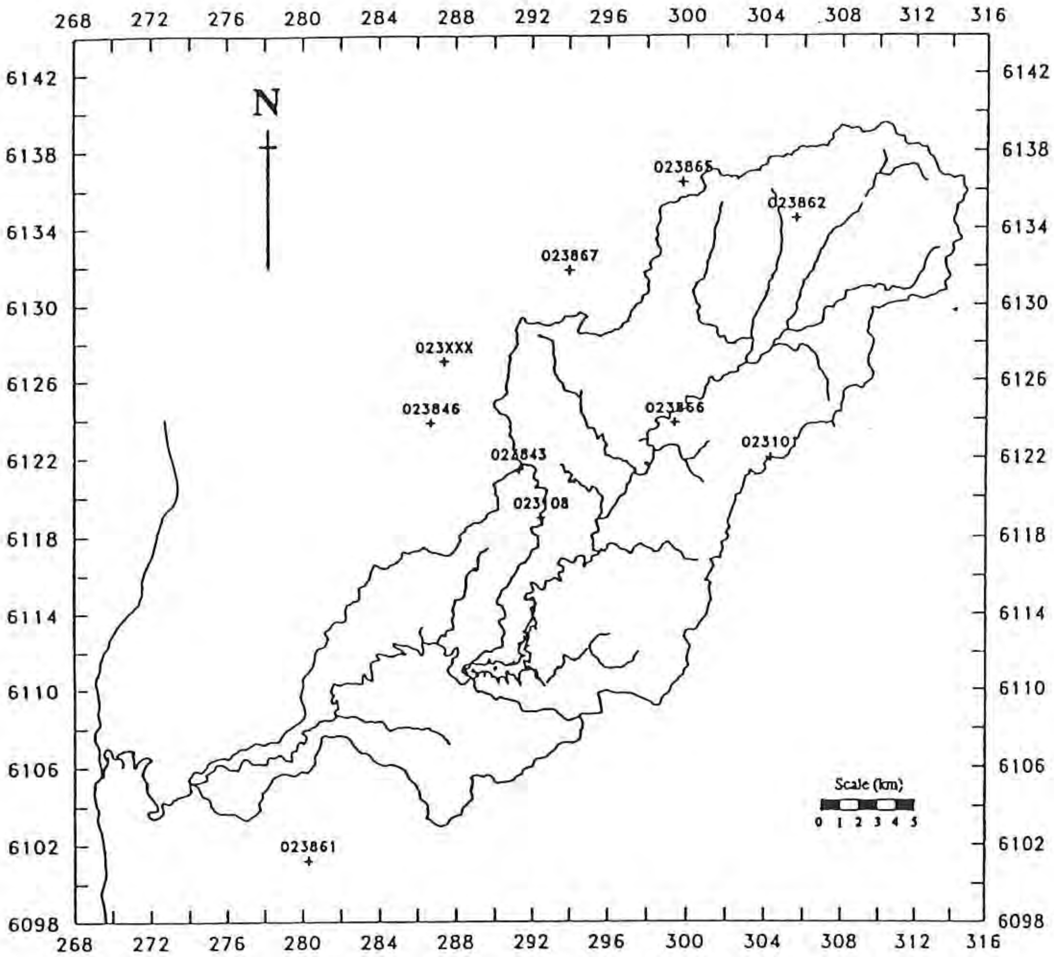


Figure E.2 Location of Bureau of Meteorology pluviometers in the Onkaparinga River catchment (Source: Hill, 1993)

Appendix F

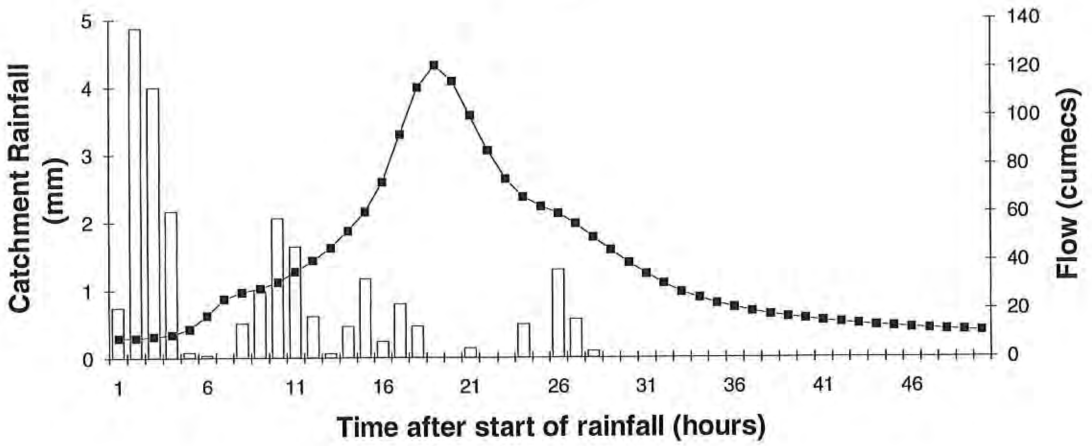
The Spatial Distribution of the Operational Pluviographs used in calculating the hyetographs for the Studied Events

Table F.1 The fraction of the total catchment area that each operational pluviograph contributes rainfall in each storm

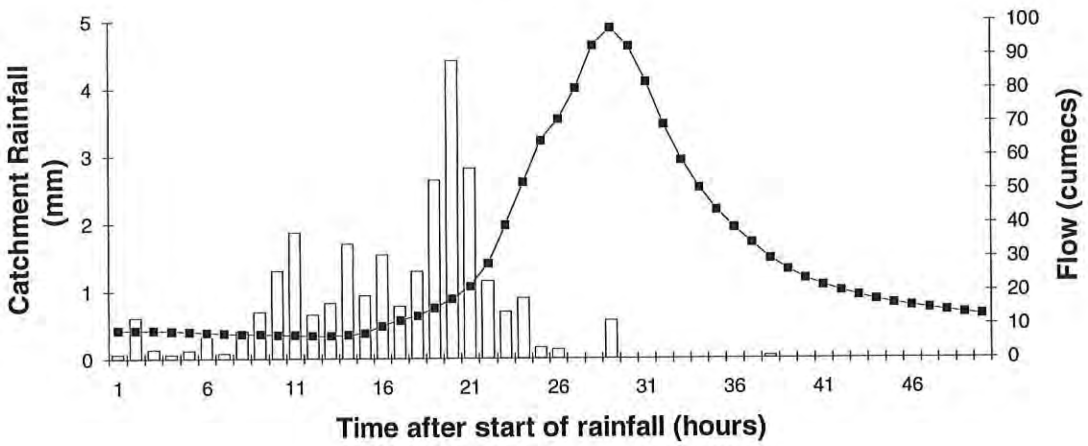
Storm	23101	23108	23862	23865	23866	AW426638	AW503502	AW503508	AW503521	AW503524	AW503525	AW503529	AW503530	AW503533	AW503534	AW504552	AW504558	AW504559
24/7/81	-	-	-	-	-	-	-	-	0.206	-	-	0.631	-	-	-	-	0.163	-
3/8/81	-	-	-	-	-	-	-	-	0.631	-	-	0.163	-	-	-	-	0.206	-
8/8/81	-	-	-	-	-	-	-	-	0.631	-	-	0.163	-	-	-	-	0.206	-
25/8/83	-	-	-	-	-	-	-	-	-	0.261	-	0.328	-	-	-	-	-	0.411
8/9/83	-	-	-	-	-	-	-	-	-	0.328	-	0.261	-	-	-	-	0.206	0.206
24/6/87	-	-	-	-	-	0.155	-	0.335	-	-	0.211	0.163	-	-	-	0.060	-	0.076
15/7/87	-	-	-	-	-	0.155	-	0.335	-	-	0.211	0.163	-	-	-	0.060	-	0.076
24/5/88	-	-	-	-	-	0.155	-	0.206	-	-	0.211	0.163	0.130	-	-	0.060	-	0.076
15/8/90	-	-	-	-	-	0.057	-	0.335	-	-	0.211	-	-	0.261	-	0.060	-	0.076
30/8/92	0.050	0.060	-	0.155	0.178	-	-	0.206	-	-	0.090	-	-	0.201	0.060	-	-	-
16/9/92	0.228	0.060	0.213	0.076	-	-	-	0.072	-	-	0.090	-	-	0.201	0.060	-	-	-
8/10/92	0.228	0.060	0.213	0.076	-	-	0.059	0.071	-	-	0.090	-	-	0.201	-	-	-	-

Appendix G
Hydrologic Characteristics of the Studied Events

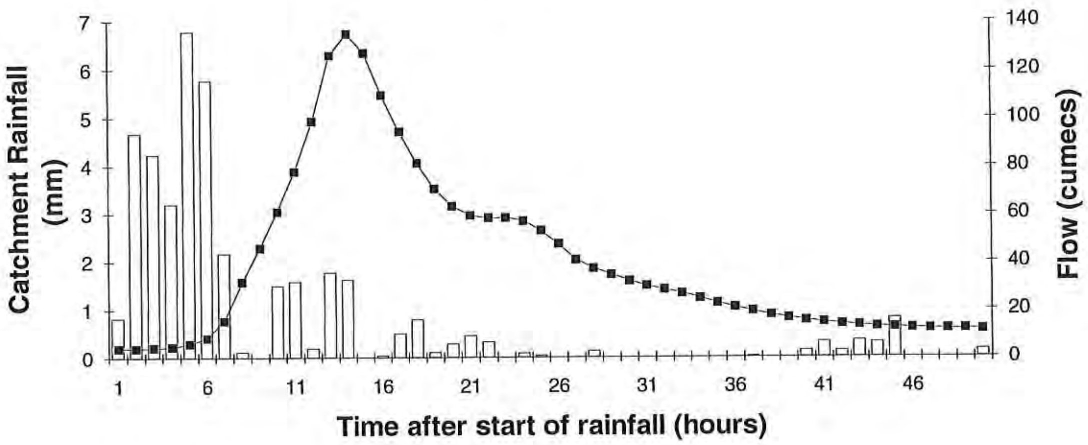
24/7/81



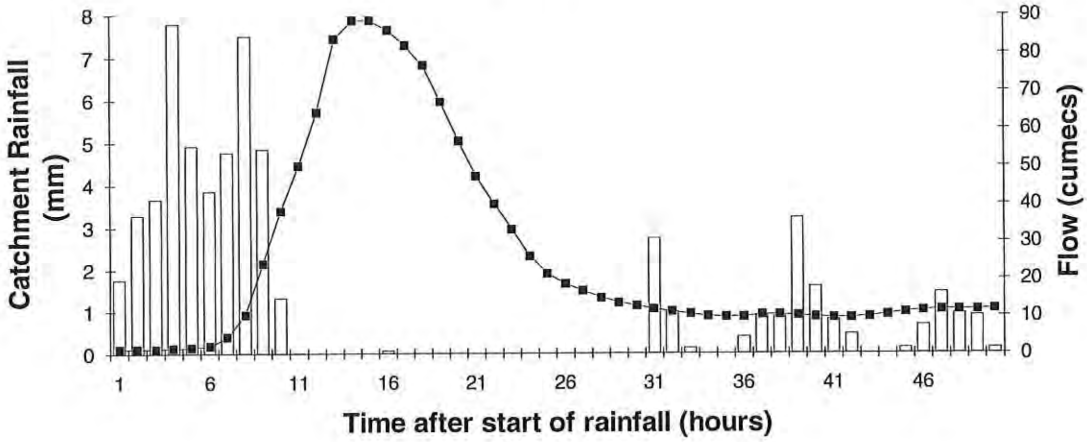
3/8/81



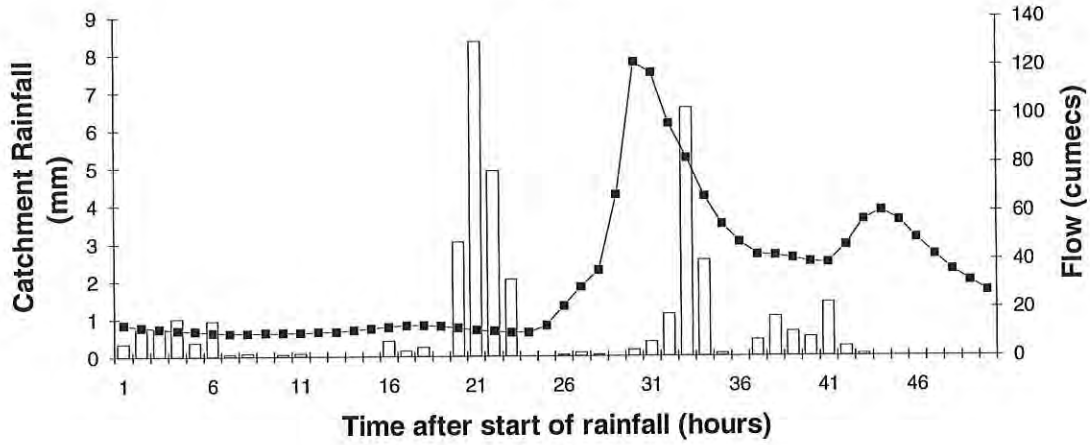
8/8/81



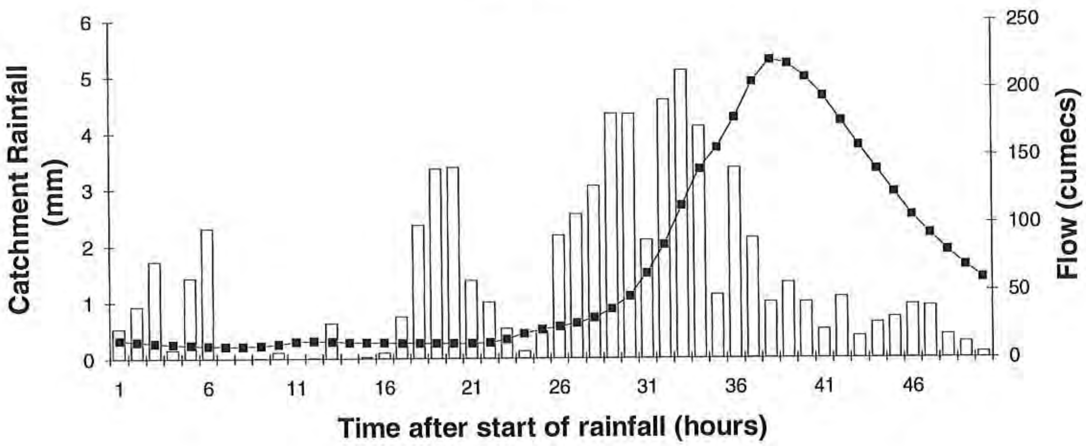
25/8/83

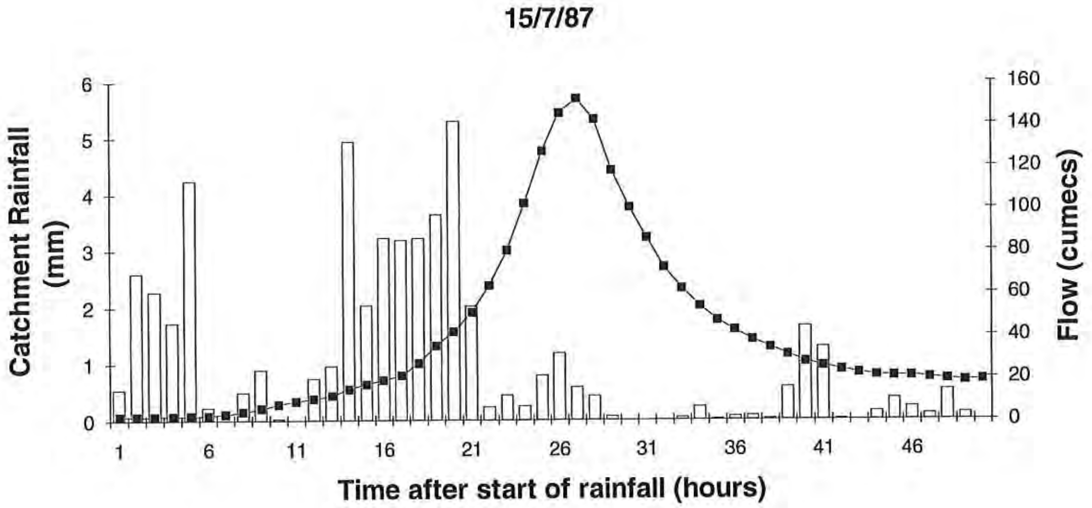


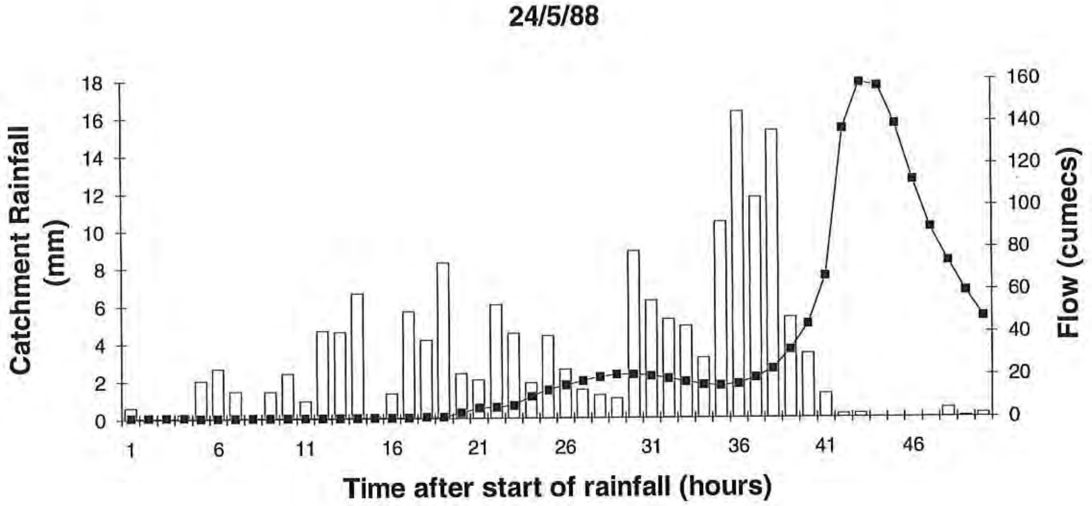
8/9/83

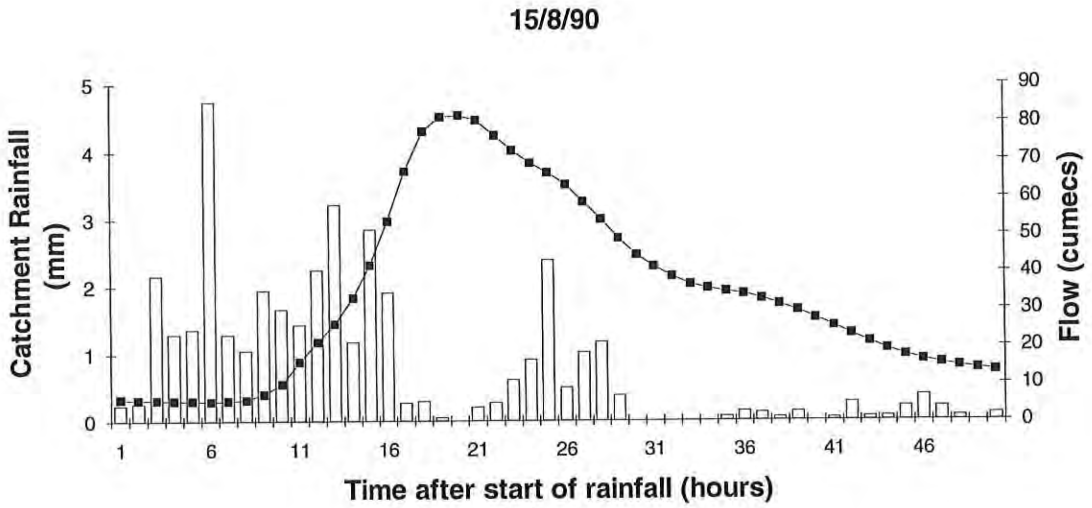


24/6/87

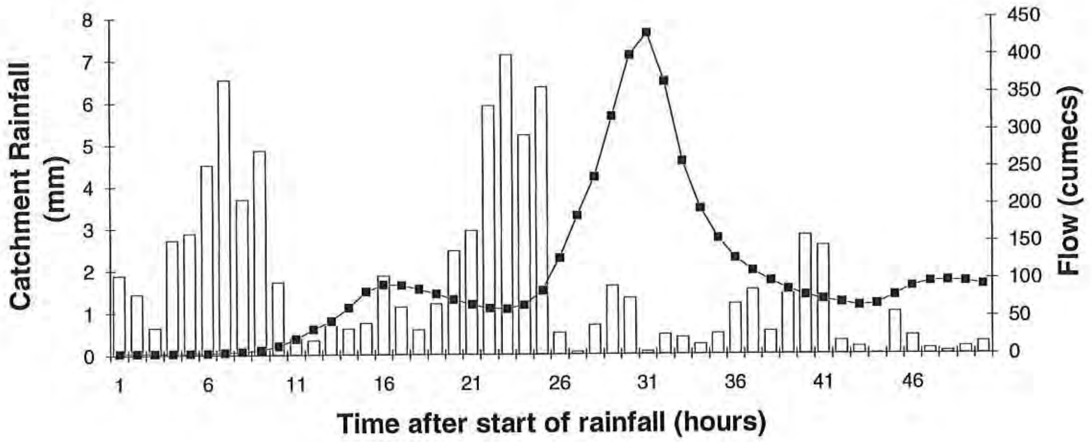



15/7/87
Catchment Rainfall (mm)
Flow (cumecs)
0
1
2
3
4
5
6
0
20
40
60
80
100
120
140
160
1
6
11
16
21
26
31
36
41
46
Time after start of rainfall (hours)

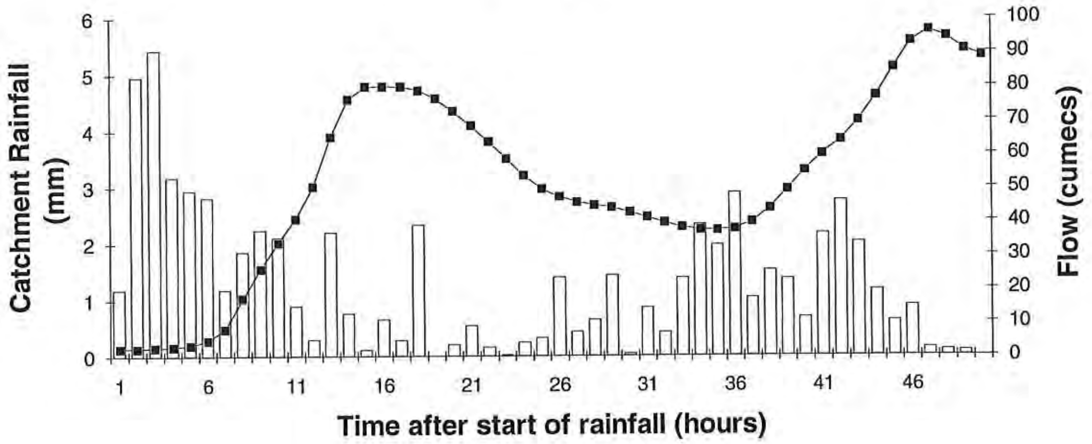

24/5/88
Catchment Rainfall (mm)
Flow (cumecs)
0
2
4
6
8
10
12
14
16
18
0
20
40
60
80
100
120
140
160
1
6
11
16
21
26
31
36
41
46
Time after start of rainfall (hours)


15/8/90
Catchment Rainfall (mm)
Flow (cumecs)
0
1
2
3
4
5
0
10
20
30
40
50
60
70
80
90
1
6
11
16
21
26
31
36
41
46
Time after start of rainfall (hours)

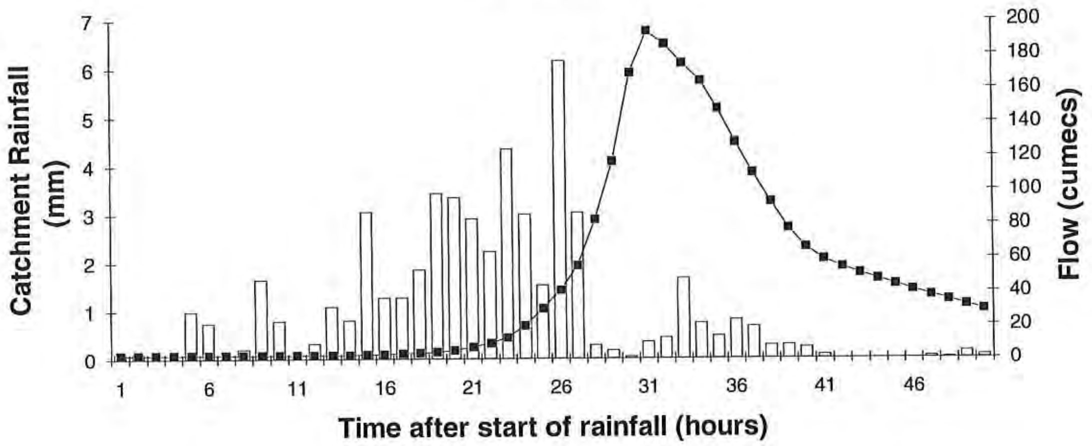
30/8/92



16/9/92



8/10/92



Appendix H

Complete Results of the Exponential Regression Analysis to Estimate Initial Loss at the Commencement of an Event for the Onkaparinga River Catchment

Table H.1 Results of Regression Analysis using Initial Loss Calibrated From RORB (Hill, 1993)

Antecedent Precipitation Index

Antecedent Period	All available storms						All available storms except 24/5/88 & 24/6/87 storms						All available storms plus antecedent period 'down'					
	$IL = a_1 . 10^{b_1 . API}$			$IL = a_2 . (\log_{10} API) + b_2$			$IL = a_1 . 10^{b_1 . API}$			$IL = a_2 . (\log_{10} API) + b_2$			$IL = a_1 . 10^{b_1 . API}$			$IL = a_2 . (\log_{10} API) + b_2$		
	a_1	b_1	R^2	a_2	b_2	R^2	a_1	b_1	R^2	a_2	b_2	R^2	a_1	b_1	R^2	a_2	b_2	R^2
7 Day	34.2	-0.00831	0.26 (14)	-12.7	38.582	0.06 (14)	26.6	-0.00545	0.40 (12)	-16.7	42.956	0.40 (12)	*	*	*	*	*	*
14 Day	22.0	-0.00258	0.08 (13)	-	-	-	23.7	-0.00357	0.46 (11)	-12.2	36.435	0.47 (11)	23.3	-0.00300	0.10 (14)	-	-	-
30 Day	26.8	-0.00421	0.11 (12)	-	-	-	30.3	-0.00577	0.68 (10)	-18.0	46.564	0.50 (10)	27.6	-0.00430	0.13 (14)	-	-	-
60 Day	27.3	-0.00452	0.10 (11)	-	-	-	29.0	-0.00546	0.54 (9)	-15.4	42.257	0.36 (9)	28.6	-0.00468	0.14 (14)	-5.9	29.023	0.01 (14)

Pre-Storm Baseflow

All available storms						All available storms except 24/5/88 and 24/6/87					
$IL = a_1 . 10^{b_1 . BF}$			$IL = a_2 . (\log_{10} API) + b_2$			$IL = a_1 . 10^{b_1 . BF}$			$IL = a_2 . (\log_{10} BF) + b_2$		
a_1	b_1	R^2	a_2	b_2	R^2	a_1	b_1	R^2	a_2	b_2	R^2
18.1	-0.00678	**0.05** (12)	-10.4	22.8	**0.08** (12)	20.4	-0.0215	**0.10** (10)	-6.5	20.74	**0.15** (10)

'-' Indicates no correlation observed

'*' Indicates analysis was not performed

( ) Indicates number of points used in regression

Table H.2 Results of Regression Analysis using Initial Loss From 'Rainfall to Hydrograph Rise'

Antecedent Precipitation Index

Antecedent Period	All available storms						All available storms except 24/5/88 & 24/6/87 storms						All available storms plus antecedent period 'down'					
	$IL = a_1 . 10^{b_1 . API}$			$IL = a_2 . (\log_{10} API) + b_2$			$IL = a_1 . 10^{b_1 . API}$			$IL = a_2 . (\log_{10} API) + b_2$			$IL = a_1 . 10^{b_1 . API}$			$IL = a_2 . (\log_{10} API) + b_2$		
	a_1	b_1	R^2	a_2	b_2	R^2	a_1	b_1	R^2	a_2	b_2	R^2	a_1	b_1	R^2	a_2	b_2	R^2
7 Day	12.7	0.00220	0.07 (12)	17.0	-8.600	0.08 (12)	41.8	-0.01505	0.54 (10)	-34.4	66.155	0.56 (10)	*	*	*	*	*	*
14 Day	11.4	0.00207	0.10 (11)	14.9	-7.010	0.06 (11)	28.3	-0.00901	0.53 (9)	-19.6	44.390	0.39 (9)	16.6	-0.00673	0.05 (12)	8.5	4.331	0.02 (12)
30 Day	8.7	0.00586	0.13 (10)	37.2	-43.298	0.19 (10)	20.6	-0.00386	0.10 (8)	-16.3	41.038	0.15 (8)	18.2	-0.00146	0.06 (12)	5.1	9.447	0.01 (12)
60 Day	5.1	0.01000	**0.21** (9)	62.1	-86.262	0.31 (9)	15.0	-0.00119	**0.02** (7)	-4.7	21.481	**0.01** (7)	19.4	-0.00205	**0.06** (12)	3.3	12.388	**0.01** (12)

Pre-Storm Baseflow

All available storms						All available storms except 24/5/88 and 24/6/87					
$IL = a_1 . 10^{b_1 . BF}$			$IL = a_2 . (\log_{10} API) + b_2$			$IL = a_1 . 10^{b_1 . BF}$			$IL = a_2 . (\log_{10} BF) + b_2$		
a_1	b_1	R^2	a_2	b_2	R^2	a_1	b_1	R^2	a_2	b_2	R^2
25.0	-0.0348	**0.23** (12)	-22.8	33.0	**0.52** (12)	22.5	-0.0376	**0.49** (10)	-15.0	24.962	**0.49** (10)

'-' Indicates no correlation observed

'*' Indicates analysis was not performed

( ) Indicates number of points used in regression

Appendix I

Example of a Training File for Real-Time Runoff Forecasting using an Artificial Neural Network Model

INPUTS											OUTPUT
Q(t)	R(t-14)	R(t-13)	R(t-12)	R(t-11)	R(t-10)	R(t-9)	R(t-8)	R(t-7)	R(t-6)	R(t-5)	Q(t+1)
11.67	0	0.396	0.919	0.876	3.222	1.588	0.804	0.459	0	0	11.86
11.05	0	0	0	0	0	0	0	0	0	0.006	10.71
13.91	0.065	0.144	0.119	0.05	0.134	0	0.042	0.278	0.057	0.064	13.38
31.86	0.476	0.813	0.67	0.279	0.287	0.232	0.074	0	0	0	29.09
31.26	0.08	0	0.439	1.058	0.662	0.517	1.429	0.265	0.062	0	26.82
11.68	0	0	0.021	0	0	0.139	0.328	0.133	0.348	0.31	11.62
13.38	0	0	0	0.041	0	0	0	0	0	0	12.84
68.59	1.126	3.373	2.136	0.995	1.34	0.994	0.504	1.085	0.39	0.629	59.47
59.36	10.39	16.28	11.71	15.27	5.294	3.396	1.27	0.196	0.209	0.006	47.39
18.57	0.017	0.067	0.077	0.024	0.58	1.658	1.289	0.017	0	0.146	18.65
90.58	1.97	2.898	1.035	1.519	1.369	0.681	2.172	2.764	2.021	1.178	88.66
11.67	0	0	0.396	0.919	0.876	3.222	1.588	0.804	0.459	0	11.67
11.39	0	0	0	0	0	0	0	0	0	0	11.05
14.51	0	0.065	0.144	0.119	0.05	0.134	0	0.042	0.278	0.057	13.91
34.87	0.739	0.476	0.813	0.67	0.279	0.287	0.232	0.074	0	0	31.86
35.83	2.566	0.08	0	0.439	1.058	0.662	0.517	1.429	0.265	0.062	31.26
11.7	0	0	0	0.021	0	0	0.139	0.328	0.133	0.348	11.68
14.02	0	0	0	0	0.041	0	0	0	0	0	13.38
79.71	4.113	1.126	3.373	2.136	0.995	1.34	0.994	0.504	1.085	0.39	68.59
73.72	3.162	10.39	16.28	11.71	15.27	5.294	3.396	1.27	0.196	0.209	59.36
19.1	0.234	0.017	0.067	0.077	0.024	0.58	1.658	1.289	0.017	0	18.57
94.27	2.335	1.97	2.898	1.035	1.519	1.369	0.681	2.172	2.764	2.021	90.58
11.67	0.132	0	0	0.396	0.919	0.876	3.222	1.588	0.804	0.459	11.67
11.76	0	0	0	0	0	0	0	0	0	0	11.39
15.32	0	0	0.065	0.144	0.119	0.05	0.134	0	0.042	0.278	14.51
37.65	1.679	0.739	0.476	0.813	0.67	0.279	0.287	0.232	0.074	0	34.87
42.06	6.589	2.566	0.08	0	0.439	1.058	0.662	0.517	1.429	0.265	35.83
11.86	0	0	0	0	0.021	0	0	0.139	0.328	0.133	11.7
14.71	0	0	0	0	0	0.041	0	0	0	0	14.02
91.87	5.11	4.113	1.126	3.373	2.136	0.995	1.34	0.994	0.504	1.085	79.71
89.58	4.851	3.162	10.39	16.28	11.71	15.27	5.294	3.396	1.27	0.196	73.72
20.07	0.044	0.234	0.017	0.067	0.077	0.024	0.58	1.658	1.289	0.017	19.1
96.18	1.388	2.335	1.97	2.898	1.035	1.519	1.369	0.681	2.172	2.764	94.27
11.47	0.991	0.132	0	0	0.396	0.919	0.876	3.222	1.588	0.804	11.67
12.22	0	0	0	0	0	0	0	0	0	0	11.76
16.29	0	0	0	0.065	0.144	0.119	0.05	0.134	0	0.042	15.32
40.73	0.436	1.679	0.739	0.476	0.813	0.67	0.279	0.287	0.232	0.074	37.65
48.92	1.114	6.589	2.566	0.08	0	0.439	1.058	0.662	0.517	1.429	42.06
12.1	0	0	0	0	0	0.021	0	0	0.139	0.328	11.86
15.43	0	0	0	0	0	0	0.041	0	0	0	14.71
105.8	4.583	5.11	4.113	1.126	3.373	2.136	0.995	1.34	0.994	0.504	91.87
112.3	5.214	4.851	3.162	10.39	16.28	11.71	15.27	5.294	3.396	1.27	89.58
20.69	0	0.044	0.234	0.017	0.067	0.077	0.024	0.58	1.658	1.289	20.07
92.84	0.42	1.388	2.335	1.97	2.898	1.035	1.519	1.369	0.681	2.172	96.18
11.03	2.736	0.991	0.132	0	0	0.396	0.919	0.876	3.222	1.588	11.47

Figure I.1 An example of a truncated portion of an ANN training file (text file, .nna extension) for Scenario 2, Training Method 1 (R/F), Lag {R(t-5),....., R(t-14)}, 1 hour forecast {Q(t+1)}, 5 previous flow inputs

Appendix J

Example of 'Flash Code' Output from the Artificial Neural Network Model for Runoff Forecasting

Example of 'Flash Code' from training using Scenario 2, Training Method 1 (R/F), Lag {R(t-5),....., R(t-14)}, 5 hour forecast {(t+1),....., (t+5)}, 5 previous flow inputs

```
/* Fri Jun 14 16:36:19 1996 (append.c) Recall-Only Run-time for <untitled> */
/*   Control Strategy is: <backprop> */

#if __STDC__
#define  ARGS(x) x
#else
#define  ARGS(x) ()
#endif /* __STDC__ */

/* --- External Routines --- */
extern double exp   ARGS((double));
/* *** MAKE SURE TO LINK IN YOUR COMPILER's MATH LIBRARIES *** */

#if __STDC__
int appendix( void *NetPtr, float Yin[15], float Yout[5] )
#else
int appendix( NetPtr, Yin, Yout )
void  *NetPtr; /* Network Pointer (not used) */
float Yin[15], Yout[5];  /* Data */
#endif /* __STDC__ */
{
   float  Xout[37]; /* work arrays */
   long   ICmpT; /* temp for comparisons */

   /* *** WARNING: Code generated assuming Recall = 0 *** */


   /* Read and scale input into network */
   Xout[2] = Yin[0] * (0.0045474803) + (-0.0022555502);
   Xout[3] = Yin[1] * (0.0045474803) + (-0.0022555502);
   Xout[4] = Yin[2] * (0.0045474803) + (-0.0022555502);
   Xout[5] = Yin[3] * (0.0045474803) + (-0.0022555502);
   Xout[6] = Yin[4] * (0.0045474803) + (-0.0022555502);
   Xout[7] = Yin[5] * (0.096222311);
   Xout[8] = Yin[6] * (0.061434876);
   Xout[9] = Yin[7] * (0.061434876);
   Xout[10] = Yin[8] * (0.061434876);
   Xout[11] = Yin[9] * (0.061434876);
   Xout[12] = Yin[10] * (0.061434876);
   Xout[13] = Yin[11] * (0.061434876);
   Xout[14] = Yin[12] * (0.061434876);
   Xout[15] = Yin[13] * (0.061434876);
   Xout[16] = Yin[14] * (0.061434876);
 LAB110:
```

```
/* Generating code for PE 0 in layer 2 */

/* Generating code for PE 1 in layer 2 */

/* Generating code for PE 2 in layer 2 */

/* Generating code for PE 3 in layer 2 */

/* Generating code for PE 4 in layer 2 */

/* Generating code for PE 5 in layer 2 */

/* Generating code for PE 6 in layer 2 */

/* Generating code for PE 7 in layer 2 */

/* Generating code for PE 8 in layer 2 */

/* Generating code for PE 9 in layer 2 */

/* Generating code for PE 10 in layer 2 */

/* Generating code for PE 11 in layer 2 */

/* Generating code for PE 12 in layer 2 */

/* Generating code for PE 13 in layer 2 */

/* Generating code for PE 14 in layer 2 */

/* Generating code for PE 0 in layer 3 */
Xout[17]  = (float)(0.15051877) + (float)(0.56424439) * Xout[2] +
   (float)(0.25435311) * Xout[3] + (float)(-0.19996831) * Xout[4] +
   (float)(-0.93406767) * Xout[5] + (float)(-2.0477102) * Xout[6] +
   (float)(0.1117599) * Xout[7] + (float)(0.18076871) * Xout[8] +
   (float)(0.17473236) * Xout[9] + (float)(0.27302328) * Xout[10] +
   (float)(0.093231484) * Xout[11] + (float)(0.056088224) * Xout[12] +
   (float)(-0.2337473) * Xout[13] + (float)(-0.43692863) * Xout[14] +
   (float)(-0.55049312) * Xout[15] + (float)(-0.89749092) * Xout[16];
Xout[17] = 1.0 / (1.0 + exp( -Xout[17] ));

/* Generating code for PE 1 in layer 3 */
Xout[18]  = (float)(-0.2584469) + (float)(-0.04702463) * Xout[2] +
   (float)(-0.17768383) * Xout[3] + (float)(-0.16219962) * Xout[4] +
   (float)(-0.31325227) * Xout[5] + (float)(-0.47725064) * Xout[6] +
   (float)(0.10288613) * Xout[7] + (float)(-0.060536806) * Xout[8] +
   (float)(0.056008056) * Xout[9] + (float)(-0.021238836) * Xout[10] +
   (float)(-0.0063244989) * Xout[11] + (float)(0.05714488) * Xout[12] +
   (float)(-0.10898693) * Xout[13] + (float)(-0.18003039) * Xout[14] +
   (float)(-0.2187476) * Xout[15] + (float)(-0.24052572) * Xout[16];
Xout[18] = 1.0 / (1.0 + exp( -Xout[18] ));
```

```
/* Generating code for PE 2 in layer 3 */
Xout[19] = (float)(-0.15962651) + (float)(-0.42676973) * Xout[2] +
   (float)(-0.41370264) * Xout[3] + (float)(-0.25270638) * Xout[4] +
   (float)(0.032348685) * Xout[5] + (float)(0.40904981) * Xout[6] +
   (float)(-0.22477138) * Xout[7] + (float)(-0.24564569) * Xout[8] +
   (float)(-0.26517168) * Xout[9] + (float)(-0.29256472) * Xout[10] +
   (float)(-0.27314591) * Xout[11] + (float)(-0.18217923) * Xout[12] +
   (float)(-0.17832233) * Xout[13] + (float)(-0.13615638) * Xout[14] +
   (float)(0.013737595) * Xout[15] + (float)(0.28736356) * Xout[16];
Xout[19] = 1.0 / (1.0 + exp( -Xout[19] ));

/* Generating code for PE 3 in layer 3 */
Xout[20] = (float)(-0.23879623) + (float)(0.050911091) * Xout[2] +
   (float)(0.046776023) * Xout[3] + (float)(-0.23234499) * Xout[4] +
   (float)(-0.66800845) * Xout[5] + (float)(-1.3425829) * Xout[6] +
   (float)(0.037236035) * Xout[7] + (float)(0.0092537757) * Xout[8] +
   (float)(0.0517735) * Xout[9] + (float)(0.12710245) * Xout[10] +
   (float)(0.15056022) * Xout[11] + (float)(0.005630306) * Xout[12] +
   (float)(-0.16055273) * Xout[13] + (float)(-0.11549558) * Xout[14] +
   (float)(-0.2929751) * Xout[15] + (float)(-0.55273056) * Xout[16];
Xout[20] = 1.0 / (1.0 + exp( -Xout[20] ));

/* Generating code for PE 4 in layer 3 */
Xout[21] = (float)(-0.13889739) + (float)(0.29278952) * Xout[2] +
   (float)(0.038162965) * Xout[3] + (float)(-0.28170344) * Xout[4] +
   (float)(-0.77351052) * Xout[5] + (float)(-1.6361622) * Xout[6] +
   (float)(-0.019188376) * Xout[7] + (float)(0.0093127964) * Xout[8] +
   (float)(0.079433188) * Xout[9] + (float)(0.017630046) * Xout[10] +
   (float)(0.13625421) * Xout[11] + (float)(-0.018075993) * Xout[12] +
   (float)(-0.090476751) * Xout[13] + (float)(-0.27749357) * Xout[14] +
   (float)(-0.40308866) * Xout[15] + (float)(-0.7085976) * Xout[16];
Xout[21] = 1.0 / (1.0 + exp( -Xout[21] ));

/* Generating code for PE 5 in layer 3 */
Xout[22] = (float)(-0.3804484) + (float)(0.13317597) * Xout[2] +
   (float)(-0.063112803) * Xout[3] + (float)(-0.042878583) * Xout[4] +
   (float)(-0.11039671) * Xout[5] + (float)(-0.42190388) * Xout[6] +
   (float)(0.10730614) * Xout[7] + (float)(0.1299486) * Xout[8] +
   (float)(0.0076055867) * Xout[9] + (float)(0.10765942) * Xout[10] +
   (float)(-0.019797627) * Xout[11] + (float)(-0.048571568) * Xout[12] +
   (float)(0.016676888) * Xout[13] + (float)(-0.16121399) * Xout[14] +
   (float)(-0.23397133) * Xout[15] + (float)(-0.2969985) * Xout[16];
Xout[22] = 1.0 / (1.0 + exp( -Xout[22] ));
```

```
/* Generating code for PE 6 in layer 3 */
Xout[23]  = (float)(-0.37515405) + (float)(-0.0028106279) * Xout[2] +
   (float)(-0.16559003) * Xout[3] + (float)(-0.095782071) * Xout[4] +
   (float)(-0.29814705) * Xout[5] + (float)(-0.37237951) * Xout[6] +
   (float)(-0.088238448) * Xout[7] + (float)(0.042285629) * Xout[8] +
   (float)(-0.087195463) * Xout[9] + (float)(-0.10367201) * Xout[10] +
   (float)(0.0030269129) * Xout[11] + (float)(0.038528312) * Xout[12] +
   (float)(-0.14900121) * Xout[13] + (float)(-0.21192354) * Xout[14] +
   (float)(-0.20913412) * Xout[15] + (float)(-0.26289719) * Xout[16];
Xout[23] = 1.0 / (1.0 + exp( -Xout[23] ));

/* Generating code for PE 7 in layer 3 */
Xout[24]  = (float)(-0.18771215) + (float)(0.46071109) * Xout[2] +
   (float)(0.21164198) * Xout[3] + (float)(0.068009719) * Xout[4] +
   (float)(-0.51976085) * Xout[5] + (float)(-1.1058261) * Xout[6] +
   (float)(0.25471079) * Xout[7] + (float)(0.24362631) * Xout[8] +
   (float)(0.18636988) * Xout[9] + (float)(0.26689571) * Xout[10] +
   (float)(0.19557519) * Xout[11] + (float)(0.18372579) * Xout[12] +
   (float)(0.058759857) * Xout[13] + (float)(-0.15922497) * Xout[14] +
   (float)(-0.33320889) * Xout[15] + (float)(-0.4963727) * Xout[16];
Xout[24] = 1.0 / (1.0 + exp( -Xout[24] ));

/* Generating code for PE 8 in layer 3 */
Xout[25]  = (float)(-0.2521643) + (float)(0.2654959) * Xout[2] +
   (float)(0.041435938) * Xout[3] + (float)(0.051798239) * Xout[4] +
   (float)(-0.2952188) * Xout[5] + (float)(-0.64027196) * Xout[6] +
   (float)(0.0034089976) * Xout[7] + (float)(0.14114481) * Xout[8] +
   (float)(0.1179435) * Xout[9] + (float)(0.033464529) * Xout[10] +
   (float)(0.037341408) * Xout[11] + (float)(-0.084738053) * Xout[12] +
   (float)(-0.13575262) * Xout[13] + (float)(-0.14954807) * Xout[14] +
   (float)(-0.39155602) * Xout[15] + (float)(-0.47556716) * Xout[16];
Xout[25] = 1.0 / (1.0 + exp( -Xout[25] ));

/* Generating code for PE 9 in layer 3 */
Xout[26]  = (float)(-0.33962968) + (float)(0.085699834) * Xout[2] +
   (float)(-0.12451591) * Xout[3] + (float)(-0.24923514) * Xout[4] +
   (float)(-0.36635578) * Xout[5] + (float)(-0.6015678) * Xout[6] +
   (float)(-0.035976581) * Xout[7] + (float)(0.03464343) * Xout[8] +
   (float)(0.087096035) * Xout[9] + (float)(0.017091846) * Xout[10] +
   (float)(0.075175181) * Xout[11] + (float)(-0.047900148) * Xout[12] +
   (float)(-0.14150132) * Xout[13] + (float)(-0.18170077) * Xout[14] +
   (float)(-0.23768406) * Xout[15] + (float)(-0.40547335) * Xout[16];
Xout[26] = 1.0 / (1.0 + exp( -Xout[26] ));
```

```
/* Generating code for PE 10 in layer 3 */
Xout[27] = (float)(-0.20591424) + (float)(-0.35370305) * Xout[2] +
   (float)(-0.33677846) * Xout[3] + (float)(-0.46602362) * Xout[4] +
   (float)(-0.31503925) * Xout[5] + (float)(-0.31063369) * Xout[6] +
   (float)(-0.13247655) * Xout[7] + (float)(0.004245501) * Xout[8] +
   (float)(-0.095692627) * Xout[9] + (float)(-0.072333463) * Xout[10] +
   (float)(-0.061676543) * Xout[11] + (float)(-0.041723628) * Xout[12] +
   (float)(-0.077325158) * Xout[13] + (float)(0.045587044) * Xout[14] +
   (float)(0.072612703) * Xout[15] + (float)(0.18614095) * Xout[16];
Xout[27] = 1.0 / (1.0 + exp( -Xout[27] ));

/* Generating code for PE 11 in layer 3 */
Xout[28] = (float)(-0.25582096) + (float)(-0.20807277) * Xout[2] +
   (float)(-0.1892539) * Xout[3] + (float)(-0.28787866) * Xout[4] +
   (float)(0.023982152) * Xout[5] + (float)(0.24292332) * Xout[6] +
   (float)(-0.19558838) * Xout[7] + (float)(-0.07671161) * Xout[8] +
   (float)(-0.20170982) * Xout[9] + (float)(-0.16665772) * Xout[10] +
   (float)(-0.25984845) * Xout[11] + (float)(-0.22910324) * Xout[12] +
   (float)(-0.14052953) * Xout[13] + (float)(-0.13036203) * Xout[14] +
   (float)(-0.04279029) * Xout[15] + (float)(0.129917) * Xout[16];
Xout[28] = 1.0 / (1.0 + exp( -Xout[28] ));

/* Generating code for PE 12 in layer 3 */
Xout[29] = (float)(-0.019264759) + (float)(0.24345189) * Xout[2] +
   (float)(-0.068368852) * Xout[3] + (float)(-0.43912908) * Xout[4] +
   (float)(-1.0846014) * Xout[5] + (float)(-1.9372557) * Xout[6] +
   (float)(0.043216564) * Xout[7] + (float)(0.042032965) * Xout[8] +
   (float)(0.10811631) * Xout[9] + (float)(-0.00019341033) * Xout[10] +
   (float)(-0.030740427) * Xout[11] + (float)(-0.1431866) * Xout[12] +
   (float)(-0.1452598) * Xout[13] + (float)(-0.3729147) * Xout[14] +
   (float)(-0.47637764) * Xout[15] + (float)(-0.61580455) * Xout[16];
Xout[29] = 1.0 / (1.0 + exp( -Xout[29] ));

/* Generating code for PE 13 in layer 3 */
Xout[30] = (float)(-0.26060101) + (float)(-0.030073948) * Xout[2] +
   (float)(-0.095843367) * Xout[3] + (float)(-0.069369093) * Xout[4] +
   (float)(-0.28643447) * Xout[5] + (float)(-0.47902611) * Xout[6] +
   (float)(0.049482785) * Xout[7] + (float)(0.070262574) * Xout[8] +
   (float)(0.10447577) * Xout[9] + (float)(-0.034682252) * Xout[10] +
   (float)(0.087689355) * Xout[11] + (float)(-0.051488508) * Xout[12] +
   (float)(-0.1121773) * Xout[13] + (float)(-0.2457439) * Xout[14] +
   (float)(-0.2755985) * Xout[15] + (float)(-0.4197883) * Xout[16];
Xout[30] = 1.0 / (1.0 + exp( -Xout[30] ));
```

```
/* Generating code for PE 14 in layer 3 */
Xout[31] = (float)(-0.21324785) + (float)(0.29103464) * Xout[2] +
   (float)(0.081147186) * Xout[3] + (float)(-0.36002126) * Xout[4] +
   (float)(-0.85425913) * Xout[5] + (float)(-1.4356953) * Xout[6] +
   (float)(0.095336773) * Xout[7] + (float)(-0.0056883441) * Xout[8] +
   (float)(0.0040121656) * Xout[9] + (float)(0.18316858) * Xout[10] +
   (float)(-0.033140674) * Xout[11] + (float)(-0.15785928) * Xout[12] +
   (float)(-0.26781452) * Xout[13] + (float)(-0.34146672) * Xout[14] +
   (float)(-0.43444768) * Xout[15] + (float)(-0.55156559) * Xout[16];
Xout[31] = 1.0 / (1.0 + exp( -Xout[31] ));

/* Generating code for PE 0 in layer 4 */
Xout[32] = (float)(1.1415792) + (float)(-1.012159) * Xout[17] +
   (float)(-0.18087691) * Xout[18] + (float)(0.16484514) * Xout[19] +
   (float)(-0.70577544) * Xout[20] + (float)(-0.76449627) * Xout[21] +
   (float)(-0.00014890368) * Xout[22] + (float)(-0.06127426) * Xout[23] +
   (float)(-0.45440757) * Xout[24] + (float)(-0.081921354) * Xout[25] +
   (float)(-0.2129706) * Xout[26] + (float)(-0.43294546) * Xout[27] +
   (float)(0.1710963) * Xout[28] + (float)(-1.083532) * Xout[29] +
   (float)(-0.034983236) * Xout[30] + (float)(-0.70328248) * Xout[31];
Xout[32] = 1.0 / (1.0 + exp( -Xout[32] ));

/* Generating code for PE 1 in layer 4 */
Xout[33] = (float)(0.88656414) + (float)(-1.0856864) * Xout[17] +
   (float)(-0.12159654) * Xout[18] + (float)(0.51328516) * Xout[19] +
   (float)(-0.62500232) * Xout[20] + (float)(-0.84968156) * Xout[21] +
   (float)(-0.013055215) * Xout[22] + (float)(-0.10012213) * Xout[23] +
   (float)(-0.58030236) * Xout[24] + (float)(-0.069324933) * Xout[25] +
   (float)(-0.22246362) * Xout[26] + (float)(-0.034222394) * Xout[27] +
   (float)(0.44296408) * Xout[28] + (float)(-1.0697694) * Xout[29] +
   (float)(-0.1494503) * Xout[30] + (float)(-0.78778225) * Xout[31];
Xout[33] = 1.0 / (1.0 + exp( -Xout[33] ));

/* Generating code for PE 2 in layer 4 */
Xout[34] = (float)(0.79677379) + (float)(-1.174497) * Xout[17] +
   (float)(-0.023173409) * Xout[18] + (float)(0.60265011) * Xout[19] +
   (float)(-0.67307419) * Xout[20] + (float)(-0.81897509) * Xout[21] +
   (float)(-0.1774347) * Xout[22] + (float)(0.017062386) * Xout[23] +
   (float)(-0.61348754) * Xout[24] + (float)(-0.30237934) * Xout[25] +
   (float)(-0.16006202) * Xout[26] + (float)(0.19617867) * Xout[27] +
   (float)(0.39018273) * Xout[28] + (float)(-0.91299158) * Xout[29] +
   (float)(-0.12637347) * Xout[30] + (float)(-0.69751072) * Xout[31];
Xout[34] = 1.0 / (1.0 + exp( -Xout[34] ));
```

```
    /* Generating code for PE 3 in layer 4 */
    Xout[35] = (float)(0.4620848) + (float)(-1.1042488) * Xout[17] +
      (float)(-0.0040111607) * Xout[18] + (float)(0.63516802) * Xout[19] +
      (float)(-0.4950152) * Xout[20] + (float)(-0.69906956) * Xout[21] +
      (float)(-0.15298688) * Xout[22] + (float)(0.024035059) * Xout[23] +
      (float)(-0.61916649) * Xout[24] + (float)(-0.37215877) * Xout[25] +
      (float)(-0.13769931) * Xout[26] + (float)(0.44326794) * Xout[27] +
      (float)(0.42466435) * Xout[28] + (float)(-0.82432663) * Xout[29] +
      (float)(-0.14980504) * Xout[30] + (float)(-0.60969347) * Xout[31];
    Xout[35] = 1.0 / (1.0 + exp( -Xout[35] ));

    /* Generating code for PE 4 in layer 4 */
    Xout[36] = (float)(-0.018335655) + (float)(-0.74335462) * Xout[17] +
      (float)(-0.075229228) * Xout[18] + (float)(0.48333579) * Xout[19] +
      (float)(-0.2202632) * Xout[20] + (float)(-0.50891531) * Xout[21] +
      (float)(-0.13222863) * Xout[22] + (float)(-0.097571284) * Xout[23] +
      (float)(-0.47163862) * Xout[24] + (float)(-0.30542621) * Xout[25] +
      (float)(-0.18258066) * Xout[26] + (float)(0.36617547) * Xout[27] +
      (float)(0.25775909) * Xout[28] + (float)(-0.48590299) * Xout[29] +
      (float)(-0.10568183) * Xout[30] + (float)(-0.43499732) * Xout[31];
    Xout[36] = 1.0 / (1.0 + exp( -Xout[36] ));

    /* De-scale and write output from network */
    Yout[0] = Xout[32] * (366.50332) + (-72.804665);
    Yout[1] = Xout[33] * (366.50332) + (-72.804665);
    Yout[2] = Xout[34] * (366.50332) + (-72.804665);
    Yout[3] = Xout[35] * (393.905) + (-78.285002);
    Yout[4] = Xout[36] * (529.49167) + (-105.40234);
    return( 0 );
}
```