An Improved Genetic Algorithm For Rainfall-Runoff Model Calibration

JOHN G. NDIRITU
BSc (Hons), MSc

Thesis Submitted for the Degree of Doctor of Philosophy

in

The University of Adelaide
(Faculty of Engineering)

August 1998

ABSTRACT

The traditional binary coded genetic algorithm method has been improved using an automatic search range variation procedure and the use of independent subpopulation searches coupled with shuffling. The range variation procedure consists of a finetuning and a hillclimbing operation. The finetuning operation enables the genetic algorithm to close in on the optimum through a gradual reduction in the size of the discretizations of the search space. The hillclimbing operation consists of shifts of the search towards the promising regions. Hillclimbing also helps to maintain robustness of the search in the presence of the finetuning operation. The use of independent subpopulations coupled with shuffling is an explicit approach for dealing with the existence of multiple regions of attraction in the search space.

The improved genetic algorithm effectively located the known global optima of a synthetic data-based rainfall-runoff model calibration problem and two theoretical functions with success rates varying between 97 and 100 percent. The traditional genetic algorithm achieved only 14 percent success with one of the functions but otherwise failed totally. The improved genetic algorithm also gave consistently better objective function values in tests applying a 7 parameter rainfall-runoff model and historical data. The validation results of a 14 parameter conceptual-empirical model obtained with the improved genetic algorithm gave higher coefficients of efficiency and lower absolute deviations than those obtained with the traditional genetic algorithm.

The improved genetic algorithm achieved the same level of effectiveness compared with the shuffled complex evolution which is an approach that has been found to be robust in rainfall-runoff model calibration and in the optimization of other continuous functions. The efficiency of the improved genetic algorithm, quantified by the number of function evaluations required to obtain the global optimum was however, on the average, lower than that of the shuffled complex evolution method.

In addition to the research on optimization, a class of simple conceptual-empirical rainfall-runoff models has been developed. The development started with a simple empirical model, was closely guided by genetic algorithm calibration and was achieved through the stepwise representation of more catchment processes as the results at each stage suggested.

The models were termed as simple time domain tuned (STDT) models owing to their greater bias towards the time domain than is customary in conceptual rainfall-runoff modelling. Two of the models, the STDT3 and the STDT4 were considered to be of acceptable performance when tested on an Australian catchment data. The two models determine total flow as the sum of a slow and a quick flow. The slow flow is obtained from the sum of the past net rainfalls up to a period obtained by calibration. The contribution of the current net rainfall to quick flow varies according to the catchment wetness state. The catchment wetness state depends on the antecedent catchment wetness which is taken as the slow flow. The SDTD4 model was found to perform acceptably with four other catchments but to fail in the calibration of one catchment. The failure could be attributed to either inadequate model structure or poor data quality or both. A comparison of the STDT3 and the STDT4 with the MODHYDROLOG model in monthly flow simulations of three Australian catchments showed that the STDT4 could perform just as adequately or even better than the MODHYDROLOG. The STDT3 failed to locate the peak flows of the driest of the three catchments while MODHYDROLOG overestimated some of the high flows of the wettest catchment.

STATEMENT OF ORIGINALITY

This thesis 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 made available for loan and photocopying.

Signed Date 11 AUGUST 1998

John G. Ndiritu

ACKNOWLEDGMENTS

I thank the Australian Agency for International Development (AusAID) for the scholarship award that enabled me to undertake the PhD work.

I wish to thank my supervisor Trevor Daniell for the cooperation, guidance and ideas he provided throughout the course of the research. Through his guidance I also improved my presentation skills considerably. This is gratefully acknowledged.

I also wish to thank Dr. Qingyun Duan of National Weather Service of the National Oceanic and Atmospheric Administration of the USA, Professors Soroosh Sorooshian and Vijai Gupta of the University of Arizona, USA for providing the source code for the SIXPAR rainfall-runoff model and the accompanying data.

I also thank Dr. Francis Chiew of the Centre for Environmental Applied Hydrology, University of Melbourne for providing the source code for the MODHYDROLOG model.

The Australian hydrological data used in this research was prepared and provided by Chiew F. H. S. and McMahon T. A. of the Centre for Environmental Applied Hydrology, University of Melbourne. This is gratefully acknowledged. Records from climate stations of the Australian Bureau of Meteorology and river gauging records from the Engineering and Water Supply Department of South Australia, the Queensland Water Resources Commission and the Western Australia Water Authority were used to prepare the data.

I thank the staff of the Kenyan Ministry of Land Reclamation, Regional and Water Development, the Kenyan Meteorological Department and the Kenyan Drought Monitoring Centre for their assistance during the data collection phase of the project. Special thanks go to J. Kariuki of the Kenyan Ministry of Land Reclamation, Regional and Water Development and P. G. Ambenje of Kenyan Drought Monitoring Centre.

Dr Stephen Carr, the department's Computing Officer offered valuable assistance at various times during the course of the research and his assistance is gratefully acknowledged. Many postgraduate students in the department, especially Matthew Burnet often provided the needed assistance when computer system problems were encountered and their assistance is acknowledged.

I am also grateful for the support and cooperation of the members of the Brahma Kumaris Raja Yoga Centres of Australia in Adelaide and the other Australian cities I visited over the four year stay in Australia.

I lastly acknowledge God's support. This helped to free me from tension and stress in face of the heavy workload especially in the last few months of the PhD program. It also made easy the difficulties I faced in the course of the research.

LIST OF PUBLICATIONS

Following is a list of the publications related to the to the research presented in this thesis.

Ndiritu, J. G., and Daniell, T. M., A Simple Time Domain Tuned Rainfall-Runoff Model Optimized Using Genetic Algorithms, *Proc., Twenty third Hydrol. and Water Resour. Symp.*, Hobart, Australia, Vol. 2, 711-713, 1996.

Ndiritu, J. G., and Daniell, T. M., Time Domain Tuned Rainfall-Runoff Models Optimized Using Genetic Algorithms, in Zannetti, P., and Brebbia, C. A., (Eds.), *Proc., Int. Conf. on Dev. and appl. of Computer Techniques to Env. studies,* Comp. Mech. Publ., Southampton, Boston , 268-275, 1996.

Ndiritu, J. G., and Daniell, T. M., An Improved Genetic Algorithm for Rainfall-Runoff Model Calibration and Function Optimization, *Proc., MODSIM* 97, *Int. Congress on Modelling and Simulation,* Hobart, Tasmania, Vol. 4, 1683-1688, 1997.

List of Contents

LIST OF FIGURES

Chapter Five

Chapter Six

Chapter Seven

Appendix A4

Appendix A5

Appendix A6

Appendix A7

LIST OF TABLES

Chapter Six

Chapter Seven

Appendix A4

Appendix A5

GLOSSARY

CRS-2	Comparative random search
DRMS	Daily root mean square
GA	Genetic algorithm
HMLE	Heteroscedastic maximum likelihood estimator
MSX	Multistart simplex
PET	Potential evapotranspiration
PEV	Pan evaporation
RGS	River gauging station
SCE-UA	Shuffled complex evolution
SCE-1	A version of the SCE-UA method
SCE-2	A version of the SCE-UA method
SEMP	Simple empirical
SLS	Simple least squares
STDT	Simple time domain tuned
WLS	Weighted least squares

NOTATION

Throughout the thesis, the notations are described as they are applied. Following are the notations that are applied frequently in the thesis.

ade	Absolute deviation
a-eval	Average number of function evaluations used for the successful trials
$arun_t$	Observed discharge in period *t*
bias	Bias
c	Probability of crossover
cc	Correlation coefficient
ce	Coefficient of efficiency
cheperf	Convergence parameter
ep_{max}	Maximum number of epochs
eval	Number of function evaluations
ev_{max}	Maximum number of function evaluations
f_{scale}	Fitness scaling index
g_{max}	Maximum number of generations per optimization
l	Bit length of parameter substring
m	Probability of mutation
nc	Number of complexes of the SCE-2 method
n_{cross}	Number of crossover positions
nf	Number of times an optimization method failed to locate the global optimum
np	Population size of the SCE-1 and the CRS-2 method

n_s	Number of subpopulations
ns	Number of subpopulations of the fully modified GA
nst	Number of starts of the MSX method
obf	Objective function value
P	GA population size
pet_t	Potential evapotranspiration in period t
p_s	GA subpopulation size
$r1_{max}$	Finetuning parameter to check range enlargement
$r1_{min}$	Finetuning parameter to check premature convergence
$rmcc1$	Residual mass curve coefficient
$rmcc2$	Residual mass curve coefficient
$rmcc3$	Residual mass curve coefficient
rn_t	Net rainfall in period t
r_t	Rainfall in period t
run_t	Estimated discharge in period t
s	Number or the percent of successful runs
$s1$	Number of previous generations used in finetuning
$s2$	Number of generations to repeat finetuning
$s3$	Number of previous generations used in hillclimbing
$s4$	Number of generations to repeat hillclimbing
t_o	Tournament size
u_{cross}	Rate of uniform crossover

Chapter One

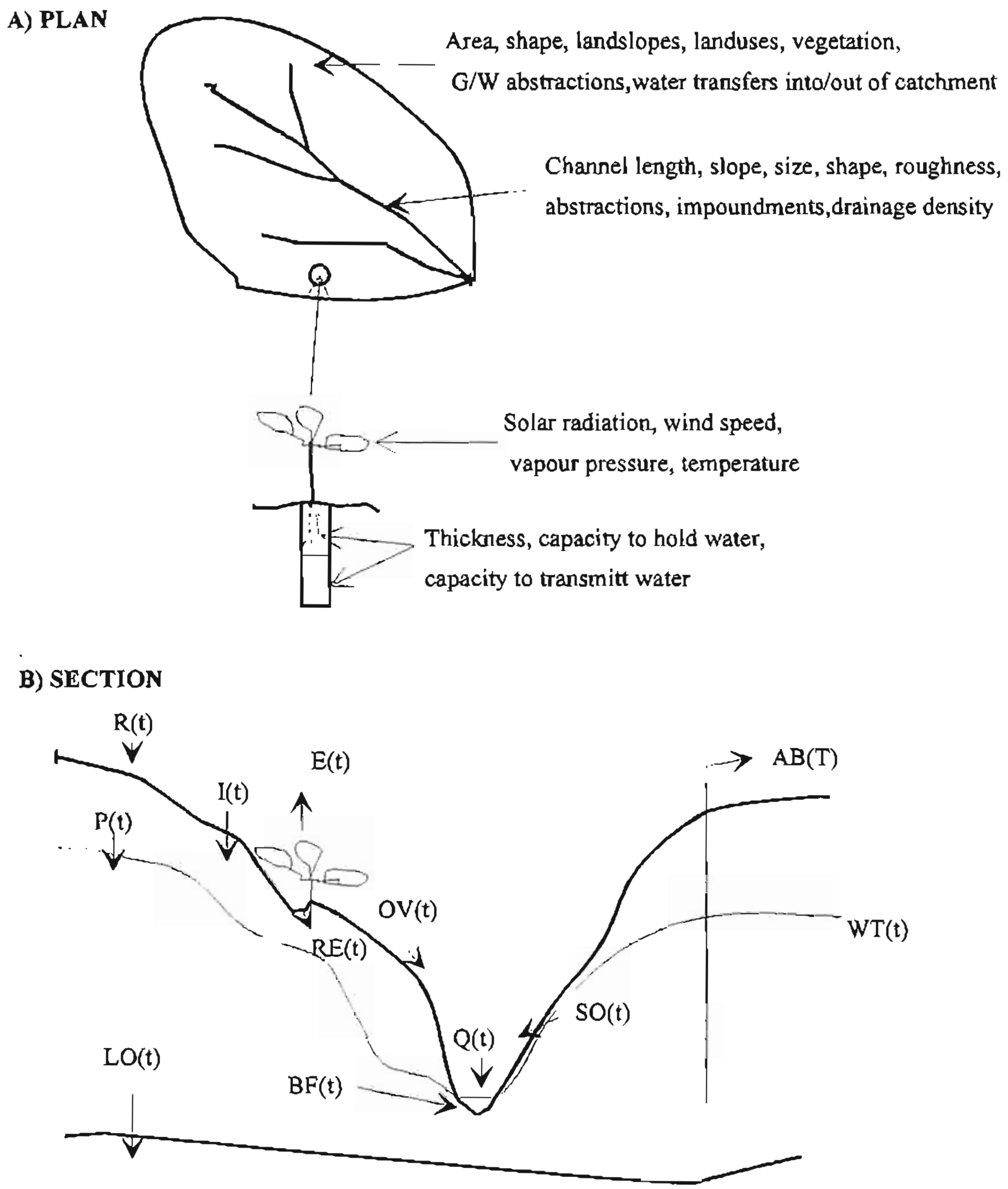
Introduction

1.1 Introduction

The rainfall runoff process is the component of the hydrological cycle involving the time - space conversion of precipitation into runoff on land. The process is obviously very complex considering the large number of factors involved and their variability. Figure 1.1 illustrates some of the main components of the process and the factors that influence it. Rainfall-Runoff models are idealizations of the rainfall-runoff process and are used for a variety of purposes including:

- extending or/and filling in missing runoff data where some runoff records are available;
- creating a runoff series in a catchment where no historical runoff data is available but rainfall data is available;
- flood peak estimation;
- flood forecasting;
- investigating the hydrological and water quality impacts of landuse change;
- investigating surface-groundwater interactions; and
- investigating the impact of climate change on the hydrological characteristics of catchments.

A popular mode of classification of rainfall-runoff models is based on the their complexity which mainly depends on the degree and form of idealization of the rainfall-runoff process. This classification uses three main groups; empirical, conceptual and process models (Grayson and Chiew (1994), Wheater *et al* (1993)). Empirical models mimic the rainfall-runoff process to a slight degree while conceptual models mimic the processes to a greater degree by using interconnected storages and simple equations to represent the water movement among them.



R(t): Rainfall
E(t): Evapotranspiration
I(t): Infiltration
OV(t): Overland flow
SO(t): Saturated overland flow
P(t): Percolation
Q(t): Channel flow
BF(t): Baseflow
W(t): Water Table
RE(t): Recharge
LO(t):Deep aquifer Loss
G/W : Ground Water
AB(T): G/W Abstractions

Figure 1.1. An illustration of the Rainfall-Runoff Process

Empirical and conceptual rainfall-runoff models are not designed to use parameters that are directly measurable in the field and their parameters are usually obtained by calibration. Process models, most of which are distributed, are designed to simulate the physical processes closely enough to enable the use of measurable parameters only. The lack of adequate data and model imperfections have however been found to limit the application of process models in this 'ideal' manner and calibration is often necessary. As an example, the TOPMODEL, which was initially described and used as a physically based model (Beven and Kirkby (1979)) has been applied with full automatic calibration in some later applications to small catchments (Hornberger *et al* (1985), Ambroise *et al* (1996)). Calibration was also involved in two recent applications of the complex distributed process model MIKE-SHE (Refsgaard and Knudsen (1996), Refsgaard (1997)). Most of the process rainfall-runoff model applications reported in a recent publication (McDonald and McAleer (1997)) also applied various forms of calibration. Calibration is thus an important ingredient of hydrological modelling and is likely to remain so even with the increasing application of distributed process models.

Calibration seeks to obtain a parameter set that will give a simulated hydrological or hydro-chemical series that matches the observed series adequately on the basis of some measures such as the coefficient of efficiency and hydrograph, scatter or other plots. Often, it is considered desirable that the global optimum, the parameter set giving the closest match of the simulated and the recorded series, is obtained. Calibration is implemented either manually or automatically with the use of an optimization method. Generally, manual calibration requires more effort and the possibility of missing superior parameter sets is usually still higher than with robust automatic calibration. This probably explains why automatic rainfall-runoff model calibration has been an active field of research for decades (Johnston and Pilgrim (1976), Gupta and Sorooshian (1985), Duan *et al* (1992)).

Automatic rainfall-runoff model calibration is a challenging problem and the location of the global optimum parameter set has proved to be difficult. The three main features that have been found to cause difficulties in calibration are:

- the existence of more than one major region of convergence (regions of attraction);
- the existence of many minor local optima in each region of attraction; and
- roughness of the response surface including discontinuous derivatives.

Optimization methods have been grouped into point-based methods and population-based methods. Point-based methods commence the search from a single point in the search space whereas population-based methods start the search from and proceed using several points in the search space. This distinction makes population-based methods less prone to local optimum traps. It also gives them a better chance of leading the search into the region of attraction in which the global optimum is located than point-based methods. Another mode of classification divides optimization methods into direct and gradient based methods. Direct methods use the actual values of the objective function while gradient methods apply derivatives of the objective function values. In the application of derivatives there is some difficulty in situations where the response surface is rough or discontinuous. As a consequence, direct methods have generally been found to be more robust than point-based methods (Hendrickson *et al* (1988)).

A review of literature on rainfall-runoff model calibration revealed that calibration studies until fairly recently had applied point-based optimization methods (Johnston and Pilgrim (1976), Hendrickson *et al* (1988), Kuczera (1987)). It was also observed that the genetic algorithm (GA) method, an approach applied extensively in other optimization problems, had not been widely applied in rainfall-runoff model calibration. Wang (1991) applied the traditional binary-coded GA in the calibration of a 7-parameter version of the Xinanjiang model. The GA is a direct population-based procedure that works on the concepts of natural evolution and the Darwinian principle of 'survival of the fittest'. Being population-based and direct, the GA is appealing as a robust global optimization method and seems capable of overcoming the three main calibration problems; multiple regions of attraction, local optima within each region and rough response surfaces. The GA has attracted considerable research and has been applied successfully in many areas of science and technology (Goldberg (1989), Schaffer (1989), Xin (1995)).

This study investigated the potential of the genetic algorithm method in rainfall-runoff calibration. Although the GA is population-based and direct, tests early in the PhD program found the traditional GA to be incapable of locating the global optima of rainfall-runoff model calibration problems. Subsequent literature also revealed the same problem in other applications of the traditional GA. (Wang *et al* (1995), Tanakamaru and Burges (1996)). It was therefore decided to focus the research towards improving the traditional GA for rainfall-runoff model calibration.

In rainfall-runoff model applications using historical data, the global optimum parameter set is not known and the objective function values are often used to evaluate model and calibration performance. In practical conceptual rainfall-runoff model applications such as the extension or filling in of missing data, the quality of the extended or filled in runoff series is more important than the precise location of the global optimum. To evaluate the adequacy of GA calibrations, the following three types of tests were applied:

- the capability of locating the known global optima of a synthetic data-based rainfall-runoff model calibration and two theoretical function problems;
- the objective function values of a historical data-based model calibration and their consistency in multiple runs; and
- the quality of the validation runoff series using a model calibrated with the GA.

In addition, a comparison of the GA with other optimization methods was considered appropriate. The shuffled complex evolution (SCE-UA) method, an optimization approach developed in the early nineties (Duan *et al* (1992)) had been found to be both efficient and effective in rainfall-runoff modelling and continuous function optimization (Duan *et al* (1993), Sorooshian *et al* (1993), Tanakamaru and Burges (1996)). Three optimization problems from a previous comparative study of four optimization methods including two versions of the SCE-UA method, the comparative random search and the multi start simplex, were selected for this comparative study. The three problems also served as the global optimum location tests of the GA.

For the GA tests based on the objective function value and model validation performance, any of the many existing rainfall-runoff models could have been applied. However, only one hybrid conceptual-empirical rainfall-runoff model; the IHACRES (Wheater *et al* (1993), Jakeman and Hornberger (1993)) was found in the review of the literature. There were also only two mentions of the application of calibration as a guide in the development of a rainfall-runoff model (Hornberger *et al* (1985), Kuczera (1988)). It was therefore decided to develop simple conceptual-empirical rainfall-runoff models, using GA optimization as a guide, and then apply the models to evaluate the GA performance. A comparison of the conceptual-empirical models with a commonly used conceptual model was undertaken as an additional component of the research. Because the performance of optimization methods is usually dependent on the optimization parameter settings, sensitivity analyses of the genetic algorithm performance to optimization parameters were also included in this research.

1.2 Study Objectives

The objectives of the research were:

1. To devise and test ways of improving the performance of the traditional genetic algorithm (GA) method in rainfall-runoff model calibration using:
   - global optimum location tests;
   - tests based on objective function values;
   - tests based on the quality of validation runoff series of a rainfall-runoff model; and

include a sensitivity analysis of the improved GA performance to optimization parameters.

2. To compare the performance of the improved GA with other optimization methods including the shuffled complex evolution (SCE-UA) method.

3. To develop a class of simple conceptual-empirical rainfall-runoff models using GA calibration as a guide.

4. To compare the performance of the conceptual-empirical models with a commonly used conceptual rainfall-runoff model; the MODHYDROLOG.

1.3 Layout of Thesis

Chapter 2 gives a review of rainfall-runoff modelling and rainfall-runoff model calibration. Rainfall-runoff model classification and typical examples of each class of models are described. This Chapter also includes a review of response surface characteristics, objective functions and comparative studies of rainfall-runoff calibration methods.

In Chapter 3, a review of the genetic algorithm method is presented. This includes a description of the traditional genetic algorithm and a derivation showing how the GA optimizes. A discussion of the capabilities of the GA in global optimization and approaches that have been applied to improve the traditional GA are also presented. This Chapter also gives a review of other studies involving the application of the GA method to rainfall-runoff model calibration.

Chapter 4 presents the research methodology and experimentation. This includes a description of the improvements made to the GA and the applied test problems. The data acquisition, data preparation and the stepwise development and performance evaluation of the simple conceptual-empirical rainfall-runoff models is given. Details of the model comparison methodology are also presented in this Chapter.

Chapter 5 gives the results, the analysis and the discussion of the experiments on the modifications to the GA and its comparison with the other four optimization methods. The results, analysis and discussion of tests of the sensitivity of the GA to optimization parameters is also given.

Chapter 6 includes the results, analysis and discussion of the development of the conceptual-empirical models.

Chapter 7 presents the results, analysis and discussion of the comparison of the conceptual-empirical models with the MODHYDROLOG model.

Chapter 8 presents the summary, conclusions and recommendations of the genetic algorithm improvements, the model development and the model comparisons.

The list of references and the Appendices then finalize the thesis.

Chapter Two

Literature Review

2.1. Rainfall-Runoff Model Classification

A large number of rainfall-runoff models exist and a convenient basis for their classification is model complexity which depends on the extent of simplification of the rainfall-runoff process and the assumptions made. The degree of simplification determines;

- the complexity of the model algorithms;
- the computational effort required;
- the model input data requirements and outputs; and
- the level of effort required to apply the model effectively.

On the basis of model algorithm, Grayson and Chiew (1994) have classified the models into empirical, conceptual and physically based. Wheater *et al* (1993) used the same classification but termed empirical models as metric models and added an additional class; hybrid metric-conceptual models. Physically based models are also termed as process models. The fundamental features that differentiate the three classes can be summarized as follows.

Empirical models: Models that give little consideration of the rainfall-runoff process and mainly depend on statistical relationships between rainfall and runoff.

Conceptual models: Models that idealize the catchment as a number of interconnected storages with mathematical relationships used to compute the water movement between, into and out of the storages at each time step.

Process models: Models that use fundamental equations of flow such as Richard's equation and empirical equations whose parameters can be estimated from the catchment characteristics such as Manning's formula to represent the rainfall-runoff process.

Depending on the degree of complexity within each class, Grayson and Chiew (1994) made further subdivisions. Empirical models were grouped into; polynomial and exponential equations, single process equations (e.g. Tanh equation (Boughton (1968)), time series equations (e.g. Tsykin (1985)) and complex time series models (e.g. IHACRES Jakeman *et al* (1990)). Conceptual models requiring 8 or less parameters to be obtained through calibration were classified as simple (e.g. RORB Laurenson and Mein (1990)) and those with more than 8 parameters (e.g. TANK Sugawara *et al* (1983)) as complex. Grayson and Chiew (1994) grouped process models into lumped (e.g.. SiB Sellers *et al* (1991)) and distributed process models in which the catchment is divided into small areas and the model structure applied to the individual areas (e.g. SHE Abbott *et al* (1986a, b)).

In an earlier review of rainfall-runoff modelling, Todini (1988) considered models to be a combination of two basic components; the physical and the stochastic and based his rainfall-runoff model classification on the levels of the two within each model. He considered the physical component as the representation of the a priori information/assumptions of the rainfall-runoff process included in the model and the stochastic component as the part that is derived statistically to express the rest of the process. Todini used the following four classes; purely stochastic, lumped integral, distributed integral and distributed differential with the level of the physical component increasing in that order. In addition, he classified model parameters as stochastic or physical depending on the method used in their estimation. Purely stochastic models were considered as those that are purely statistical in that they do not assume a cause and effect relationship between rainfall and runoff. Integral models were considered to be those models where the process is represented in integral form. Models not subdividing the catchment were termed as lumped. Most conceptual models and those that utilize the unit hydrograph concept substantially were considered as lumped integral models. Integral models that could handle the catchment as a combination of subcatchments were classified as distributed integral models (e.g. Stanford watershed model of Crawford and Linsley (1966)). Distributed differential models were considered as those that use the differential equations discretized in time and space expressing both mass and momentum balance (e.g. the SHE model).

The modes of classification given by Wheater *et al* (1993) and Grayson and Chiew (1994) include lumped process models that are not included in Todini's (1988) classification. Most hydrological modelling literature also uses the terminologies of Grayson and Chiew's classification. This classification has therefore been adopted and modified in this study to allow for hybrid models. Wheater *et al* (1993) give the IHACRES as an example of a hybrid conceptual-empirical model. Ye *et al* (1997) also consider the IHACRES as a hybrid empirical-conceptual model although Grayson and Chiew (1994) have classified it as a complex empirical model. The classification of Todini (1988) places IHACRES in the same class as most lumped conceptual models as it utilizes the unit hydrograph concept (Jakeman *et al* (1990), Jakeman and Hornberger (1993)). Models that feature the principles of both process and conceptual models are also in existence. These include the Variable time interval (VTI) model of Hughes and Sami (1994) and the TOPMODEL (Beven and Kirkby (1979)) in some of its applications. Hybrid models referred to as conceptual-empirical and process-conceptual are therefore added to Grayson and Chiew's classification. Each of the five classes of models is reviewed in the following sections. A typical example of each class is described.

2.2. Empirical Models

As empirical models do not seek to mimic the rainfall-runoff process, they are easy to apply and do not generally involve intense computation. A study by Chiew *et al* (1993) indicates that empirical models are not suited for applications where time steps of less than 1 month are used. Todini (1988) suggests the same for stochastic models of his classification mode which are essentially empirical models. Even at the monthly time step, Chiew *et al* (1993) suggest that the simple polynomial and the Tanh equation (Boughton (1968)) may not be reliable. The Tsykin equation (Tsykin (1985)) was found to perform adequately at the monthly time step for the wet catchments. This study involved 8 unregulated Australian catchments. In an earlier research (Tsykin (1985)), Tsykin's multiple regression models gave flows of high coefficients of determination at both daily and monthly time steps. For the daily time step however, the flows exhibited very high standard errors of estimate while low standard errors were obtained with the monthly time step. Following are descriptions of Tsykin's regression model and Boughton's Tanh equation.

The Tsykin Equation (Tsykin (1985))

$$run_i = a + b\,rain_i^c\,rain_{i-1}^d\,rain_{i-2}^e \qquad (2.1)$$

where run_i is the runoff in period i;

$rain_i$ is the rainfall in period i; and

a, b, c, d, e, are empirical parameters obtained by calibration.

The Tanh Equation (Boughton (1968))

$$run_i = rain_i - a - bTanh\left(\frac{rain_i - a}{b}\right) \qquad (2.2)$$

where a is the maximum value of precipitation below which runoff would not occur (a simple representation of interception and depression storages);

b is a rate factor determining the additional precipitation losses such as evaporation, deep seepage or ground water losses to neighbouring catchments; and

a *and* b are parameters obtained by calibration.

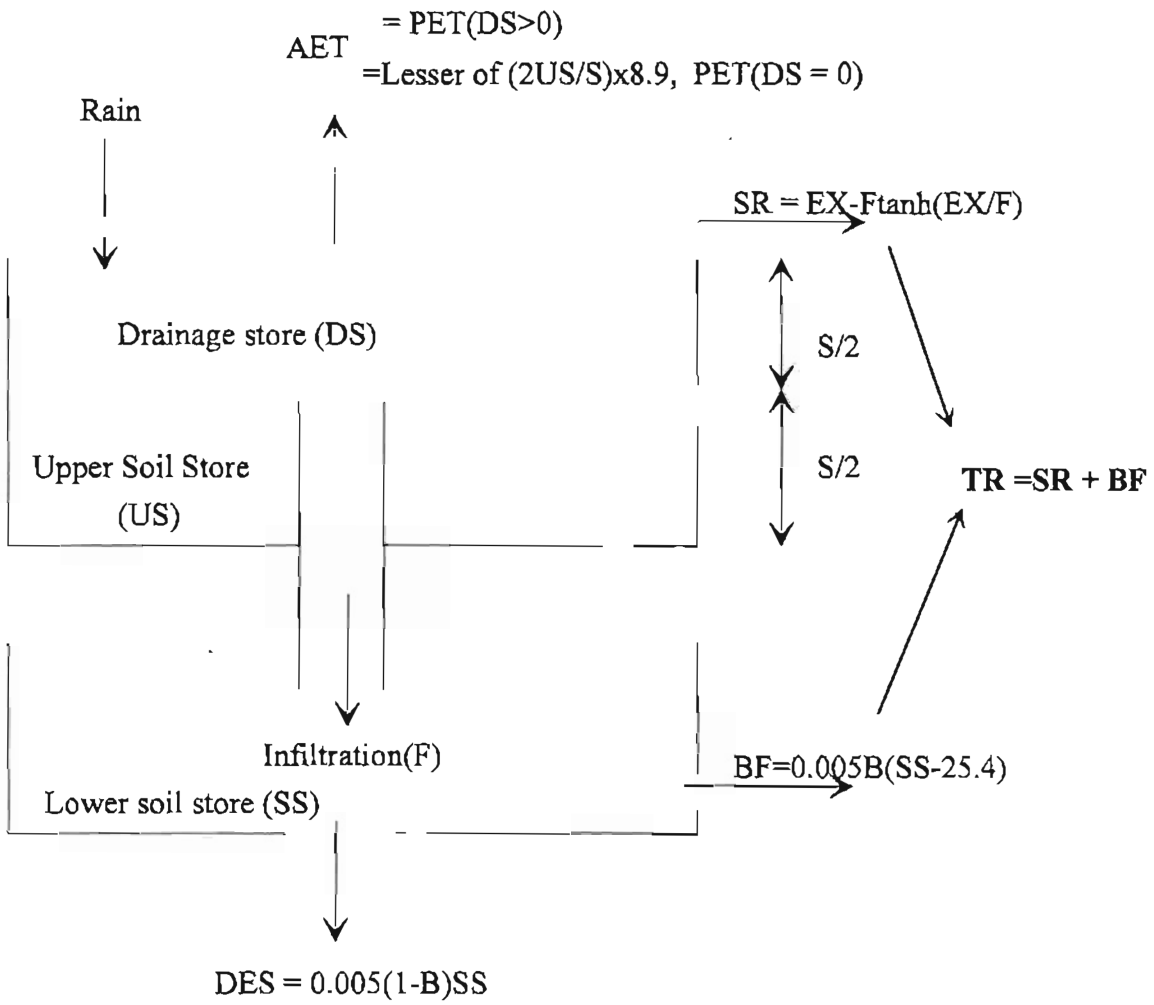
2.3. Conceptual Models

Conceptual models treat the catchment as a number of interconnected storages with mathematical relationships used to compute the water movement between, into and out of the storages at each time step. By routing the rainfall through the model and comparing the computed runoff with the expected values, the parameters of the model are varied until the generated and the expected runoff match adequately or as closely as can be practically attained. The parameters are usually the storages and/or components of the mathematical functions. Numerous conceptual models have been developed and Wheater *et al* (1993) state that this number runs into the hundreds. A detailed analysis of the structure of seven well known conceptual models is given by Franchini and Pacciani (1991). The complexity of the model mainly depends on the number of parameters. Model parameters can be set to constant values for a given application in which case the modelling becomes simpler for calibration. A study by Chiew and McMahon (1994) indicates that the use of more than 5 parameters for monthly and longer time steps may not be necessary except for arid and semi-arid catchments. Beven (1989) suggests the same. Jakeman and Hornberger (1993) also point out that only limited benefit may be obtained by the use of complex conceptual or physically based models in a wide variety of catchment types and applications. For daily time intervals, Chiew *et al* (1993) found that more parameters are necessary. In Chiew's study involving eight unregulated Australian catchments, the 3-parameter SFB model could not model daily flows adequately while the 19-parameter MODHYDROLOG was successful with the wet catchments. However, this cannot be taken as a general rule as the results of Ye *et al* (1997) indicate. The daily calibrations and validations of 5-year long low-flow sequences obtained by a 6-parameter version of IHACRES were comparable to those obtained with the 22-parameter LASCAM model. A 7-parameter version of the SFB model, the GSFB, performed less successfully than the IHACRES and the LASCAM.

As conceptual models mimic the catchment processes, a great deal of research has gone into the development of effective methods of model calibration. Most of these have been geared towards determining the single most appropriate set of parameters for a catchment termed as the global optimum. To determine the closeness of the predicted and the observed runoff series, objective functions are used. Because the calibration problem is one of the main components of this research, it is discussed separately in section 2.7. The SFB conceptual model is described in the next section.

The SFB model

The SFB model is one of the more commonly known and extensively used conceptual models in Australia (Nathan and McMahon (1990), Chiew and McMahon (1993a)). Figure 2.1 gives a schematic presentation of the model. The surface storage capacity S is divided into two equal components; the upper soil and the drainage store. Water first fills the upper soil store and then starts occupying the drainage store. Water infiltrates from the drainage store at an infiltration rate F and any excess from the drainage store is used to determine the surface runoff.



LEGEND

Rain: Rainfall

AET: Actual evapotranspiration

PET: Potential evaporation

SR: Surface runoff

S: Surface storage capacity

BF: Baseflow

DES: Deep seepage

EX: Overflow from drainage store

TR: Total runoff

(numbers in mm units)

Figure 2.1. Structure of the SFB Rainfall-Runoff Model (After Boughton (1984))

Evapotranspiration from the drainage store occurs at the potential rate. When the drainage store is empty, evapotranspiration from the upper soil store occurs at the rate indicated on Figure 2.1. The Lower soil store is depleted each day at a rate of 0.005 of the water available. The baseflow parameter *B* determines how much of this is lost as deep seepage and how much contributes to the stream runoff as baseflow. The sum of the surface runoff and the baseflow gives the total runoff. The SFB model uses daily rainfall and potential evapotranspiration to obtain runoff and actual evapotranspiration estimates. The SFB is usually calibrated to optimize monthly flows. Recent studies have been applying generalized six parameter versions of the SFB (Bates (1994), Kuczera (1997), Ye *et al* (1997))

2.4. Process Models

The literature indicates that most process models are distributed with a notable exception being global climatic models that lump parameters over large grids. Most distributed models subdivide the catchment into small gridded areas (SHE Abbott *et al* (1986b)) or hillslopes (IHDM Beven *et al* (1987), THALES Grayson (1990)) within which the water movement is modelled individually. This requires the determination of parameters for each small area. Distributed process models have been developed to try deal with some of the problems that the simpler conceptual models cannot. A major objective has been the assessment of the hydrological effects of landuse changes in the catchment. It has been argued that only with models that have physical basis and allow for spatial variations can landuse/management change problems be tackled adequately (Abbott *et al* (1986a)). The application of distributed process models has however encountered several difficulties. The most serious limitation cited has been the lack of adequate data for the effective application of the models (Grayson *et al* (1992a), Grayson and Nathan (1993), Beven (1989), Grayson and Chiew (1994), Vertessy *et al* (1993), Jakeman *et al* (1997)). Although the application of process models has increased, many of the applications have included calibration to varying degrees (Rogers *et al* (1985), Bathurst (1986), Refsgaard and Knudsen (1996), Demetriou and Punthakey (1997), Dietrick and Jakeman (1997), Gao and Merrick (1997), Refsgaard (1997)). Further, it has been found that even where extensive data has been collected, model calibration has at times been necessary. Grayson and Nathan (1993) give an example where even after extensive data collection, calibration of the SHE model was necessary and resulted in some physically unrealistic parameter values. Western *et al* (1997), also did some manual calibration of

THALES, a distributed process model in spite of the availability of high resolution data for the 10.5 hectare catchment they studied. The need for model calibration could therefore be attributed to the fact: that the reality is much more complex than any model is capable of simulating. Within each subarea (grid or hillslopes) that is assumed uniform, there is obviously variability. Grayson and Nathan (1993) for instance question how the capillary suction over an element area of several hectares could be measured. Some parameters such as saturated hydraulic conductivity can vary greatly within a small area (Rogers *et al* (1985), O'Loughlin (1986), Grayson (1990)). In addition, errors definitely occur in field measurements. Many of the empirical relationships used in distributed process models are based on small scale tests and may not represent the field scale problem adequately (Hughes and Sami (1994)). According to Grayson and Chiew (1994), when process models are calibrated, they effectively act as very complex conceptual models. By the classification used in section 2.1, process models in such situations would more likely be functioning as process-conceptual models. Woolhiser (1996) acknowledges the uncertainty in applying distributed process models at large scales but suggests that they could be used for predictive purposes for small watersheds where the overland flow is generated by the Hortonian mechanism. While acknowledging the limitations of distributed process models, Vertessy *et al* (1993) regard them as the only class of models that can describe the interplay between multiple catchment attributes and processes which they consider an essential part of land-use change hydrology. An alternative taken has been the development of process models with due consideration of data availability (SWRRM, Williams *et al* (1985), Arnold *et al* (1993), Arnold and Williams (1987)). The VTI model (Hughes and Sami (1994)) and the TOPMODEL (Beven and Kirkby (1979)) were also developed with consideration of data availability limitations. Table 2.1 below gives examples of process models. The SHE model, one of the well known distributed process models is then briefly described.

The SHE Model (Abbott et al (1986 a, b))

The hydrological processes of water movement are modelled either by finite difference representations of the partial differential equations of mass, momentum and energy conservation, or by empirical equations derived from experimental research. The catchment is modelled as a network of orthogonal grids to achieve horizontal spatial variability. In the vertical direction, spatial variability is achieved by the use of a column of horizontal layers in each grid. The model includes snowmelt, canopy interception, evapotranspiration, overland

and channel flow and unsaturated and saturated subsurface flow. These processes are modelled in each grid. The frame component coordinates the parallel running of the other components. Interception is modelled by a modified Rutter model (Rutter *et al* (1971/72)). Actual evapotranspiration is determined using the Penman-Monteith equation (Monteith (1965)) with the potential evapotranspiration used as the upper limit of actual evapotranspiration. A two dimensional solution based on the diffusion wave approximation of the St. Venant equations is used to model overland flow. A one dimensional form of the same equation models channel flow. The unsaturated soil zone component is modelled using the one dimensional Richard's equation and the saturated zone by the non linear Boussinesq equation. Application of the model requires a massive number of parameters for each grid (estimated to be at least 30 from Abbott *et al* (1986b)) and has high computational demands. Gaining competence in its application also takes considerable effort (Grayson and Nathan (1993), Mudgway *et al* (1994)). Further developments to the original SHE model have been made. Examples are the MIKE-SHE (Refsgaard and Knudsen (1996)) and the SHETRAN (O'Connell and Todini (1996)) which models sediment and solute transport in addition to water flow.

Table 2.1. Some Process Models

Model	Developer and/or User
SHE	Abott *et al* (1986 a, b)
TOPOG	Vertessy *et al* (1993)
THALES	Grayson *et al* (1992b)
ANSWERS	Beasley *et al* (1980)
IHDM	Beven *et al* (1987)
SH	Smith and Herbert (1983)
SWRRM	Williams *et al* (1985)

2.5. Process-Conceptual Models

These models incorporate the principles of conceptual models in the sense that some parameters with no direct physical meaning have to be estimated or obtained by model calibration. Other catchment processes are modelled on a 'physical' basis as in process models. Examples of process-conceptual models are the VTI of Hughes and Sami (1994), the LASCAM (Sivapalan and Viney (1994)), the RAFFLES of Stephenson and Paling (1992) and the WATBAL of Knudsen *et al* (1986). The STANFORD watershed model (Crawford and Linsley (1966)) also fits into this class although it is mostly considered a conceptual model. In some of its applications (e.g. Ambroise *et al* (1996), Franchini *et al* (1996)) the TOPMODEL also fits into this class.

The VTI model (Hughes and Sami (1994))

Figure 2.2. presents the basic structure of the model. The model is distributed as the catchment can be subdivided into up to 30 subareas each having its own set of parameter values and rainfall input time series. To account for spatial variability of infiltration and soil moisture within each subarea, probability distribution functions are used. The model uses variable time intervals that depend on the intensity of rainfall. Time intervals of 5min, 1, 2, 6, 12 and 24 hours can be used in a model run. This model requires 57 parameters for each sub area 50 of which can be measured or estimated from available information (e.g. maps) or field measurements and 7 of which are empirical and may be best quantified by calibration. This model was designed as a compromise between the "grid" or "hillslope" distributed process models such as the SHE and the simpler conceptual models. Its developers state that the model is aimed at a range of situations where simulation of components of catchment hydrology is required to solve a problem. A study by Hughes (1994) indicates that the VTI model modelled the rainfall-runoff process (especially soil moisture variability) better than three other simpler models; the RAFFLES, the P-Export and the Pitman model. This study used South African data from a 0.18 Km2 grassland catchment.

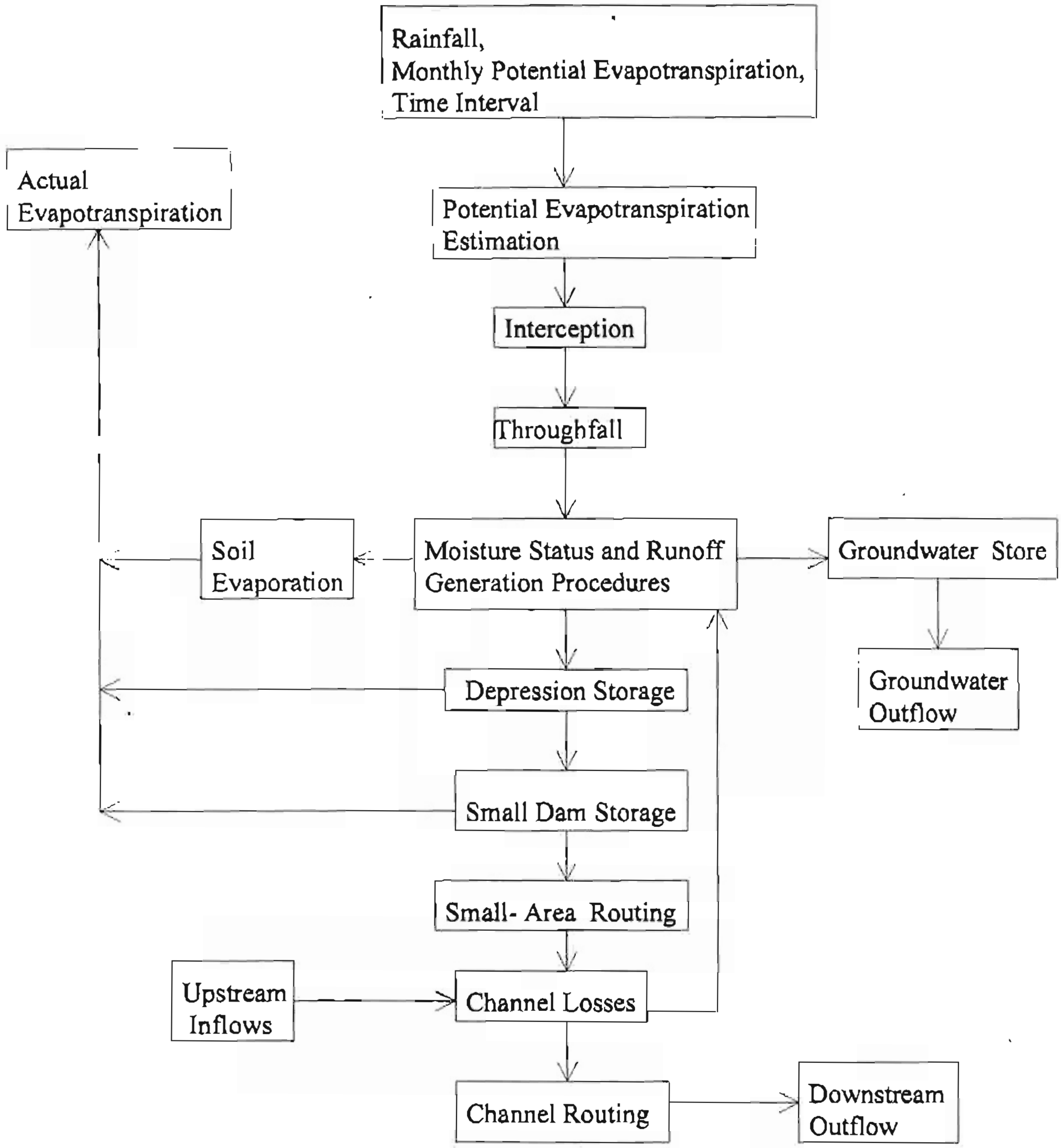


Figure 2.2. Basic Structure of the Variable Time Interval Model (After Hughes and Sami (1994))

2.6. Conceptual-Empirical Models

In their review of rainfall-runoff modelling, Wheater *et al* (1993) state that the idea behind conceptual-empirical models is the use of hydrological time series to obtain a structure of the model in addition to determining the model parameters. Jakeman and Hornberger (1993) have demonstrated how the IHACRES can be applied in this way. In two other applications of the IHACRES, Chiew *et al* (1993) and Ye *et al* (1997), fixed model structures have been used. Kuczera (1988) reported the use of calibration in the development of the structure of the SDI model and it is likely that this has been done in the development of other models. It seems more reasonable that model classification should depend on the actual structure rather than the process through which the model has been developed. Models that use a number of empirical relationships and also mimic the rainfall-runoff process significantly but to a lesser degree than conceptual models are classified as conceptual-empirical models. Beck *et al* (1990) and Kleissen *et al* (1990) present applications of conceptual-empirical hydrochemical models.

The IHACRES Model

To the knowledge of the author, the IHACRES model (Jakeman *et al* 1990) is the only conceptual-empirical model that has been applied extensively in hydrological modelling to date (Jakeman and Hornberger (1993), Chiew *et al* (1993), Ye *et al* (1997), Jakeman *et al* (1997)). IHACRES consists of two components; one is a nonlinear module for obtaining rainfall excess from the incident precipitation and the other is a linear module that converts the effective rainfall to runoff. The rainfall excess for period t, u_t is obtained using equation 2.3, where r_t is the incident rainfall and s_t is the catchment wetness index or the antecedent precipitation index. The catchment wetness s_t is obtained by a decaying weighting of the rainfall time series as shown in equation 2.4. Parameter τ_{wt} determines the rate at which the catchment dries out and is obtained by equation 2.5 which accounts for variations of evapotranspiration. The evapotranspiration rate is assumed to be a function of the temperature te_t (degrees Celsius) and the τ_{wt} value at 20°C, τ_{w20} is used as a datum. Parameter f is a modulation factor that quantifies the change of τ_{wt} with temperature. To obtain rainfall excess in low-yielding catchments, Ye *et al* (1997) modified equation 2.3 using an additional two parameters; a threshold l and an exponent p as presented in equation 2.6. The linear module for converting the rainfall excess u_t to runoff q_t for time step t takes the general form of equation 2.7.

$$u_t = r_t s_t \tag{2.3}$$

$$s_t = cr_t + \left(1-\tau_{wt}^{-1}\right)s_{t-1} = c\left(r_t + \left(1-\tau_{wt}^{-1}\right)r_{t-1} + \left(1-\tau_{wt}^{-2}\right)r_{t-2} + .\right) \tag{2.4}$$

$$\tau_{wt} = \tau_{w20} exp\left[\left(20 - te_t\right)f\right] \tag{2.5}$$

$$\begin{matrix} u_t = r_t\left(s_t - l\right)^p & if \quad s_t > l \\ u_t = 0 & otherwise \end{matrix} \tag{2.6}$$

$$q_t = -a_1 q_{t-1} - a_2 q_{t-2} - \cdots - a_n q_{t-n} + b_0 u_t + b_1 u_{t-1} + \cdots + b_m u_{t-m} \tag{2.7}$$

Jakeman *et al* (1990) and Jakeman and Hornberger (1993) provide analyses to show that q_t is a linear convolution of the unit hydrograph with the rainfall excess u_t and that the linear module effectively acts as a combination of linear stores in parallel and/or series. Jakeman and Hornberger (1993) therefore consider the model to be consistent with the general design of lumped conceptual models. The parameters a_i (i=1,2,...,n), b_j (j=0,1,..,m) and the order n and m have been obtained by the simple refined instrument variable (SRIV) method (Jakeman *et al* (1990), Jakeman and Hornberger (1993)). In the latter study, an order of 2 (n=2 and m=1) was found adequate to extract the available information in seven hydrological time series of varying characteristics. Chiew *et al* (1993) also used an order of 2 in their study. For low-yielding catchments with negligible baseflow, Jakeman and Hornberger (1993) recommended an order of 1 and this was successfully used later by Ye *et al* (1997).

2.7 Rainfall-Runoff Model Calibration

2.7.1 Calibration Methods and Response Surface Characteristics

Rainfall-runoff model calibration is one of the many form of problems generally termed as global optimization problems. The global optimization problem arises in many fields of engineering, technology and economics as a consequence of the need to implement optimal plans and designs. When a mathematical model is applied in the analysis of a practical problem, it is desired that:

- the model represents the real life problem adequately; and
- on the basis of some quantifiable criteria, the optimal value from the range of the feasible alternatives is identified.

The general form of the global optimization problem can be described by equation 2.8.

minimize $f(x_1, x_2, \ \ , x_i, \ \ x_n)$ (2.8)

subject to $pmin_i \leq x_i \leq pmax_i$,

$g(x_j) \leq 0$

where x_i are the decision variables;

$g(x_j)$ are the inequality constraints on some or all the design variables; and

$[pmin_i - pmax_i]$ is the feasible range of the decision variables $i=1,2, \ldots ,n$.

The function f is often termed as the objective function. In the calibration of a rainfall-runoff model, f could be the sum of least squares of the differences between the simulated and the historical flow and x_i the model parameters. In a water distribution network optimization, f could be the cost of implementing the system while x_i could take on different variables such as pipe diameters and reservoir sizes. The difficulty in solving the global optimization problem depends on the characteristics of f in the search space and the dimension of the problem n is one of the main factors that determine this. The problems associated with global optimization are widely published (e.g. Duan *et al* (1992), Johnston and Pilgrim (1976), Bates (1994), Pinter (1996), Sorooshian *et al* (1993), Hendrickson *et al* (1988), Torn and Zilinskas (1989)). In most multidimensional optimization problems, the parameter-objective function response surface is often complex and the search for the global optimum is usually a difficult task. Some of the major problems encountered in automatic calibration as reported in the literature are:

- multiple regions of attraction: separate regions with low objective function values;
- minor local optima: many small pits in each region of attraction;
- roughness of the response surface and discontinuous derivatives;
- long curved ridges on the response surface;
- parameter interdependence;

- objective function indifference to parameters; and
- sparsely located optima.

Figure 2.3 graphically demonstrates the difficulty of global optimization. This is the result of a response surface analysis of the six-parameter SIXPAR model using a simple least squares objective function and a 200-day long synthetic rainfall and runoff series (Duan *et al* (1992)). 10,000 points from the feasible parameter space were obtained by uniform random sampling. The results demonstrate the difficulty of obtaining the global optimum as there are so many points with very low function values. Another observation that was termed as disturbing by the researchers was the large difference between the parameter set that gave the least objective function and the "true" parameter set. This was UM = 30, BM = 0.56, UK = 0.23, BK = 0.75, A = 0.76 and X = 9.3 as compared to the "true" set: UM = 10, BM = 20, UK = 0.5, BK = 0.2, A = 0.31 and X = 3 although the objective function value of the two sets was indistinguishable.

Global optimization methods could be classified into i) point-based and ii) population-based methods. Point-based methods start the search from a single point while population-based methods start from and continue the search at several points of the search space. By their nature, population-based methods therefore conduct global searches while point-based methods have to be repeated several times for a global search. A single search with a point-based method is termed a local search. Another mode of classification depends on whether the method uses direct values of the objective function f or its derivatives. Direct methods use direct values and derivative or gradient methods use derivatives of f. Torn and Zilinskas (1989) present other classification modes that global optimization researchers have used. Table 2.2 presents some of the optimization methods that have been used in rainfall-runoff model calibration including a classification.

Studies of global optimization methods could be considered to take three main forms according to the optimization problems applied. These are:

i. studies involving artificial functions developed specifically for testing global optimization methods;

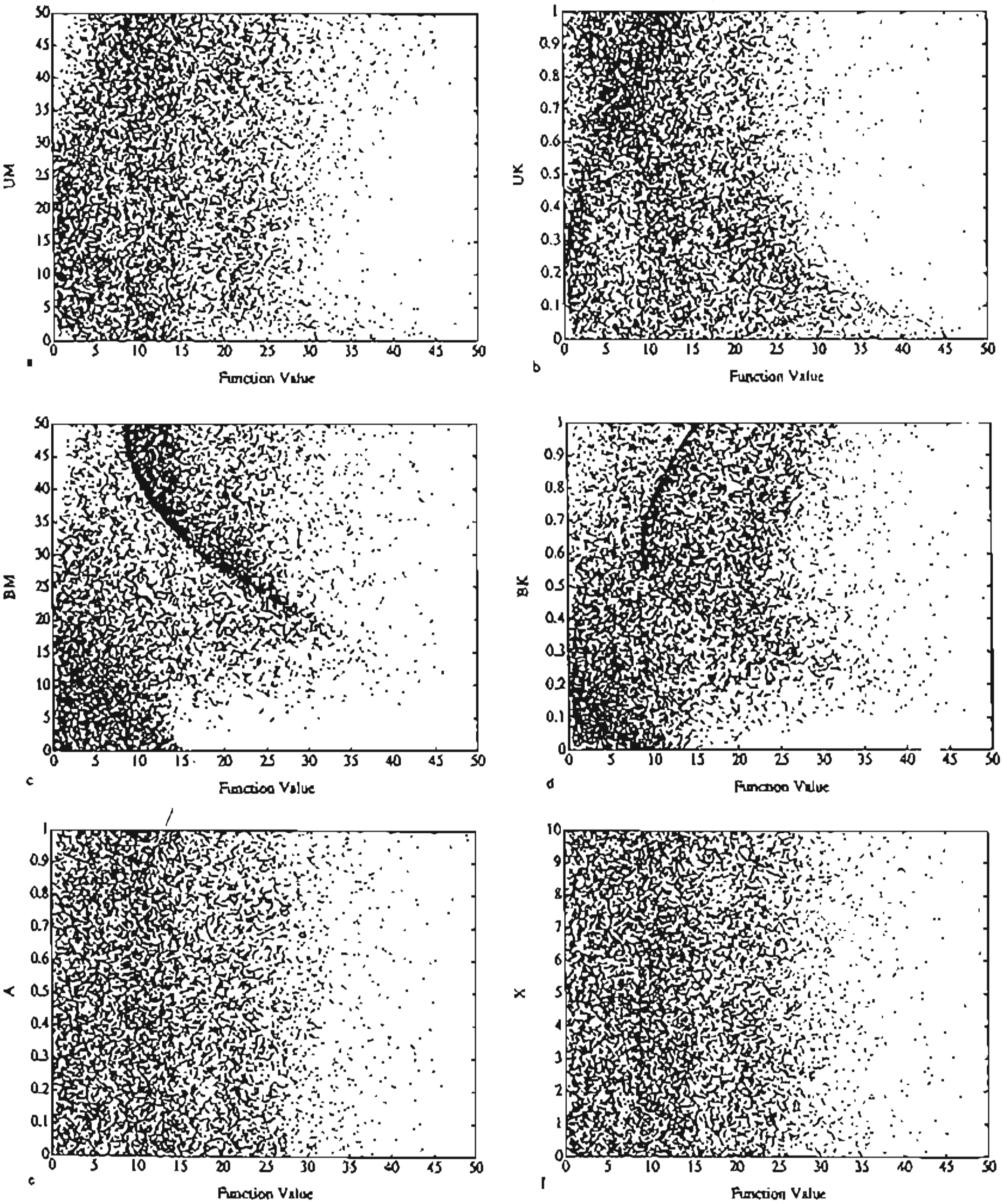


Figure 2.3. An example of Objective Function versus Parameter Value relationships (from Duan *et al* (1992))

Table 2.2. Some Optimization methods used in Rainfall-Runoff Model Calibration

Method: Developer	Applications in Rainfall-Runoff Model Calibration
Point-direct	
Simplex: Nelder and Mead (1965)	Ambroise *et al* (1996) Sorooshian (1981)
Pattern search: Hooke and Jeeves (1961)	Chiew and McMahon (1993) Diskin and Simon (1977)
Powell's: Powell (1964)	Tanakamaru and Burges (1996)
Rotating directions: Rosenbrock (1960)	Hendrickson *et al* (1988) Hornberger *et al* (1985)
Simulated Annealing: Kirkpatrick *et al* (1983)	Bates (1994), Ye *et al* (1997)
Point-derivative	
Davidon-Fletcher-Powell: Fletcher and Powell (1963)	Johnston and Pilgrim (1976)
Newton Raphson	Gupta and Sorooshian (1985)
NLFIT: Kuczera (1987)	Kuczera (1988) Nandarkumar and Mein (1994)
Marquardt-Gauss-Newton: Marquardt (1963)	Hendrickson *et al* (1988) Sukvanachaikul and Laurenson (1983)
Population	
SCE-UA: Duan *et al* (1992)	Duan *et al* (1992), Gan and Biftu (1996)
Genetic Algorithm: Holland (1975)	Wang 1991, Mohan (1997)
Comparative Random Search: Price (1983)	Duan *et al* (1993)

ii. studies using mathematical models applied in practice with synthetic data designed for testing global optimization methods; and

iii. studies using models applied in practice with real life data.

Many studies reported in global optimization literature (e.g.. Torn and Zilinskas (1989), Pinter (1996)) belong to the first group and some popular global optimization test problems of varying levels of difficulty and characteristics have been developed. Examples are the Shekel, the Rastrigin, the Hartman and the Griewank function (Torn and Zilinskas (1989)). The global optimum/optima of these functions are mostly known and when used, it is not difficult to quantify the performance of a global optimization method comprehensively with respect to global optimum location. However, the performance of an optimization procedure on a theoretical function may not be a strong indicator of how well or badly it could handle a practical problem. This is a major drawback of using theoretical functions.

The second group includes studies of the automatic calibration of conceptual rainfall-runoff models with the use of artificial data derived from a model run using an assumed set of 'true' parameters (e.g.. Tanakamaru and Burges (1996), Duan *et al* (1992, 1993), Sorooshian *et al* (1993), Bates (1994)). These sets of 'true' parameters are then the global optima that the search methods have been tested on. As with the theoretical functions, the use of artificial data is a limitation. These studies are however closer to reality than the purely artificial ones. Also considering that it is not uncommon to use synthetically generated data in the practice of hydrology, the use of synthetic data in rainfall-runoff model calibration studies may not be a serious drawback. Some of the conceptual model calibration studies quoted above (Tanakamaru and Burges (1996), Sorooshian *et al* (1993) and Bates (1994)) also included analyses using field hydrological data. Other conceptual model calibration problems such as those of Gan and Biftu (1996), Kuczera (1997), Wang (1991) and Wang *et al* (1995) also used actual field data. This approach has also been used extensively in the genetic algorithm optimization research (e.g.. see GALESIA '95 and Xin (1995)). Pinter (1996) and Torn and Zilinskas (1989) give examples of real world applications of global optimization methods. As Torn and Zilinskas (1989) indicate, real life problems are not as freely available as theoretical functions and are also more expensive to implement. A notable practical problem that has however been used in many pipe network optimization studies is the New York Tunnels Problem (Dandy *et al* (1996)). Until fairly recently (e.g. Yapo *et al* (1996)), there has not been a lot of confidence that the global optima of rainfall-runoff models applying historical data could be obtained. The same probably applies in other practical optimization problems. There is however the advantage that the optimization results of practical problems (or further analyses using the optimization results) can often be related directly to real life situations.

The main criteria used in evaluating and comparing optimization methods are:

i. effectiveness: the ability to locate or get close to the global optimum or the optimized value of the objective function;
ii. efficiency: the number of function evaluations or model runs made before the specified convergence criteria is met; and
iii. consistency: closeness of results from multiple optimizations obtained from random initializations within the search space.

As expected, population-based optimization approaches have generally been found to perform better than single point-based ones (Tanakamaru and Burges (1996), Kuczera (1997)). Derivative methods have been observed to be more susceptible to the roughness of the response surfaces than direct methods which therefore have tended to perform better (Johnston and Pilgrim (1976), Hendrickson *et al* (1988)). Gupta and Sorooshian (1985) however report the comparable effectiveness of a gradient based method (a modified Newton Raphson approach) and a direct method (the simplex). The Newton method was found to use a lesser number of function evaluations than the simplex. Hybrid approaches consisting of two methods have also been applied. Some of these have been calibrations involving an initial genetic algorithm (GA) search followed by finetuning with a point-based method (e.g. Wang *et al* (1995), Wang (1991)). Johnston and Pilgrim (1976) used combinations of the Davidon and the simplex method and Bates (1994) applied a hybrid simulated annealing-simplex approach. Recently, Kuczera (1997) used a derivative point-based based method, the Marquardt-Gauss-Newton to efficiently locate local optimum clusters in the search space and then applied population-based methods, the GA and the shuffled complex evolution to search for the global optimum within the clusters.

Even with the developments in automatic calibration, manual calibration has still persisted (e.g. Franchini *et al* (1996), Refsgaard and Knudsen (1996)). Franchini and Pacciani (1991) argued that manual calibration enables the modeller to maintain a sense of the physical meaning of the parameters and available geomophological information can be used in the calibration unlike in automatic calibration. The application of automatic calibration however does not prevent the use of available catchment information as some parameters could be set to constant values or within the realistic range as the physical meaning and the available catchment information suggest. The danger of ignoring such information and/or the validity of the optimized parameters is however more likely with automatic than with manual calibration. Interactive approaches are effectively hybrids of fully automatic and the fully manual methods. The NLFIT interactive optimization suite (Kuczera (1987)) has been applied in a number of rainfall-runoff model calibrations (Raper and Kuczera (1991), Kuczera (1988), Nandarkumar and Mein (1994)). Obled *et al* (1994) calibrated the TOPMODEL by searching for optima systematically through the exploration of multidimensional grids and stated that the simplex method gave essentially similar results but took a shorter time. It is recognized that an extent of interaction still exists even in the application of fully automatic optimization methods as the search space may need to be altered. Also, optimization parameters may need to be changed for more effective calibration (Duan *et al* (1994)). As Wang *et al* (1995) and Chiew and McMahon (1994) indicate, the modeller's experience is one of the factors that determine the time taken to calibrate complex models. The objective function is an important component of the calibration process and is the subject of the next two sections.

2.7.2 Rainfall-runoff Model Objective Functions

Given a specific data set and a specific model, the response surface characteristics mainly depend on the objective function selected. As Diskin and Simon (1977) indicate, the objective function needs to be selected on the basis of the task at hand. For instance, peak flows are more relevant than low flows in flood mitigation studies whereas low flows could be more important for dry season water quality studies. The simple least squares (SLS) (equation 2.9) is one of the most commonly used objective function probably due to its simplicity. Use of the SLS assumes that the residuals $arun_i$ - run_i have a constant variance, are normally distributed and are independent but the assumptions may often not hold good in practice (Sorooshian and Dracup (1980), Kuczera (1983)).

$$\textit{Minimize} \quad \sum_{i=1}^{N}\left(arun_i - run_i\right)^2 \qquad (2.9)$$

where N is the length of data; $arun_i$ is the observed discharge; and run_i is the estimated discharge.

It is suggested that diagnostic checks should be performed to check for the violation of the two assumptions and corrective measures be taken if significant violations exist. To satisfy the constant variance assumption, some of the objective functions that have been used are:

a) Use of the logarithms of the time series as given in equation 2.10 (Gan and Burges (1990)).

$$\text{Minimize} \quad \sum_{i=1}^{N}\left(\log arun_i - \log run_i\right)/N \qquad (2.10)$$

b) Use of the square roots of the observed and predicted values to obtain an objective function of the form of equation 2.11 (Chiew and McMahon (1990), 1993a, 1994)). In another study, Chiew *et al* (1993) used an objective function given as equation 2.12. In a more recent work, (Ye *et al* (1997)), an objective function of equation 2.11 was used to calibrate the generalized SFB (GSFB) model.

$$\text{Minimize} \quad \sum_{i=1}^{N}\left(\sqrt{arun_i} - \sqrt{run_i}\right)^2 \qquad (2.11)$$

$$\text{Minimize} \quad \sum_{i=1}^{N}\left(arun_i^{0.2} - run_i^{0.2}\right)^2 \qquad (2.12)$$

c) Dividing the error by the sum of the observed and predicted values to give equation 2.13 (Diskin and Simon (1977)).

$$\text{Minimize} \quad \sum_{i=1}^{N}\left[\frac{2\left(arun_i - run_i\right)}{arun_i + run_i}\right]^2 \qquad (2.13)$$

d) The use of the heteroscedastic maximum likelihood estimator (HMLE) (Sorooshian and Dracup (1980), Sorooshian (1981), Sorooshian *et al* (1983, 1993), Yapo *et al* (1996)). The HMLE is the maximum likelihood minimum variance estimator. It assumes the errors are normally distributed with zero mean. Sorooshian *et al* (1993) present a description of the function and more details can be obtained from Sorooshian (1981) and Sorooshian and Dracup (1980).

e) The Box-Cox Transformation (Kuczera (1983, 1987)). The observed and predicted values are transformed as presented in equations 2.14 and 2.15. A K value of zero has been used in all the rainfall-runoff calibration studies found. Ye *et al* (1997) used a similar form of objective function in the calibration of the LASCAM model with a λ of 0.5.

$$arunt_i = \left((arun_i + K)^\lambda - 1\right)/\lambda \tag{2.14}$$

and

$$runt_i = \left((run_i + K)^\lambda - 1\right)/\lambda \tag{2.15}$$

where $arunt_i$ and $runt_i$ are the transformed values; and

K and λ are transformation parameters.

To check the assumption of independence of the errors, Kuczera (1983, 1987) fitted an autoregressive moving average time series (equation 2.16) to the transformed values $arunt_i$ and $runt_i$ to obtain the transformed errors a_i. A simple least squares summation of the transformed errors was then used in the optimization as in equation 2.17.

$$\eta_i = \phi_1\eta_{i-1} + \ldots + \phi_p\eta_{i-p} + a_i + \theta_1 a_{i-1} + \ldots + \theta_q a_{i-q} \tag{2.16}$$

where $\eta_i = arunt_i - runt_i$;

$\phi_1, \ldots \phi_p$ are the autoregressive parameters; and

$\theta_1, \ldots \theta_q$ are the moving average parameters.

$$Minimize \quad \sum_{i=p+1}^{N} a_i^2 \tag{2.17}$$

The objective function of the form of equations 2.14 to 2.17 has been used by Bates (1994) and Kuczera (1983) with λ=0.5, p=1 and q=0 to give a transformed error $a_i = \eta_i - \phi\eta_{i-1}$. Sukvanachaikul and Laurenson (1983) and Kuczera (1997) used a slightly different function given as equation 2.18.

$$Minimize \quad \sum_{i=1}^{N} \left(arun_i\lambda - run_i^\lambda\right) - \phi\left(arun_{i-1}^\lambda - run_{i-1}^\lambda\right) \tag{2.18}$$

Although most of the objective functions have used only discharge rate errors, combinations of discharge rate and other quantities have been applied as well in flood event model calibrations. Liong *et al* (1996) used an objective function that sums the square of the peak flow and hydrograph volume residuals in the calibration of the SWMM model (equation 2.19). Michaud and Sorooshian (1994) used an objective function based on the square of the peak flow, volume and time to peak in calibrations of the SCS model.

$$Minimize \quad \sum_{ie=1}^{Ne}\left(\Delta pf_{ie}^{2} + \Delta hv_{ie}^{2}\right)^{1/2} \qquad (2.19)$$

where ie is the flood event;

Ne the number of flood events;

Δpf_{ie} is the peak flow error; and

Δhv_{ie} is the flood volume error.

2.7.3 Studies on the Effect of Objective Functions

In a comparative study of 12 types of objective functions, Diskin and Simon (1977) demonstrated the suitability of the objective functions to specific hydrological purposes. None of the functions was found to be universally acceptable for all the purposes although some performed better on the average than others. In a number of studies mostly conducted at the University of Arizona the heteroscedastic maximum likelihood estimator (HMLE) has been found to give more consistent parameter sets than the simple least squares (SLS) (equation 2.9). Sorooshian and Gupta (1983) found the HMLE to give response surface with fewer local optima than the SLS and had no elongated valleys unlike the SLS. Sorooshian (1981) used synthetic data with noise introduced and then determined how close to the known global optimum calibrations using the HMLE, the SLS and a weighted least squares (WLS) objective function. Equations 2.20 and 2.21 describe the WLS function applied.

$$Minimize \quad \sum_{i=1}^{N} w_i (arun_i - run_i)^2 \qquad (2.20)$$

$$w_i = \left(arun_i + \overline{arun_o}\right) / 2\,\overline{arun_o} \qquad (2.21)$$

where $\overline{arun_o}$ is the mean of the observed flows.

The HMLE was found consistently to perform better than the other two and the WLS was the poorest. Plots of the optimized parameter locations in the search space with repeated optimization runs presented by Sorooshian *et al* (1993) reveal a closer grouping with the

HMLE than the SLS. Sorooshian *et al* (1983) also reported that the HMLE gave more consistent parameter sets and better model performance than the SLS. Yapo *et al* (1996) found the SLS to give better simulations of high flows and poorer simulations of low flows in comparison to the HMLE. This underlines the need for the selection of the objective function to be guided by the use/s the data is intended for as Diskin and Simon (1977) recommended.

Hornberger *et al* (1985) compared the relative performance of eight objective functions in the calibration of a 13-parameter version of the TOPMODEL. these were;

i. the sum of squared errors (SLS) of the flows,
ii. the sum of the squared errors of the logarithms of the flows,
iii. the sum of the absolute values of the errors,
iv. the sum of squared errors of preselected points,
v. the sum of the squared errors of the logarithms of the flows of preselected points,
vi. the sum of the absolute values of the errors of preselected points,
vii. a hybrid of i) and ii) and
viii. the log likelihood function (Sorooshian and Dracup (1980))

No significant difference was found among them. The analysis used approximately 1 month long sequences with a discretization of 3 hours.

Applying a simple 2-parameter single linear store model Johnston and Pilgrim (1976) tested the effect of index *j* of an objective function described by equation 2.22.

$$\text{Minimize} \quad \sum_{i=1}^{N} \left| arun_i - run_i \right|^j \tag{2.22}$$

It was observed that changing the index did not change the optimum parameter values but altered the shape of the response surface such that gradient-based optimization would get more difficulties with a low index (*j=1/2*) than with a high one (*j=2*). Johnston and Pilgrim (1976) also report another analysis in which the interception store parameter of the Boughton model was used to investigate the effect of transforming the flows with an index (say *k*) before computing the errors (equation 2.23).

$$\text{Minimize} \quad \sum_{i=1}^{N} \left| arun_i^{\,k} - run_i^{\,k} \right|^2 \tag{2.23}$$

The index was found to affect the optimal parameter value with a k value of 2 favouring the reproduction of large events and a low k value of 1/2 favouring the reproduction of low flows. Chiew *et al* (1993) also report a similar result by a comparison of flow-duration curves obtained from calibrations performed using the SLS (equation 2.9) and the transformed SLS (equation 2.12).

Bates (1994), applying equations 2.14 to 2.17 found three parameters of a generalized SFB model to be highly sensitive to the value of λ. A change of 0.1 in λ halved the estimate of the surface storage capacity, doubled the baseflow factor and trebled the proportion of the surface storage that does not drain to the lower store. He however stated that some model structure modifications resulted in a lower sensitivity.

2.7.4 Comparative Studies of Rainfall-Runoff Model Calibration

Study by Hendrickson et al (1988)

This was a comparative study of the Marquardt-Gauss-Newton and the Pattern search method. Synthetic data assuming a "true" parameter set was generated with the Sacramento model (Burnash *et al* (1973)). It was then possible to determine how close the calibration methods could get to the "true" set of parameters. It was found that the pattern search was more likely to find the "true' parameter set than the Marquardt-Gauss-Newton method. This was attributed to the roughness of the response surface including the presence of discontinuous derivatives. The Marquardt-Gauss-Newton approach, being a derivative method was bound to suffer more from the roughness of response surfaces. It was consequently concluded that derivative methods are not as well suited as direct methods for rainfall-runoff model calibration. Both methods however did not perform satisfactorily with regards to locating the global optimum. By combining them sequentially, better parameter values were obtained. The "pattern search followed by Marquardt-Gauss-Newton" performed better than the "Marquardt-Gauss-Newton followed by Pattern search" combination. This was probably an indication that the response surface was rougher at lower objective function values and smoother closer to the optima.

Study by Duan et al (1992, 1993)

An investigation of response surfaces and the comparison of three global search methods including one developed by the authors were some of the main components of the study. The response surface study has already been discussed earlier in section 2.7.1. A 200-day synthetic streamflow sequence generated using the SIXPAR, a simplified six-parameter version of the Sacramento model was used and the rainfall sequence selected ensured that all the modes of model operation were activated. The three optimization procedures involved in the comparison were, the multistart simplex (MSX), adaptive random sampling and the shuffled complex evolution method (SCE-UA) developed by the authors. Each evaluation involved 100 trials. With a single start, the MSX method gave a failure rate of 65%. This dropped to 1% with an MSX method of 12 restarts. This was attained with an average of 10500 function evaluations. The SCE-UA method attained the same level of success (1% failure) with an average of 3300 function evaluations. The adaptive random search method gave a success rate of 30% with an average of 25000 function evaluations. When coupled with a simplex algorithm, the adaptive random search attained a 55% success rate with an average of 5000 evaluations. The use of either the MSX or the SCE-UA method was recommended. The SCE-UA was favoured as it involved a lesser number of function evaluations. There was no comment on the comparative computational demands of the two procedures. Duan *et al* (1993) reported the performance of the comparative random search method (Price (1983)) on the same SIXPAR global search problem. The comparative random search performed almost as efficiently and effectively as the SCE-UA attaining 4% failure with an average of 2745 function evaluations. However a comparison using 6 theoretical test problems in the same study revealed the superior performance of the SCE-UA to that of the comparative random search and the MSX.

Study by Sorooshian et al (1993)

A comparison of the SCE-UA and the MSX method in the calibration of the Sacramento model was the main objective of this study. The procedures were tested for 2 cases, one using synthetically generated and the other historical runoff data. In the "ideal" case, a "true" parameter set was assumed and used to generate a stream flow sequence. This sequence was then used to find out the success of the two procedures in locating the "true" parameters. The SCE-UA was found to attain 100% success in 100 trials while the MSX did not locate the true set in any of the 100 attempts. Its estimates were however found to be close. When calibrated to a 7-year long daily historical data, the SCE-UA parameters gave consistently lower objective function values than the MSX parameters for each of the 10 trials conducted. Using the parameter sets that gave the least objective function, a verification was conducted using the 7 year long series' that followed the calibration series'. The percent biases obtained indicated that neither of the parameter sets obtained with the SCE-UA and with the MSX was superior to the other. The authors stated that model structure imperfections, data errors and the choice of the objective functions are some of the issues that need to be addressed before global optima can be obtained.

Study by Johnston and Pilgrim (1976)

This study was aimed at determining the optimum parameter set for a 13 hectare catchment using an 8 parameter version of the Boughton model (Boughton (1966)). A 2 year and 5 months long set of daily data was used. The calibration was attempted applying the Davidon, the Simplex and several combinations of these two methods. The authors reported that optimal set of parameters was not found after two years of effort. Several complexities of the response surface that pose difficulties were highlighted. These have been given earlier in section 2.7.1.

Study by Bates (1994)

Bates (1994), compared a hybrid of the simulated annealing and the simplex method (SA-SX) with the MSX method and found the SA-SX to perform better than the MSX. In the theoretical data case, the SA-SX located the global optimum with about 60% success while the MSX attained about 20% success. In the historical data case, the MSX attained about 10% and the SA-SX about 60% success in locating the presumed global optimum. In the experiment, 100 trials were made with each method and each trial consisted of 100 runs. The SA-SX was found to stall in long valleys along the response surface and it was suggested that a possible solution to this may be the use of a derivative search once a valley was encountered. A total of 16 years of daily data (9 for the theoretical and 7 for the historical study) from a 27 Km2 catchment and a generalized 6-parameter SFB model were used in the study.

Study by Wang (1991)

In this study, the genetic algorithm method was used to calibrate a 7-parameter version of the Xinanjiang model (Zhao (1977)) and was found to be robust. Further tuning of the genetic algorithms search with the sequential simplex method (Beveridge and Schectiter (1970)) improved the results only slightly. Six years of daily rainfall, potential evapotranspiration and runoff from a 2344 Km2 catchment with a moderately humid climate was used.

Study by Tanakamaru and Burges (1996)

Tanakamaru and Burges tested eight optimization approaches using a four year long daily synthetic data set and a known global optimum of the 16-parameter TANK rainfall-runoff model (Sugawara *et al* (1983)). The optimization approaches used were:

- the simplex;
- Powell's conjugate gradient;
- the traditional GA;
- the traditional GA finetuned with the simplex;
- the traditional GA finetuned with Powell's conjugate gradient;
- the SCE-UA;
- the MSX; and
- the multistart Powell's method.

Out of 20 independent trials, the number of successes in obtaining the global optimum for the optimization procedures in the same order as listed were 0, 2, 0, 0, 11, 20, 0, and 20. The SCE-UA and the multistart Powell's method attained 100 % success with an average of 39271 and 67244 function evaluations respectively. The SCE-UA was then used to calibrate a four year long historical series and was found to give a close grouping of the parameter and objective function values for the 20 independent optimizations that were conducted.

Study by Wang et al (1995)

Wang *et al* (1995) applied the GA and the pattern search method to calibrate a 10 parameter version of the HYDROLOG rainfall-runoff model. Ten parameters were optimized and historical data from two Australian catchments was used. Finetuning the GA with the pattern search method was found to improve the objective function by up to 15 % with one catchment and up to 30 % with the other. Comparing the results of multiple optimizations of the finetuned GA with those of the pattern search, the GA was found to be more effective in searching for multiple optima. However, considerably different performances were obtained with the 10 randomly initialized trials (up to a 25% difference in the objective function value with one of the catchments). This indicated the GA was getting trapped in local optima in some of the runs. Wang *et al* (1995) concluded that the GA was not always robust but was considered useful in model calibration particularly when finetuned with a standard optimization technique.

Study by Kuczera (1997)

This is a more recent study which compared the following four methods; the SCE-UA, the GA, the (MSX) and the multistart quasi-Newton method. This study also proposed and tested a strategy for improving the efficiency (as quantified by the number of function evaluations) of population-based search methods such as the SCE-UA and the GA. This proposal involved the efficient location of a cluster of local optima using a gradient based search method and then performing the population based search in a subspace (hyperellipsoid) enclosing the cluster instead of over the entire search space as is customary. A 5-parameter version of the SFB model, termed the mSFB and 180 months of hydrological data of an Australian catchment were used. This study revealed a better effectiveness and efficiency of the SCE-UA over the GA, the MSX and the multistart quasi-Newton method. The SCE-UA consistently gave good objective function values unlike the three other methods. Only in a few optimizations did the MSX and the multistart quasi-Newton give results of a similar quality to those of the SCE-UA. The GA persistently failed to achieve results of that quality. That the GA consistently failed to obtain high quality results could be attributed to its inability to finetune. The same reason could also explain why the GA performed worst with the subspace strategy applied but better than the MSX and the multistart quasi-Newton when the customary hypercube approach was used. The subspace search strategy was found to typically reduce the number of evaluations by two on the SCE-UA. It was however noted that the mSFB model was well posed and without significant parameter interaction and the result could be different in situations where significant interdependence of the parameters exists.

Study by Gan and Biftu (1996)

This study mainly investigated the effects of the rainfall-runoff model structure, the use of alternative optimization algorithms and data availability and quality on automatic model calibration in practical (real life) situations. The Sacramento (Burnash *et al* (1973)), NAM (DHI (1994)), SMAR (Kachroo (1992)), and the Xinanjiang (Zhao *et al* (1977)) models were used. The number of parameters optimized in the study were 13 out of 21, 15 out of 15, 13 out of 15, and 9 out of 9 for the Sacramento, NAM, SMAR and the Xinanjiang model respectively. Three optimization methods, the SCE-UA, the simplex and the MSX were applied. The study used eight catchments of varying sizes and wetness with 6-year long calibration and 2-year long validation series' (3 years for one catchment). The daily root mean square (DRMS) objective function, given in equation 2.24 was used throughout and the assessment of model performance was mainly based on the coefficient of efficiency.

$$DRMS = (SLS/N)^{0.5} \qquad (2.24)$$

where SLS is the simple least squares objective function (equation 2.9); and

N is the number of data points.

Gan and Biftu found that the calibration results depended only slightly on the optimization method with the SCE-UA performing marginally better than the MSX and the local simplex a bit worse that the MSX. The local simplex was however found to take about half the number of evaluations of the SCE-UA (about 5000 compared with about 10000) while the MSX always terminated on attaining the allowed number of function evaluations of 50000. The local simplex searches were however done interactively in stages with individual parameters being varied at each stage and were reported to actually take more time than the SCE-UA and the MSX. The application of the local simplex also required more familiarity with the model behaviour than the SCE-UA and the MSX. None of the three optimization methods gave notably superior results at the validation stage. This was attributed to model structure inadequacies including the effect of lumping the time and space-variant rainfall-runoff process, data inadequacies and errors, and model identifiability problems. Another possible reason was the use of the DRMS objective function as no diagnostic checks for the assumption of constant variance and independence of errors were conducted. However, except for a few exceptions with the driest of the eight catchments, the parameters obtained, though at times varying considerably with the optimization method, were considered realistic and physically meaningful. The power of the SCE-UA was therefore found to be mainly operational and not in obtaining superior parameter sets. Sorooshian *et al* (1993) observed the same in a comparison of the SCE-UA with the MSX applying historical data to the Sacramento model. Among the four models used, the Xinanjiang model was found to perform better over the varied range of catchment conditions. This was considered to result from the variable contributing area concept included in this model which was not in the three others.

Study by Ndiritu and Daniell (1997)

This publication reported the comparison of the GA with the methods used in a previous study (Duan *et al* (1993)). These were the MSX, the SCE-UA and the comparative random search. The SIXPAR problem given in Section 2.7.1 and 4.4.1 was used. Two theoretical functions used by Duan *et al* (1993), the Hartman and the Griewank function were also included in the study. The results obtained are similar to those reported in Section 5.2.1. The traditional GA failed totally to locate the global optimum while the GA with improvements developed in this research achieved 98 percent success with about three times more the average number of function evaluations used by the SCE-UA for the same level of success.

2.8 Discussion

The review of the comparative studies on rainfall-runoff model calibration has revealed that:

1) The application of point-based calibration methods has been more prevalent than population-based methods until fairly recently. When this research started in 1994, the following studies on population-based rainfall-runoff model calibration had been found:

- the work of Wang (1991) with the GA;
- the studies by Daun *et al* (1992) and Sorooshian *et al* (1993) with the SCE-UA; and
- the study by Duan *et al* (1993) which included two population-based methods; the SCE-UA and the comparative random search.

2) The performance of the SCE-UA has consistently been very good both in terms of efficiency and effectiveness when compared with the GA and other optimization methods in rainfall-runoff model calibration. The SCE-UA can arguably be considered as one of the most powerful optimization methods used in rainfall-runoff modelling to date. The GA and several other calibration methods have generally been observed to be less satisfactory for global optimum location.

Wang (1991), Liong *et al* (1995, 1996) and Mohan (1997) report satisfactory performance of the GA but the global optimum location capability of the GA was not tested in these studies. In addition, the comparison of the GA with other procedures was also not done in these studies. Wang *et al* (1995) recommended the use of the GA with point-based finetuning for the calibration of environmental models but found the GA not to be always robust as it at times got trapped in local optima. In the work of Tanakamaru and Burges (1996), the standard GA did not locate the global optimum in all the 20 trials performed. Finetuning with the simplex did not improve the result while finetuning with Powell's method resulted in 11 out of 20 successes. The GA was declared 'neither effective nor efficient but could be improved with point-based finetuning'. Kuczera (1997) found the GA to stall at an objective function level that the SCE-UA consistently exceeded and which two point-based methods, the MSX and the multistart quasi-Newton also occasionally exceeded. Kuczera considered the GA not to be reliable for global optimum location. He however pointed out that possibilities of improving the GA in rainfall-runoff model calibration exist and quoted the example of Dandy *et al* (1996) where the GA was improved for pipe network optimization.

This research aimed at improving the performance of the GA in rainfall-runoff model calibration. Investigating how the GA could be improved specifically for rainfall-runoff model calibration is worthwhile especially considering the GA has the two fundamental advantages of being direct and population-based. In all the applications of the GA to rainfall-runoff model calibration found to date, the improvement of GA performance has not been a main focus. The only significant addition that has been tried out seems to be the finetuning of the standard GA with point based methods. This research has aimed to investigate other ways of improving the performance of the GA and thus prevent the possibility of the dismissal of a potentially robust method of rainfall-runoff model calibration. Genetic algorithm optimization is currently an active field of research and the standard GA has been improved in a varied number of ways in most of the studies (e.g. Cohoon *et al* (1991), Mühlenbein *et al* (1991), Murphy *et al* (1993), Simpson *et al* (1994), Hassanli and Dandy (1994), Wong and Wong (1995), Donne *et al* (1995), Dandy *et al* (1996), Hirayama *et al* (1996), Wu and Simpson (1996), Savic and Walters (1997)). An investigation of the potential of the GA in rainfall-runoff model calibration was therefore considered a worthwhile exercise and undertaken as the main aim and objective of this research.

Several choices were considered as to the rainfall-runoff model that could be applied in the study. Although the number of existing rainfall-runoff models could be running into the hundreds (Wheater *et al* (1993)), IHACRES seemed to be the only model of the conceptual-empirical class that had been used considerably in hydrology. It was also observed that the use of calibration as a guide to modelling had not been widely published in hydrological modelling literature. Hornberger *et al* (1985) obtained a simpler 4-parameter version of the TOPMODEL from a 13-parameter version through a sensitivity analysis based on the Monte-Carlo approach. The simpler model was obtained by removing the parts of the more complex model that were using the parameters that were considered insensitive. Hornberger *et al* (1985) found the performance of the 4-parameter model to be comparable to that of the 13-parameter version. In the case where the insensitive parameters of the 13-parameter version were set to constant values, the model performance was found to be poorer than the two other versions. Simplifying calibration by setting some parameters to constant values does not therefore have the same effect as restructuring the model to eliminate the 'inactive' components. Kuczera (1988) states that the covariance matrix obtained from the NLFIT optimization suite was useful in the development of the SDI model. There is therefore validity in the use of optimization as a guide to model development. It was decided that the development of a simple conceptual-empirical model be coupled with the research on GA performance. The model development was to be guided by GA calibration. The developed models in turn were then to be applied in the evaluation of GA calibration performance.

For a comparative study of the genetic algorithm with other optimization methods, three problems used by Duan *et al* (1993) were selected. Duan's study included the SCE-UA and two other methods; the multi start simplex and the comparative random search. The three optimization problems selected included the SIXPAR rainfall-runoff model calibration reported in Section 2.7.5 and two theoretical function optimizations; the Hartman and the Griewank problem. The three problems were also used to evaluate the performance of the traditional and the improved GAs in global optimum location.

Chapter Three

The Genetic Algorithm Method

3.1. The Traditional Genetic Algorithm

3.1.1 A description of the Traditional Genetic Algorithm

The genetic algorithm (GA) method is a population based optimization method based on the concepts of natural selection and natural evolution as hypothesized by Darwin in his theory of evolution. The GA approach was initiated by Holland (1975) and has been used and studied extensively since then. Goldberg (1989), Davis (1991) and Bäck (1996) give comprehensive reviews of the genetic algorithm method. The Following description considers the traditional GA to consist of the steps of binary coding followed by repetitions of selection, crossover and mutation and uses the general form of the global optimization problem given as equation 2.8 (Section 2.7.1) and repeated here as equation 3.1.

$$\text{minimize} \quad f(x_1, x_2, \ldots\ldots, x_i, \ldots\ldots x_n) \qquad (3.1)$$

$$\text{subject to } pmin_i \leq x_i \leq pmax_i,$$

$$g(x_j) \leq 0$$

where x_i are the decision variables;

$g(x_j)$ are the inequality constraints on some or all the design variables; and

$[pmin_i - pmax_i]$ is the feasible range of the decision variables $i=1,2, \ldots\ldots, n$

It is recognized that many other versions of the traditional GA exist. Figure 3.1 is a flowchart of the basic steps of the GA. The task is the determination of the parameters x_i that give the minimum value of f. Each decision variable is represented by a binary substring of bit length l.

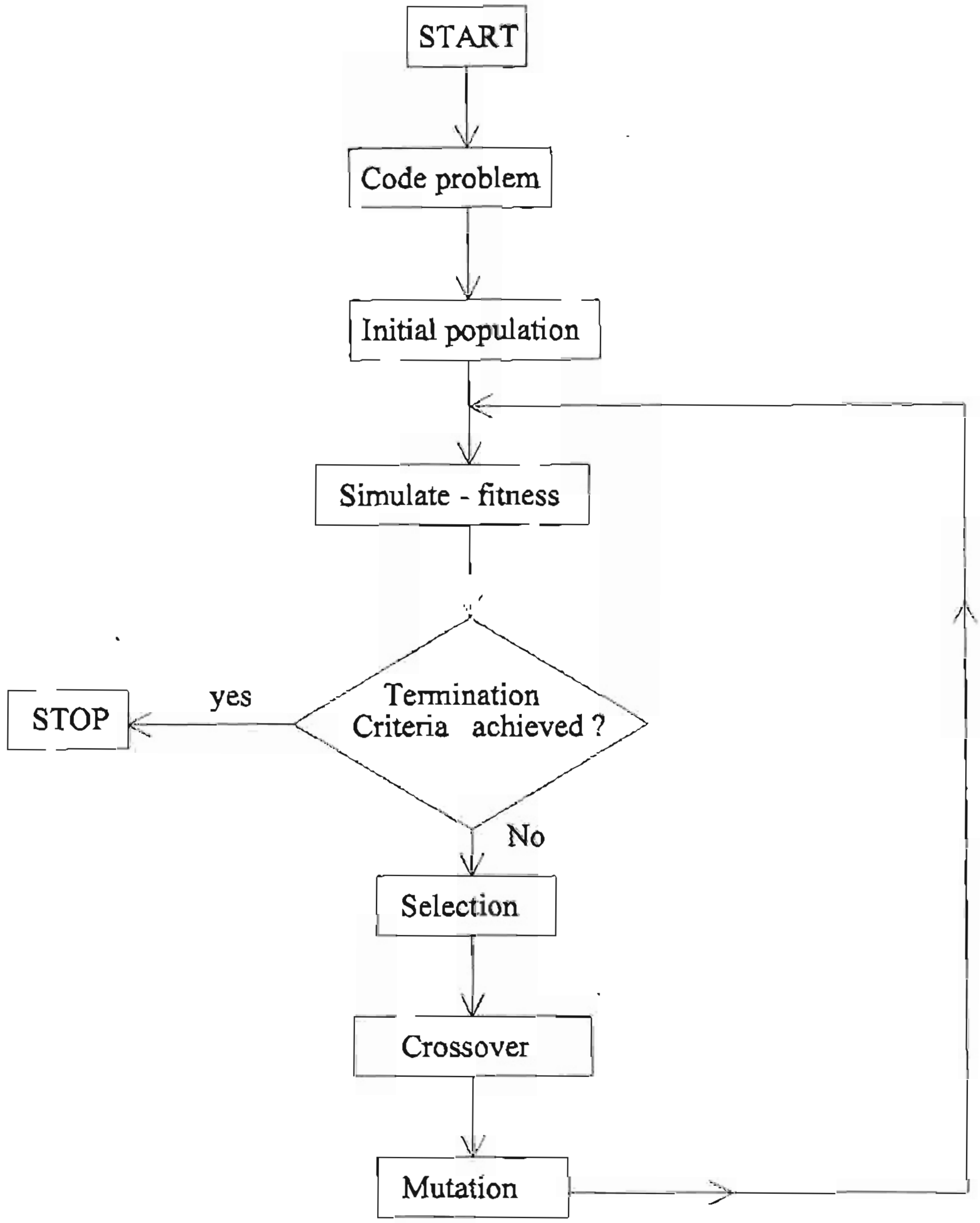


Figure 3.1 The Basic Steps of the Traditional Genetic Algorithm Method

The lower limit of the search range $pmin_i$ is therefore represented by the decoded integer 0 and the upper limit $pmax_i$ by the decoded integer 2^l-1. The actual value of the decision variable x_i is determined by linear interpolation of its decoded integer value. As an example, let the 6 bit binary substring for parameter x_i have the code '1 0 1 0 1 1' at some point in the optimization. The decoded integer value is $2^0\times1 + 2^1\times1 + 2^2\times0 + 2^3\times1 + 2^4\times0 + 2^5\times1 = 43$ and $x_i = pmin_i + [43/(2^6-1)] \times (pmax_i - pmin_i) = pmin_i + (43/63)\times(pmax_i - pmin_i)$. A complete parameter set in the n dimensional search space consists of the n decision variables, x_i where i=1, 2, ... , n and is represented as a binary string of length $n\times l$. The string is customarily referred to as a chromosome. A population of p chromosomes is generated randomly in the search space where p is the population size. The processes of selection, crossover and mutation are then implemented as follows.

1. The chromosomes are decoded and the fitnesses of the p individuals are computed. For the optimization problem of equation 3.1, the fitter individuals are those with lower objective function values. The selection of the chromosomes (parents) to use for the generation of new chromosomes (children) of the next generation is done in proportion to the fitness. Each population member is assigned to a segment in the range zero to one in proportion to its fitnesses. Two randomly generated numbers lying between zero and one are generated. The members whose assigned segments the random numbers lie are selected as a pair of parents. This is repeated $0.5 \times c \times p$ times where c is the probability of crossover.

2. A point is selected randomly in the range $l \times n$, the length of each chromosome and the codes of the pairs of parents are exchanged. This is repeated for all the $0.5 \times c \times p$ pairs of parents. In the illustration of Figure 3.2, parents 1 and 2 are individuals of a 6 parameter problem in which a 5 bit binary coding has been used. With a cross over point of say 15 obtained randomly within the range 1 to 29, the chromosome of the two children are as shown.

Chromosome for parent 1:	000111000101010↓101000110010101
Chromosome for parent 2:	*010100011100001*↓*101010100000110*
Chromosome for child 1	000111000101010↓*101010100000110*
Chromosome for child 2	*010100011100001*↓101000110010101

Figure 3.2 An Illustration of crossover

3. To implement mutation, the bit values of $m \times n \times l \times p$ randomly selected positions of the children are reversed (replace 0 with 1 and 1 with 0) where m is the probability of mutation.

4. The $c \times p$ children then randomly replace $c \times p$ individuals of the initial population.

5. Steps 2 to 4 are repeated until a designated termination criteria is met. This could be set at the maximum number of generations, the minimum improvement of the best performance in successive generations, or the known global optimum.

The traditional GA optimizes mainly through the selection (step 1), the crossover (step 2) and the replacement (step 4). The selection and replacement gradually increase the amount of useful information in the population while the crossover provides a means of searching for better combinations of that information. Mutation helps in maintaining diversity and in creating new useful genetic material. The schema theorem, a quantitative explanation of how the traditional GA optimizes has been presented by Goldberg (1989). The theorem is described in the following Section.

3.1.2 The Schema Theorem

A schema is a template applied to express similarities and differences among binary strings. A schema uses the binary alphabet of 0 and 1 and an additional 'don't care' symbol denoted by *. A position with the don't care symbol can take on a 0 or a 1 while the rest of the positions are fixed with either a 0 or a 1. The schema 0*11* for example matches the two strings, 01111 and 00110 as the two have a 0, a 1 and a 1 in the first, third and fourth positions respectively. The string 11101 does not match the schema at the first and the fourth position. Considering all the possible combinations, a large number of schemata exist in typical GA optimizations. Goldberg (1989) gives the number as lying between 2^l and $n \times 2^l$ depending on the diversity of the population. l is the bit length of the binary substring for a decision variable and n is the number of decision variables. For the derivation of the schema theorem, the fitness of a schema is given by the average fitness of the individuals in the population whose chromosomes match the given schema. Two additional properties, the defining length $d(H)$ and the order $o(H)$ of schema H are used in the schema theorem. The defining length is the difference in position between the first and the last fixed position of the schema and the order is the number of fixed positions in the schema. As an example, the schema *001****10** has a defining length of 10-2=8 and an order of 5. The schema theorem quantifies the effect of selection, crossover and mutation on the propagation of schemata as optimization proceeds.

Consider a schema H that has n_h members present in the population at generation g. n_h can be expressed as $n_h(H,g)$ since it depends on the generation g. The selection of parents in the traditional GA is done in direct proportion to the fitness of the individuals. By the definition of schema fitness, the propagation of a schema as a result of selection also happens in proportion to its fitness. The number of schema H after selection, $n_{hs}(H,g+1)$ can therefore be expressed by equation 3.2 where $fi(H)$ is the average fitness of the individuals matching schema H in the population and $\bar{fi}$ is the average fitness of the population.

$$n_{hs}(H, g+1) = n_h(H, g)\frac{fi(H)}{\overline{fi}} \quad (3.2)$$

An explanation of the effect of one point crossover on schema propagation uses Figure 3.3. A chromosome *CR*, two schema *H1* and *H2* that match it, and the possible crossover positions are shown on the Figure.

Chromosome *CR*	0		1		1		1		0		1		1		1
Schema *H1*	*		1		*		1		*		*		1		*
Schema *H2*	*		*		*		1		0		*		*		*
Crossover position		*1*		*2*		*3*		*4*		*5*		*6*		*7*	

Figure 3.3 The effect of one point crossover on schema propagation

Ignoring the chances that a schema will be rebuilt once destroyed, any crossover at position 2 to 6 will destroy schema *H1* but schema *H2* will survive all crossovers except that at position 4. As the crossover position selection is random, *H1* has a 2/7 chance of surviving and *H2* a 6/7 chance of surviving. The chance of a schema surviving crossover is therefore highly dependent on the defining length and is given by $1-d(H)/(l-1)$ for the general case. For a crossover probability of c, the probability of a schema surviving equals or exceeds $1-c \times d(H)/(l-1)$. The number of schema H surviving after the selection and crossover operation is therefore given by

$$n_{hsc}(H, g+1) = n_h(H, g)\frac{fi(H)}{\overline{fi}}(1 - c \times d(H)/(l-1)) \quad (3.3)$$

With a probability of mutation of m, the chance of the survival of any fixed position member of a schema is $1-m$. For a schema of an order $o(H)$, the chance that all the $o(H)$ members will survive the mutation and thereby retain the schema is the product of the probabilities of the individual members surviving which equals $(1-m)^{o(H)}$. Assuming a small value of the probability of mutation m, the second order terms can be ignored giving a survival probability of the schema of $1-m \times o(H)$. This effect of mutation added to the effects of selection and crossover gives the schema theorem, equation 3.4.

$$n(H, g+1) = n_h(H, g)\frac{fi(H)}{\overline{fi}}(1 - c \times d(H)/(l-1) - m \times o(h)) \quad (3.4)$$

The schema theorem implies that the traditional GA optimization favours schemata that are fit, of short defining length and of a small order. Depending on the variations to the GA, other derivations of the theorem can be obtained. For example, the traditional GA described in Section 3.1 performs selection and crossover for only the cxp individuals to be used in crossover and not for the total population p. It also performs mutation only on the newly generated cxp individuals. For this GA, the number of schema in generation $g+1$, defined as $n_h1(H,g+1)$ would therefore be given by equation 3.5 with $n_h(H,g+1)$ as obtained in equation 3.4.

$$n_h 1(H, g+1) = (1-c)n_h(H, g) + c \times n_h(H, g+1) \tag{3.5}$$

3.1.3. The Traditional Genetic Algorithm in Global Optimization

The effectiveness and the efficiency of the traditional GA in handling the response surface characteristics of typical global optimization problems given in Section 2.7.1 is the focus of this Section. The GA uses the objective function values and a population of points in the search space. It is therefore expected to deal with rough response surfaces satisfactorily unlike the gradient based techniques. The GA uses multiple points to search and this increases the chance of locating the global optimum in comparison to point based methods. The use of a multiple points method however has the tendency of reducing the efficiency of the search as it generally means a greater number of function evaluations than would be used by a point based search.

The traditional GA does not restrict selection and crossover within the population. Although the search is population based, independent individual or group searches are consequently not encouraged and there is the tendency for highly similar individuals to dominate the population as the optimization proceeds. The search therefore closes in to a single region of attraction or peak. If this region of attraction is not that containing the global optimum, then the GA at best converges to a local optimum.

The search domain of the traditional GA is a multidimensional grid that remains fixed throughout an optimization. For the GA to achieve the required precision the binary length l has to be large enough. With some problems like the model development in this research (see Chapter 4), the appropriate precision or even the search domain itself of some decision variables may not be known. The use of a large binary length *l* takes more computer space and if inadequate, the GA does not finetune to the required level.

The one point crossover of the traditional GA has the tendency to disrupt relationships among decision variables that are positioned far apart in the chromosome more than those positioned closely as illustrated in Figure 3.4.

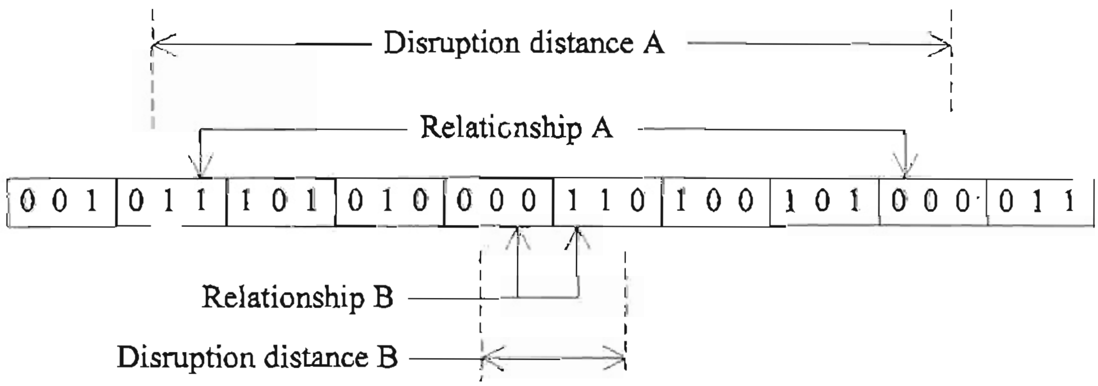


Figure 3.4 Positional Bias of the One Point Crossover

In this hypothetical 10 decision variable problem, using an *l* value of 3, relationship A between variable 2 and 9 will most likely be disrupted by a crossover placed between position 4 and position 26, a probability of 23/29. Relationship B between variable 5 and 6 has a 5/29 chance of being disrupted by a one point crossover. This effect, termed as positional bias (Eshelman *et al* (1989)), effectively treats the closely placed variables as being more closely related than those far apart which may not necessarily be the case. Intuitively this would be expected to slow down the search or lead to a poorer optimization.

The selection of the parents in the GA of Section 3.1.1 depends on the direct value of their fitness. Depending on the distribution of this fitness in the population, a few individuals could dominate the population early in the optimization leading to an inexhaustive search and a premature convergence. Conversely, the distribution may lead to a low level of competition if a considerable proportion of the individuals have almost the same fitness. This would be expected to slow down the optimization

The use of the traditional GA requires the choice of the population size *p*, the crossover probability *c*, the mutation probability *m*, and the length of the binary code length *l*. The choice of these parameters has an impact on performance and trial runs and/or sensitivity analyses may be needed in order to obtain reasonable values for the specific problem. This may not be a problem if the analyst has experience and/or relevant information from a similar problem.

The traditional GA has the advantages of being direct and population based but also exhibits several limitations. Depending on the problem at hand, the traditional GA is often modified or used in conjunction with other methods that may handle the specific GA limitations more effectively. Some of the modifications to the traditional GA and their impacts on performance are discussed in Section 3.2.

3.2. Modifications to the Traditional Genetic Algorithm

Numerous modifications to the traditional GA have been made and it is not the intention here to attempt an exhaustive review but present some of the major ones that have been found in the literature.

3.2.1. Genetic Algorithm Coding

A number of alternatives to the binary coding of the traditional GA have been devised and applied. Gray coding which ensures that neighbouring decision values differ by only one bit position has been applied by Dandy *et al* (1996) and Savic and Walters (1997) for cost optimization in the design of pipe networks. The sum of the differences of the corresponding bits between two strings is termed as the hamming distance. Gray coding therefore maintains a hamming distance of 1 between adjacent values in the search space. Table 3.1 gives a comparison of gray and binary coding for a hypothetical decision variable that can take on values ranging of 0 to 7 using a coding length of 3. While the gray coding maintains a hamming distance of 1 for all neighbours, binary coding exhibits hamming distances varying from 1 (eg. between 0 and 1) and 3 (eg. between 3 and 4).

Table 3.1 An illustration of gray and binary coding

Value	0	1	2	3	4	5	6	7
Binary code	000	001	010	011	100	101	110	111
Gray code	000	001	011	010	110	111	101	100

Dandy *et al* (1996) quote examples where the use of gray codes gave better performance than binary coding. Savic and Walters (1997) mention the existence of a neighbourhood structure which means that groups of similar solutions tend to lie close in the search space. This then implies that the best among a group of good solutions can be accessed through mutation. The hamming cliff of binary coding however makes this 'hillclimbing' more difficult than with gray coding. Schaffer *et al* (1989) also state the preference for gray to binary coding arguing that the elimination of hamming cliffs makes mutation more effective.

Other codings that have been used are integer and real (floating point) number coding. Halhal *et al* (1997) used integer coding in the optimization of water distribution system rehabilitation. Kwong *et al* (1995) and Mühlenbein *et al* (1991) used floating point coding in GA optimizations of theoretical functions. The two codings are free of the hamming cliff problem of binary coding. Intuitively, real number codes seem better suited for continuous variable problems and less suited than the other codings for integer and discrete variable problems. It is however possible that the creativity of the systems analyst could obviate some of the shortcomings typically associated with the various codings.

3.2.2. Selection in Genetic Algorithms

A commonly used alternative to the proportionate selection of the traditional GA is tournament selection. Tournament selection is implemented as follows. Individuals are randomly selected from the population to form two groups each of a size termed as the tournament size. The best performing individuals from each group are then identified and are stored as parents for the production of a pair of children. The process is repeated $0.5 \times c \times p$ times where c is the probability of cross-over. Comparison of the two approaches by Hassanli and Dandy (1994) and Simpson and Goldberg (1994) found tournament selection to converge considerably faster than proportionate selection.

Fitness scaling of the raw fitnesses is often done before selection to avoid potential shortcomings that could result from unsuitable distributions of the raw fitnesses. Three scaling approaches presented and described by Goldberg (1989) are linear, sigma truncation and power law scaling. Linear scaling uses an equation of the form

$$fi_s = afi + b \qquad (3.6)$$

where fi_s and fi are the scaled fitness and the raw fitness respectively. Coefficients a and b are selected to give an average scaled fitness value equal to that of the raw fitness and to limit the highest fitness to a small multiple (usual maximum value of 2) of the average fitness. To avoid the possibility of negative fitnesses, the linear equation 3.6 is transformed to equation 3.7 giving the sigma truncation scaling. $\overline{fi}$ is the average fitness of the population, σ the standard deviation of the fitness values and c is a coefficient usually lying between 1 and 3. Any fi_s values less than zero after the application of equation 3.7 are arbitrarily increased to zero.

$$fi_s = fi - \left(\overline{fi} - c\sigma\right) \qquad (3.7)$$

Equation 3.8 describes power fitness scaling where ps is a scaling index. Savic and Walters(1997), Dandy *et al* (1996) and Simpson *et al* (1994) used variable scaling indices ps in order to increase competition among individuals as optimization proceeds. Wu and Chow (1995) used a normalization process given as equation 3.9 to effect fitness scaling. In equation 3.9, fi_{max} and fi_{min} are the maximum and the minimum raw fitness values respectively.

$$fi_s = fi^{ps} \qquad (3.8)$$

$$fi_s = 1 - \left(\left(fi_{max} - fi\right)/\left(fi_{max} - fi_{min}\right)\right) \qquad (3.9)$$

Wang (1991) used a combination of ranking and linear scaling. The individuals were ranked in order of fitness giving rank 1 to the least fit and rank p to the fittest individual. The highest ranking individual was then assigned a selection probability $c_{max} \times p_{av}$ where c_{max} is a value greater than 1 and p_{av} is the average value of the selection probabilities. To obtain the required sum of selection probabilities of unity, this average value equals $1/p$. Linear scaling then gives the probability of selection of the least fit individual as $(2-c_{max})/p$. To ensure this value does not take a negative value, c_{max} takes a maximum value of 2. Wang (1991) considered low values of c_{max} to give slower and more robust searches than higher values. The linear interpolation applied to obtain the selection probabilities for the rest of the population is given in equation 3.10. pr_j is the probability of selecting the j th ranked individual, pr_l the probability of selection of the least fit individual and pr_h the probability of selection of the fittest individual.

$$pr_j = pr_l + \left(\frac{pr_h - pr_l}{p-1}\right)(j-1) \qquad (3.10)$$

3.2.3. Crossover

Some alternatives to the one point crossover are, the two point traditional, the multi-point traditional, the segmented, the uniform and the shuffle crossover (Eshelman *et al* (1989). The two point is a special type of the even numbered multi-point crossover with two crossover points. In the multi-point crossover, the parents are considered as rings and crossover positions are selected randomly at any locations of the rings. The segments from the two parents are then exchanged to form a pair of children. If the number of crossover points is odd, then an extra fixed position is specified to ensure the separation of all adjacent segments of the parents in the crossover. Positional bias (Figure 3.4) decreases as the number of crossover points increases. Figure 3.5 gives an illustration of a four point traditional crossover with the four crossover positions indicated as 1 to 4 on the two parents.

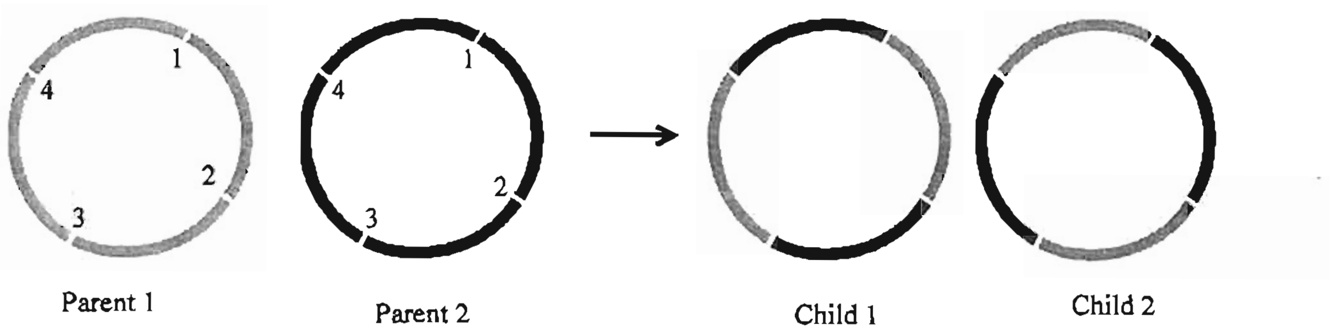


Figure 3.5 An Illustration of the Traditional 4 Point Crossover

In the segmented crossover, a distribution of the number of crossover positions is used instead of the constant number specified in traditional multipoint crossover. The mean of this distribution is the expected number of crossover positions. Eshelman *et al* (1989) give a more detailed description. Uniform crossover exchanges a specified proportion (crossover probability) of the bits of the pair of parents at randomly selected positions and therefore does not exhibit positional bias. Uniform crossover could however be highly disruptive at crossover probabilities of around 0.5 where most of the bits in the children are obtained randomly from the parents. The shuffle crossover consists of a random shuffling of the bit positions in tandem, followed by the traditional crossover and then the unshuffling of the strings.

Eshelman *et al* (1989) tested 12 crossover versions involving the traditional multipoint, the segmented, the shuffle and the uniform crossover on five theoretical test functions used earlier by Dejong (1975). The 8 point traditional crossover was found to use the least number of function evaluations in locating the global optima. Eshelman *et al* (1989) however reported a less exemplary performance of the 8 point traditional crossover in applications to other multi-modal functions where it ranked sixth. The traditional one point crossover did the worst in the two studies. Wu and Chow (1995) compared one point, two point, three point and four point traditional crossover in the optimization of three mixed variable type problems; a gear train, a pressure vessel and a coil compression spring design. The four point crossover was found to give the fastest convergence with all the three problems. It also gave a better solution for the pressure vessel design optimization.

Syswerda (1989) compared the one point, two point and uniform crossover in the optimization of 6 theoretical functions. On the average, uniform crossover performed better than the two others and the one point was the poorest performer. A theoretical analysis in the same study based on the schema theorem also favoured uniform crossover. The performance was however found to be problem dependent to some degree as uniform crossover performed the worst with the Shekel's foxholes problem. Savic and Walters (1997) also report their preference of uniform crossover for their water distribution network optimization after experimenting with several crossover operators. Bäck (1996) presents another crossover operator termed as the punctuated crossover and Cohoon *et al* (1991) give some other approaches to crossover.

3.2.4 Mutation

In the traditional GA, the position to mutate the string is selected randomly and could therefore either cause a small or a big change in the value of the decision variable. For example, the mutation of the 5 bit binary code 00010 at the first and the fifth positions gives 10010 and 00011 respectively. The first position and the fifth position 'mutant' give values of 18/31 and 3/31 respectively expressed as ratios of the range, 2^5-1. Although this feature of the traditional mutation serves to broaden the search, it could be disruptive as the optimum is approached. A mutation that varies the decision variable by known small amounts could serve better to close in to the optimum. Adjacency or creep mutation has been used to serve this purpose. Adjacency mutation changes the value by a specific amount (usually small) and is applied at a pre-specified probability level just as with the traditional mutation. Dandy *et al* (1996) used both traditional and adjacency mutation in their improved GA.

3.2.5 Use of Parallel Independent Searches

As stated in Section 3.1.3, the traditional GA lacks an explicit approach for dealing with multiple regions of attraction. Parallel GAs, GAs that apply simultaneous subpopulation searches, mostly on parallel processors have been applied in many optimizations (Cohoon *et al* (1991), Mühlenbein *et al* (1991), Donne *et al* (1995)). The subpopulation searches make the parallel GAs more suited to deal with multiple regions of attraction. Apart from the need for more robust searches and the availability of parallel processors, parallel GAs have also been inspired by analogy with nature (Tommasini (1993), Cohoon *et al* (1987)). Selection and crossover are restricted to the subpopulation members in parallel GAs therefore enabling a more robust search for multiple peaks than the traditional GA. In most implementations, the migration of the best or a set of good individuals among neighbouring subpopulations is done. The migrated individuals then replace some of the individuals of the subpopulation, either the most similar ones on the basis of hamming distance (Pettey *et al* (1987)) or those of low fitness (Tanesse (1987)). Several neighbourhood structures such as the ladder-population approach used by Mühlenbein *et al* (1991) can be applied. Tomassini (1993) used a massively parallel GA that assigned a large population to a two-dimensional grid and allowed crossover and replacements among the four neighbours of each individual and occasionally among those at more distant locations. The parallel GAs used by Mühlenbein *et al* (1991) and Tomassini (1993) were found to obtain the global optimum of the Griewank function, considered a difficult problem in the global optimization literature (Törn and Zilinskas (1989)). Tomassini (1993) reported that the standard GA consistently failed to obtain the global optimum of the Griewank function.

3.2.6 Nitching

Nitching is an alternative to subpopulation searches used for locating multiple peaks or regions of attraction. The two common nitching methods are *crowding* and *sharing*. Crowding works on the presumption that the initially generated population is adequately diverse and that this diversity can be maintained in the search by replacing only the population members that are most similar to the generated children. In the traditional GA, the replacement is done randomly. The similarity could be based on the actual values of the decision variables or the hamming distance of the binary strings of the two individuals. In sharing, the fitness *fi* of the individual is weighted in proportion to the degree of similarity of the individual with the other members of the population. The aim is to prevent the proliferation of highly similar members and to encourage the growth of unique subgroups. The subgroups then have the chance of converging to different regions of attraction. The equations below describe sharing as given by Miller and Shaw (1995).

$$shfi_i = fi_i / dt_i \tag{3.11}$$

$$dt_i = \sum_{j=1}^{N_i} sd_{i,j} \tag{3.12}$$

$$sd_{i,j} = \begin{cases} 1 - \left(d_{i,j} / s_{sh}\right)^{a_{sh}} \\ 0 \quad otherwise \end{cases} \tag{3.13}$$

$shfi_i$ is the shared fitness of individual i and dt_i the sum of the distances $sd_{i,j}$ between individual i and the N_i individuals that are within a distance σ_{sh} of individual i. α_{sh} is an index commonly taken as 1. The distances $sd_{i,j}$ are obtained from the raw distances $d_{i,j}$. The raw distances $d_{i,j}$ are determined through consideration of the differences of the actual decision variables or by using hamming distances of the binary strings and are computed to give lower values at higher similarities. Miller and Shaw (1995) also present improved approaches of crowding and sharing. The work of Halhal *et al* (1997) is an example of the application of sharing to an engineering problem; a water distribution system rehabilitation. Goldberg (1989) gives a lucid demonstration of nitching and Mahfoud (1995) gives a comprehensive review.

3.3 Applications Of The Genetic Algorithm To Rainfall Runoff Model Calibration

Five applications of the GA to rainfall-runoff model calibration have been located in the literature. Four of these were published during the course of the current research. The author and the supervisor of this research have also presented three papers to international conferences and these provide benchmarks for the progression of the GA modifications over the period of this study.

3.3.1 Calibration of the Xinanjiang Model (Wang (1991))

Wang (1991) applied the GA in the calibration of a seven parameter variant of the Xinanjiang model. In this application, which is also reported in Section 2.7.4, the traditional GA was used with binary coding and a 2 point traditional crossover. The proportionate selection with ranking and linear fitness scaling that Wang applied has been given in Section 3.2.2. Wang used a population of 100, a bit length of 10 for each parameter, a crossover of unity and a mutation of 0.01. A linear fitness scaling factor c_{max} of 2 was applied and the optimization allowed a maximum of 5000 evaluations. Wang reported a good performance of the GA and concluded that the global optimum was located in 8 out of the 10 trials used. Further searches did not obtain better results. Finetuning the GA with the sequential simplex method also did not improve the results significantly.

3.3.2 Calibration of the HYDROLOG Model (Wang *et al* (1995))

Wang *et al* (1995) used the GA to calibrate a 10 parameter version of the HYDROLOG model for two Australian catchments. The results of this research are also reported in Section 2.7.4. The GA applied here was similar to that used by Wang (1991) in the earlier study but a bit length of 7 and a fitness scaling factoı c_{max} of 1.5 was applied. As reported in Section 2.7.4, the GA was found to be less successful than in the earlier study (Wang (1991)) especially with one of the two catchments. It was evident that the GA was optimizing to local optimums in a substantial proportion of the trials. Unlike the earlier study (Wang (1991)) where finetuning was not very significant, this study reported improvements of the objective function of up to 30 % on finetuning the GA. with the pattern search method.

3.3.3 Calibration of the SWMM Model (Liong *et al* (1995))

Liong *et al* (1995) calibrated an event model, the storm water management model (SWMM) using a real number coded GA. A crossover probability of 0.6 and a mutation probability of 0.001 was used. A maximum of 50 generations were allowed. Peak flow prediction errors ranging from 0.045 to –1.339% were obtained with the three calibration runs. The three validations yielded peak flow errors ranging from 1.767 to 7.265%. Liong *et al* (1995) considered the calibration to be successful.

3.3.4 Calibration of the TANK Model (Tanakamaru and Burges (1996))

Tanakamaru and Burges (1996) undertook a comparative study of 8 optimization approaches. Three of the 8 approaches involved the GA; the plain GA, the GA finetuned with the Simplex method and the GA finetuned with Powell's conjugate gradient method. The optimization problem involved obtaining the 16 parameters of the TANK model used to generate a synthetic 4 year long daily precipitation and evapotranspiration series. The synthetic data series were used as the 'actual' series in the optimizations. As reported earlier in Section 2.7.4, the GA performed poorly in comparison with the SCE-UA and the multistart Powell's method. The SCE-UA and Powell's method obtained the global optimum in all the 20 trials performed. The traditional GA and the GA finetuned with the simplex failed in all the trials. Finetuning with Powell's method gave 11 out of 20 successes. The GA was dismissed as being neither efficient nor effective but it was added that its performance could be improved by the use of local search methods. However, the GA that was applied seemed to be a traditional one with a bit length of 7 for each parameter, a population of 200 and allowed a maximum of 100 generations.

3.3.5 Calibration of the MSFB Model (Kuczera (1997))

Kuczera (1997) incorporated the following modifications to the traditional GA:

- the use of tournament selection with a tournament size of 2;
- a swap–crossover that increased linearly with the generation from 0 to 0.35 at 5000 evaluations;
- a variable mutation that also increased linearly with the generation from 0 to 0.1 at 5000 evaluations; and
- an elitist scheme in which the worst 50% individuals of a generation were replaced with the best 50% of the previous generation.

A crossover probability of 0.9 was applied and binary coding with 10 bits per parameter used. As reported in Section 2.7.4, Kuczera found the GA to be inferior to the SCE-UA and considered it to be unsuitable for global optimum location. The GA was also found to be sensitive to the population size with a higher population size of 100 performing more poorly on the average than a population size of 20. Kuczera however still considered the GA he applied to be traditional and stated that it could be improved.

3.3.6 Calibration of STDT Models (Ndiritu and Daniell (1996a, b))

The two publications by the author and his PhD supervisor report the calibration of versions of the simple time-domain tuned (STDT) models, the conceptual-empirical models developed in the current research with a modified GA. The first, Ndiritu and Daniell (1996a) reports the use of a 12 parameter STDT model applied to a tropical Australian catchment. The modifications to the traditional GA were the use of tournament selection and a procedure for varying the parameter search range to achieve finetuning and hillclimbing as the optimization proceeds. The good calibration results obtained were considered partly to be an indication of the robustness of the GA. In the second study, a 14 parameter version of the STDT model was applied and data from a more typical, higher variability Australian catchment used. An investigation of the automatic search range variations on GA performance was reported. The two modifications of a range reduction and a range shifting strategy were both found to improve the optimizations. A theoretical data case study in the same paper obtained a simulated series almost identical to the 'real' one but the GA did not obtain the global optimum. The GA was however still considered robust judging from the near perfect fit of the 'actual' and the simulated runoff series. It is evident however that the tests on the GA were not rigorous and further tests indicated that the search range varying GA was still highly prone to local optimum traps. This observation and the results reported in Sections 3.3.2 and 3.3.4 prompted the search for additional means of improving the GA.

3.3.7 Calibration of the SIXPAR Model (Ndiritu and Daniell (1997))

This study tested a GA with a further improvement consisting of the application of independent subpopulation searches coupled with shuffling. The problem applied synthetically generated data and is described in detail in Section 4.4.1. Details of the performance of the improved GA are reported in Section 5.2.1. Briefly, the traditional GA was found to fail totally in the location of the global optimum while the improved GA achieved up to 98 percent success. The GA applying finetuning and hillclimbing only applied in the earlier studies (Ndiritu and Daniell (1996a, b), achieved about 70 percent success.

3.4 Discussion

The limitations of the GA in handling the global optimization problem have been discussed in Section 3.1.3 and some of the major modifications to the traditional GA in its applications were the subject of Section 3.2. As mentioned in Section 2.8, improvements to the GA have not been a main focus in the rainfall-runoff model calibration studies where GAs have been involved. A notable limitation of the traditional GA common to the rainfall-runoff model calibration studies reported in Section 3.3 is the absence of an explicit approach of searching for multiple regions of attraction and a means of obtaining the fittest solutions out of the multiple regions. One of the main objectives of this study was to devise and test ways of improving the performance of the traditional GA method in rainfall-runoff model calibration.

Chapter Four

Methodology and Experimentation

4.1 Summary

This chapter presents the steps followed during the course of the research including data collection, data processing and numerical experimentation. The work was performed in a flexible manner to allow appropriate changes and additions as results obtained at each stage suggested and also in the light of newly found information in the literature. The literature was reviewed continuously throughout the research period. Every step was performed keeping in mind the main objectives of the study given in Section 1.2 as:

1. To devise and test ways of improving the performance of the traditional genetic algorithm (GA) method in rainfall-runoff model calibration using:

- global optimum location tests;
- tests based on objective function values;
- tests based on the quality of validation runoff series of a rainfall-runoff model; and

   include a sensitivity analysis of the improved GA performance to optimization parameters.

2. To compare the performance of the improved GA with other optimization methods including the shuffled complex evolution (SCE-UA) method.

3. To develop a class of simple conceptual-empirical rainfall-runoff models using GA calibration as a guide.

4. To compare the performance of the conceptual-empirical models with a commonly used conceptual rainfall-runoff model; the MODHYDROLOG.

The first objective was undertaken over most of the study period and the improved GA obtained at this stage can most likely still be improved upon. Tests on the GA modifications were carried out using a synthetic data-based calibration of a simplified research version of the Sacramento soil moisture accounting (SAC-SMA) rainfall runoff model, the SIXPAR; two theoretical global optimization functions; the Griewank and the Hartman function and historical data-based calibrations of two of the models developed in this study, the STDT3 and the STDT4 model. Performance evaluation in the tests was based on:

- *Effectiveness*: the ability to locate or get close to the global optimum and the performance of model validation results;
- *Efficiency*: the number of function evaluations or model runs made before the specified convergence criteria is met; and
- *Consistency*: closeness of results from multiple optimizations obtained from random initializations within the search space.

The SIXPAR rainfall-runoff model calibration and the theoretical functions had been used previously in a comparative study of several optimization procedures including the SCE-UA (Duan *et al* (1993)). The three problems were also used in the implementation of the second objective.

The third objective was implemented by a stepwise model development starting from a simple empirical model adopted from the literature. Further modifications were then made with the aim of improving the model performance. This was mainly achieved by the inclusion of more catchment processes in the modelling using simple approaches and equations. Following the suggestions of Jakeman and Hornberger (1993), all the models were limited to a quick and a slow flow component. A class of models termed as simple time domain tuned (STDT) models owing to their more than customary emphasis on the time domain were the result of this effort. The models were tested on three Australian and three Kenyan catchments. Model performance evaluation was based on hydrograph plots of the actual and the simulated flow, the coefficient of efficiency, the bias, the absolute deviation and a residual mass curve coefficient.

The third objective involved a comparison of two STDT models, the STDT3 and the STDT4 with the MODHYDROLOG model using data from three Australian catchments. Five randomly initialized split-sample calibration - validations were done and comparisons of the calibration and validation performances were made. The parameter identification and correlations of the models were also compared.

The numerical experiments were performed using FORTRAN 77 programs. All the programs except the code for the SIXPAR and the MODHYDROLOG model were written by the Author. As in typical code developments, debugging the programs was one of the challenging parts of the research. The model development and GA modifications were undertaken-simultaneously. Some of the models developed earlier had therefore been calibrated using less robust GA optimizations. Recalibration of the models using the most robust GA obtained was therefore necessary for an accurate evaluation and comparison of the models.

4.2 Modifications to the Genetic Algorithm Method

Seven modifications to the traditional GA were made at different times over the period of this study. Initially, three modifications, the use of a hybrid tournament-proportionate selection, an automatic search range reduction (finetuning) and a automatic search range shifting strategy (hillclimbing) were incorporated into the GA. The effects of the two search range modification procedures were found to improve GA calibration of the simple time domain tuned (STDT) models. A publication by Ndiritu and Daniell (1996b) presents some of the results obtained with the search range varying GA. When tested more stringently however, this GA was found to be prone to local optimum traps. Although it consistently gave better performance than the traditional GA, the optimized parameter and objective function values were found to vary with different initializations. Different initializations were obtained by changing the random number generation seed. The continuing review of the literature also indicated some unsatisfactory performances of the GA as reported in Sections 2.7.4 and 3.3. Among the global optimization difficulties given in Section 2.7.1, the likely cause of the search range varying GAs failure to locate global optimums was identified as the lack of an explicit means of dealing with multiple regions of attraction or peaks. The use of independent subpopulation searches coupled with the concept of shuffling (Duan *et al* (1992)) was then adopted and incorporated into the search range varying GA. The new GA improved consistency and exhibited a much greater independence from the initial population. This GA was also found capable of locating the global optimums of theoretical functions more successfully. Ongoing literature review revealed that the single point crossover was generally a poorer performer than multi-point and uniform crossover (Section 3.2.3). The incorporation of multi-point and uniform crossover however brought no notable improvements to the shuffled, range varying GA. The seven modifications to the traditional GA which were undertaken are listed below.

- A hybrid tournament-proportionate selection incorporating variable fitness scaling;
- An elitist strategy that includes the best individual of the previous generation in the current population;
- A finetuning procedure involving periodic automatic reduction of the search range and its centralizing about the parameter value of the best individual of the current generation;
- A hillclimbing procedure involving periodic automatic search range shifting towards the more promising search regions;
- Independent subpopulation searches coupled with shuffling;
- Multi-point and uniform crossover; and
- Creep mutation of the elitist parameter set.

The basic steps of the improved GA are presented in the flow chart of Figure 4.1. Some of the modifications, namely multi-point crossover, uniform crossover and creep mutation were implemented as described in Section 3.2. Detailed descriptions of the rest of the modifications follow.

4.2.1 Hybrid Tournament-Proportionate Selection

The hybrid approach differs from the tournament selection described in Section 3.2.2 in two aspects. Firstly, instead of a random selection of the individuals to form the two tournaments, a proportionate selection (Section 3.1.1) incorporating a variable power fitness scaling given in equation 4.1 was applied. The individuals with a lower objective function were fitter as all the optimizations done aimed at lowering the objective function value. Secondly, the fittest individuals from each tournament, the parents, were used to produce one and not a pair of children. The selection process was therefore repeated $c \times p$ times where c is the probability of crossover.

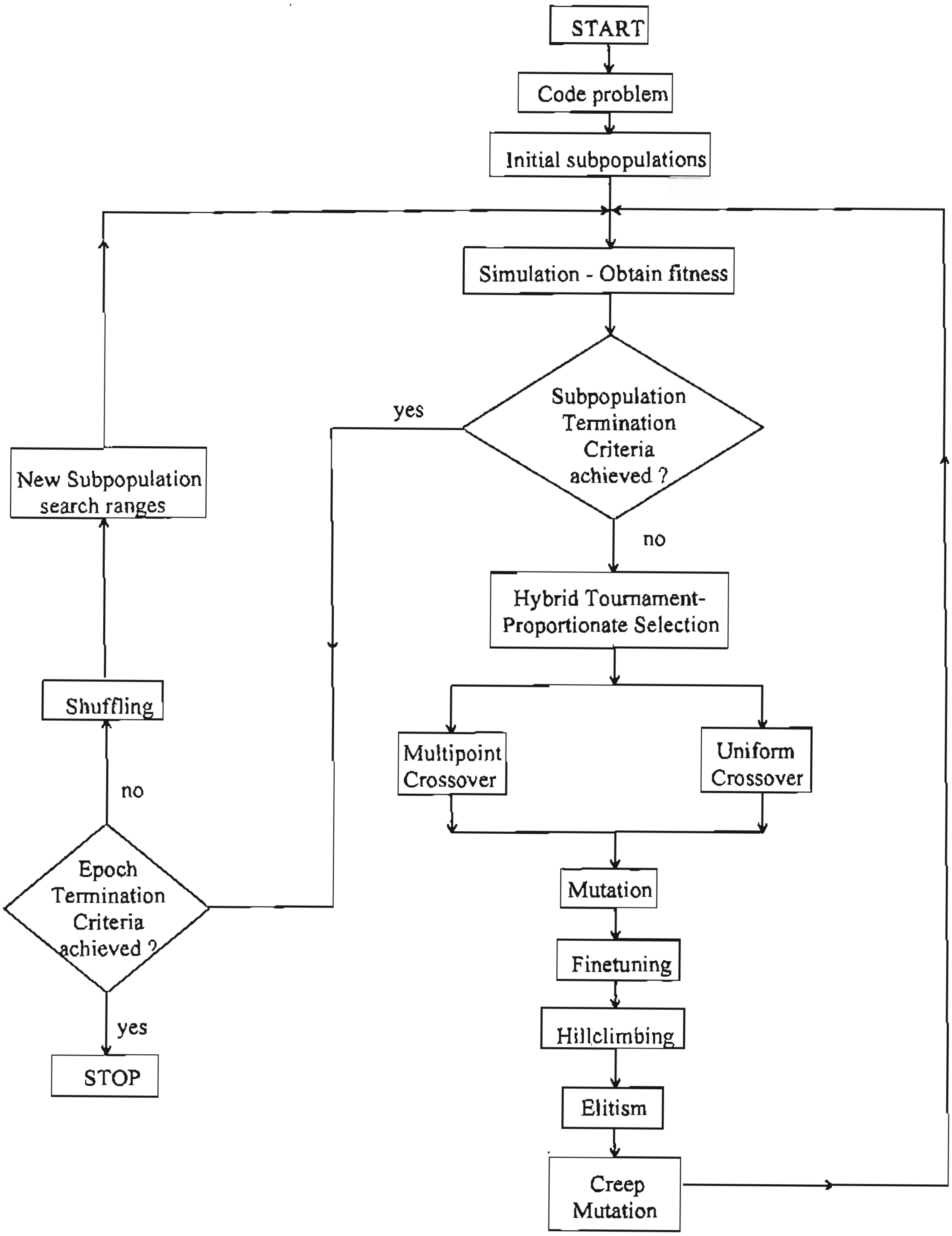


Figure 4.1 Basic Components of Improved Genetic Algorithm

$$fi_{si} = \left(\sum_{i=1}^{p_s} obf_i \Big/ obf_i \right)^{\left(\frac{g + f_{scale} \cdot g_{max}}{f_{scale} \cdot g_{max}} \right)} \qquad (4.1)$$

where fi_{si} is the scaled fitness, p_s is the population or subpopulation size, obf_i is the raw objective function value for individual i, g is the current generation, f_{scale} is the fitness scaling index; and g_{max} is the allowed maximum number of generations in a population or subpopulation optimization.

4.2.2 Finetuning

Finetuning was achieved through the gradual reduction and shifting of the search range. After every specified number of generations denoted as $s1$, the locations of the parameters of the best performing individuals in a specified number of successive previous generations denoted as $s2$ are checked. If the values are within a small portion of the search space, then the search range for that parameter is reduced and centralized around the parameter value of the best individual of the current generation. This gives a finer grid and a more concentrated search. The finetuning strategy is given in equations 4.2 to 4.5.

After every $s1$ generations and for all dimensions $i = 1,2, \ldots, n$,

$$r1_{i,g} = 2 \frac{\left(\max xb_i^j - \min xb_i^j : \quad j = g - s_2 + 1, g - s_2 + 2, \ldots, g \right)}{\left(p\,max_i - p\,min_i \right)} \qquad (4.2)$$

$$r1_{min} \le r1_{i,g} \le r1_{max} \qquad (4.3)$$

$$p\,max_{ig} = xb_i^g + r1_{i,g}\left(p\,max_i - p\,min_i \right) \qquad (4.4)$$

$$p\,max_{i,g} = xb_i^g + r1_{i,g}\left(p\,max_i - p\,min_i \right) \qquad (4.4)$$

$$p\,min_{i,g} = xb_i^g - r1_{i,g}\left(p\,max_i - p\,min_i \right) \qquad (4.5)$$

$$p\,min_{ig} = xb_i^g - r1_{i,g}\left(p\,max_i - p\,min_i \right) \qquad (4.5)$$

where xb_i^j is the value of parameter x_i for the best performing individual in generation j, $max\ xb_i^j$ and $min\ xb_i^j$ are the maximum and minimum values of xb_i^j in the past $s2$ generations (including the current generation g). $r1_{min}$ and $r1_{max}$, are the finetuning control parameters to check premature convergence as a result of exceedingly low $r1_{i,g}$ values and enlargement of the search range in case $r1_{i,g}$ values are too high.

The value $r1_{i,g}$ is twice the decision variable range within which the best values of the best performing individuals in the past $s2$ generations are contained taken as a ratio of the search range. $pmin_i$ and $pmax_i$ are the search range limits before finetuning and $pmin_{ig}$ and $pmax_{ig}$ are the search range limits after finetuning. After a series of trials and as experience was gained, suitable values for the parameters of the finetuning strategy were obtained. These values are 5, 5, 0.4 and 0.5 for $s1$, $s2$, $r1_{min}$ and $r1_{max}$ respectively. Figure 4.2 is an illustration of finetuning. In Figure 4.2a, the same notation as in equations 4.2 to 4.5 has been used. Figure 4.2b demonstrates how a search with a finer grid has a better chance of reaching solutions closer to the optimum than a search with a coarser grid. This figure shows that a finer gridded search can obtain objective function value obf_f which is better than obf_c, the best value the coarser gridded search can achieve.

4.2.3 Hillclimbing

Hillclimbing consists of range shifting towards regions of the search space that are more promising. The range shift is also considered as a means of preventing premature convergence of the search when the finetuning routine is in operation. Hillclimbing is implemented after every given number of generations (denoted as $s3$). The strategy is described in equations 4.6 to 4.8 and is illustrated in Figure 4.3 using the same notation as for finetuning. x_{ki}^g in Figure 4.3 denotes the parameter values for all the individuals excluding that of the best individual whose value is xb_i^g. The Figure shows the automatic shift of the x_{ki}^g values up the 'hill' as the relative positions are maintained with respect to the search range limits after the shifting. This shift is automatic as the binary codes of the individuals are maintained after the shifting. Elitism maintains the best performing individual at the same value xb_i^g ignoring the effect of creep mutation if applied. To implement elitism with any range shifting, decimal to binary conversion is necessary.

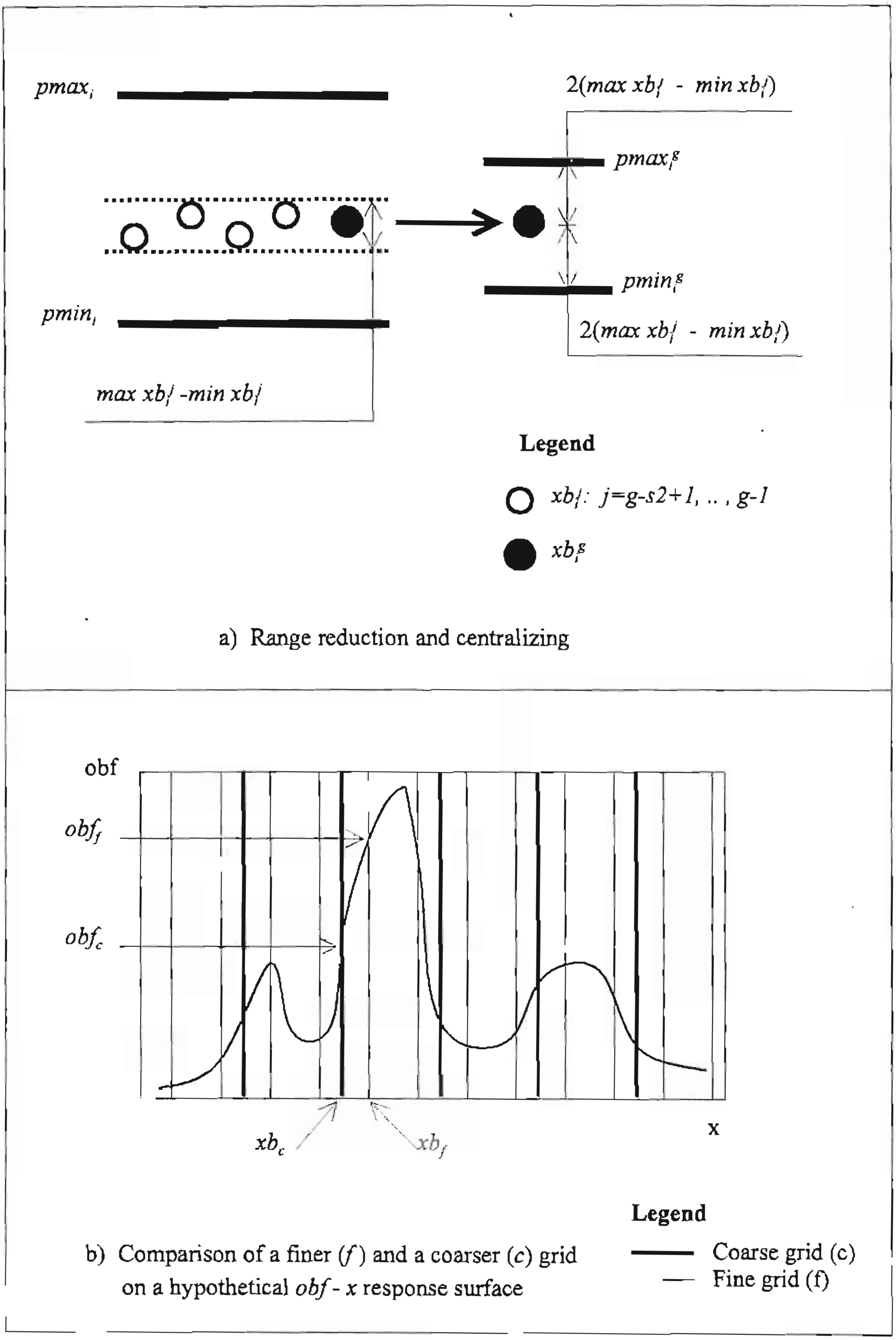


Figure 4.2 An Illustration of Finetuning

The shift $sh_{i,g}(pmax_i\text{-}pmin_i)$ in equations 4.7 and 4.8 is the deviation from the middle of the current search range of the mean of the values of the best individuals in the last *s4* generations including the current one. As with finetuning a value of 5 was found reasonable for both *s3* and *s4*. After every *s3* generations and for all dimensions $i = 1,2, ..., n$,

$$sh_{i,g} = \frac{\left(\left[\sum_{j=g-s4+1}^{g} xb_{i,g} \Big/ s4\right] - 0.5(pmax_i + pmin_i)\right)}{(pmax_i - pmin_i)} \tag{4.6}$$

$$pmax_{i,g} = pmax_i + sh_{i,g}(pmax_i - pmin_i) \tag{4.7}$$

$$pmin_{i,g} = pmin_i + sh_{i,g}(pmax_i - pmin_i) \tag{4.8}$$

The finetuning and hillclimbing approaches handle each variable independently contrasting with heuristic crossover hillclimbing (Kwong *et al* (1995)) in which lumped movements of the whole parameter sets were applied.

The finetuning and the hillclimbing procedure enable the GA to search beyond the initially prescribed search domain. This could be particularly useful when dealing with unfamiliar problems or data as in the model development of this research. To make use of this capability but also to ensure that the search does not shift into obviously unrealistic regions, two search spaces are specified. One is the initial search space $[Xmin_{1i} - Xmax_{1i}]$ which allows for the input of the known constraints and also the optimizer's intuition and experience but which the search can go beyond. The other is the limiting search space $[XLmin_i - XLmax_i]$ with $i=1,2,...,n$ beyond which the search is not allowed. The known constraints are also included in the limiting search domain and wider ranges of the unknown constraints are used than in the initial search domain. To avoid interference of the finetuning and hillclimbing, simultaneous application of the two (hillclimbing and finetuning in the same generation) was not allowed. The hillclimbing was performed two generations after every finetuning as experimentation with some trial runs suggested.

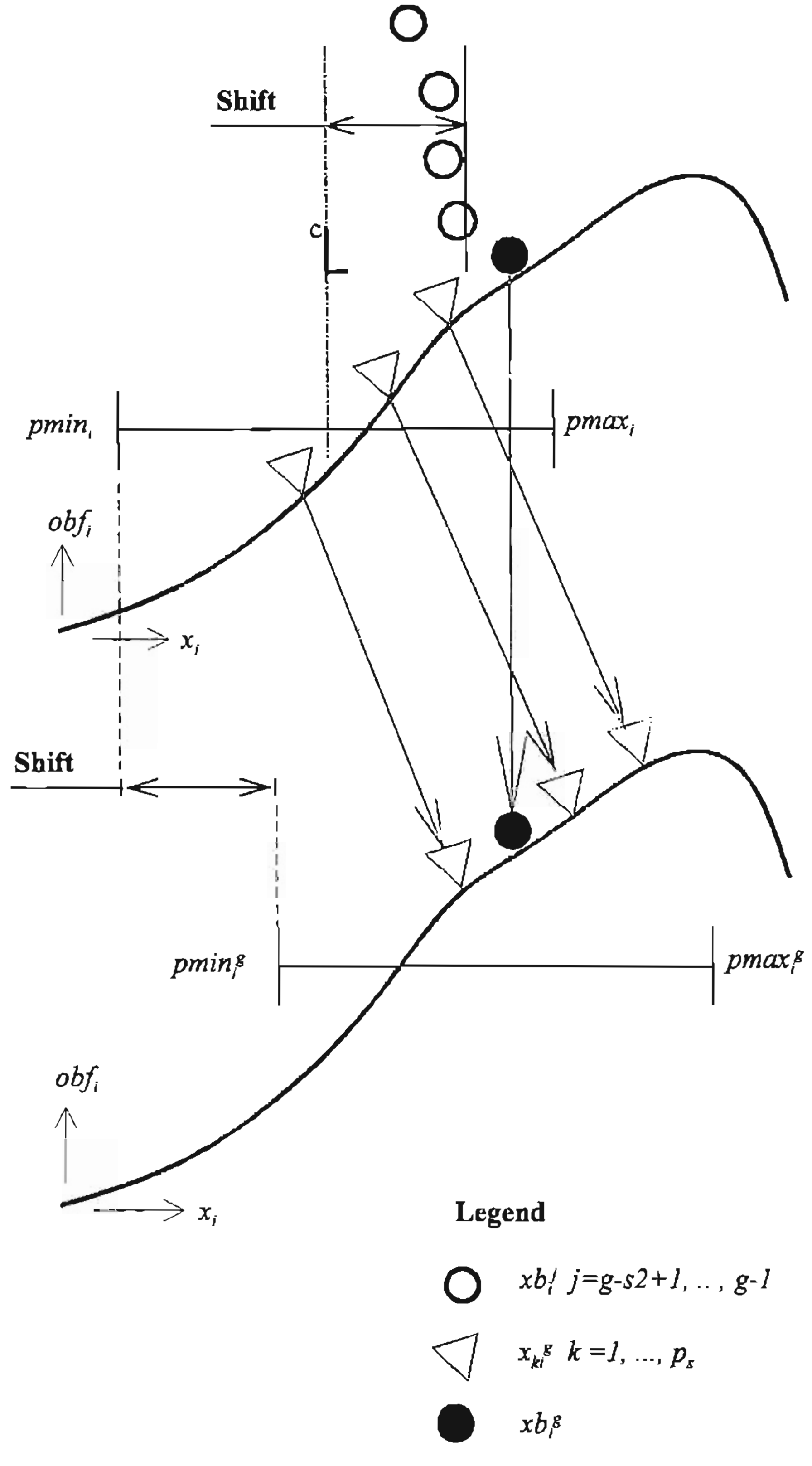


Figure 4.3 An Illustration of Hillclimbing

4.2.4 Independent Subpopulation Searches and Shuffling

The total population p is split into n_s subpopulations of size p_s each. Each subpopulation searches independently to an optimum without any migration of individuals among the subpopulations. The subpopulations are then shuffled and new parameter ranges obtained for each subpopulation for the next level of search referred to as the epoch. Shuffling involves the following steps.

The total population (from all the subpopulations) is ranked in order of performance to form a matrix $[ch(i),\ i=1,2,\ \ldots\ldots,\ p\ ]$ where $ch(1)$ is the best performing and $ch(p)$ is the worst performing individual. The individuals are then allocated to the subpopulations using equation 4.9 to effect the shuffling procedure of Duan *et al* (1992) or equation 4.10 to effect what is termed hereby as the overlapping shuffling. Overlapping shuffling has been developed in this study.

$$sch(i,j) = ch(i + p_s(j-1)) \tag{4.9}$$

$$sch(i,j) = ch(j + p_s(i-1)) \tag{4.10}$$

where $sch(i,j)$ is the j th (j=1,2, ..., p_s) individual in the i th (i=1,2, ..., n_s) subpopulation.

For a hypothetical case of four subpopulations, SP1 to SP4, each having five individuals, shuffling would allocate the ranked individuals as illustrated in Figure 4.4. In the Figure, 1 denotes the best and 20 the worst performing individual.

For all the n dimensions, the least and highest parameter values of each subpopulation are then used as the lower $Xmin_{1i}$ and upper $Xmax_{1i}$ bounds of the initial search space of the next epoch. The first subpopulation retains all the p_s individuals from the previous epoch and uses them as the initial population. The initial individuals for the other subpopulations are generated randomly.

SP1	SP2	SP3	SP4	SP1	SP2	SP3	SP4
1	2	3	4	1	6	11	16
5	6	7	8	2	7	12	17
9	10	11	12	3	8	13	18
13	14	15	16	4	9	14	19
17	18	19	20	5	10	15	20
Duan *et al* (1992)				Overlapping			

Figure 4.4 An Illustration of Shuffling

4.3 Tests on the Modifications to the Genetic Algorithm

The effects of all the modifications with the exception of the hybrid tournament-proportionate selection, elitism and creep mutation were tested systematically. Optimization runs were made with;

- the traditional GA;
- the GA with hillclimbing and finetuning alone hereafter termed as the range varying GA;
- the GA with independent subpopulation searches and shuffling alone hereafter termed as the shuffled GA; and
- the GA with independent subpopulation searches, shuffling, hillclimbing and finetuning hereafter termed as the fully modified GA. This does not imply it cannot be modified further but the term is used for briefness.

For the optimizations both multi point and uniform crossover were applied. The traditional one point crossover was treated as a special case of the multi-point crossover. No comprehensive comparison of Duan *et al*'s shuffling and overlapping shuffling was made. Most of the GAs used Duan's approach although some trials indicated that the overlapping shuffling approach could be just as effective or at times more effective.

The traditional GA contains a number of parameters where the reasonable values that need to be obtained for successful optimization. Theoretically, an exhaustive sensitivity analysis of all reasonable parameter combinations may be required to obtain the optimal values. However, this may not be practical due to time constraints. The generality of the results from such an analysis may also be questionable as the optimal parameters for a specific problem may not be ideal to another. A feasible alternative is the use of fewer trials based on the optimizer's intuition, past experience and information available from other sources. An approach taken by Wu and Chow (1995) was to use a GA to optimize the GA optimization parameters. This vastly reduces the number of evaluations in comparison with the theoretical exhaustive analysis using all the parameter combinations. The number of evaluations however still tends to be high as Wu and Chow (1995) mention. In this study, the sensitivity of GA performance to some optimization parameters was undertaken. The parameter in question was varied, keeping all the other parameters to reasonable and constant values. The GA performance with the variation of that parameter was then obtained. Table 4.1 presents details of the optimization parameters of the improved GA indicating those included in the sensitivity analysis. The sensitivity analysis was performed using the SIXPAR and the STDT3 models. The following three convergence parameters were also applied in the optimizations;

- *perfmin*: the value of the objective function for theoretical optimizations below which the global optimum was considered located. This was set to 0.001 of the known global optimum.
- *perconv*: a value indicating the convergence of a parameter. If the ratio of the current search range to the initial search range of the first epoch reduced to this or lower values for all the parameters, convergence was considered achieved and the search terminated. A *perconv* value of 0.001 was used throughout.
- *cheperf*: an optimization termination parameter. Equation 4.11 shows how this parameter was applied to population and subpopulation optimizations. obf_i is the objective function of the best individual in generation *i*. The epoch convergence criteria is given in equation 4.12 where obf_{pep} and obf_{cep} are the best objective function values of the previous and the current epoch respectively. The sensitivity of GA performance to *cheperf* was also studied.

$$if \quad \sum_{i=g-4}^{g} obf_i \Big/ \sum_{i=g-9}^{g-5} obf_i \geq cheperf \qquad terminate\ the\ search \tag{4.11}$$

$$if \quad obf_{cep} \; / obf_{pep} \geq cheperf \qquad terminate\ the\ search \tag{4.12}$$

Table 4.1 Optimization Parameters of Improved Genetic Algorithm

Parameter	Symbol	Sensitivity Analysis (Y/N)	Typical Values
Population size	P	Y	
Subpopulation size	p_s	N	$2\times n_p$
Number of subpopulations	n_s	Y	
Bit length of parameter substring	l	Y	10-20
Maximum number of generations per optimization	g_{max}	N	1000
Maximum number of function evaluations	ev_{max}	Y	
Probability of crossover	c	Y	1.0
Number of crossover positions	n_{cross}	Y	n_p
Rate of uniform crossover	u_{cross}	Y	0.5
Probability of mutation	m	Y	0.05
Tournament size	t_o	N	$P/3$, $p_s/3$
Fitness scaling index	f_{scale}	Y	3
Number of previous generations used in finetuning	$s1$	N	5
Number of generations to repeat finetuning	$s2$	N	5
Number of previous generations used in hillclimbing	$s3$	N	5
Number of generations to repeat hillclimbing	$s4$	N	5
Finetuning parameter to check premature convergence	$r1_{min}$	N	0.4
Finetuning parameter to check range enlargement	$r1_{max}$	N	0.5
Convergence parameter	$cheperf$	Y	0.9-0.999
Maximum number of epochs	ep_{max}	N	0, 50

4.4 Problems for Testing Modifications to the Genetic Algorithm

Three problems that had been used in a comparative study of four other optimization methods (Duan *et al* (1993)) and two of the rainfall runoff models developed in this study were selected to test the modifications to the GA. Duan *et al* (1993) used the SIXPAR model calibration, the Hartman, and the Griewank function as three of the eight functions applied in a comparative study of the Multistart Simplex (MSX), the Comparative Random Search (CRS-2), and two versions of the SCE-UA method, the SCE-1 and the SCE-2. With each of the methods 100 trials were performed. An optimization was considered a success if the sum of the least squares of the difference between the 'observed' and the modelled flow reduced to at least 0.001 of the global optimum value of 0. A trial was considered a failure if it reached 25000 evaluations or if the region spanned by the population converged to within 10^{-12} of the parameter range in each direction without the 0.001 mark being attained. The number of failures out of 100 and the average number of function evaluations for the successful trials were obtained for each run. In order to ensure a valid comparison, the same settings were used in the GA optimizations of this study. These three problems are now presented. The STDT3 and the STDT4 rainfall-runoff models, which were developed in this study and also used to test the GA modifications, are described in Section 4.5.6 and 4.5.7 respectively.

4.4.1 The SIXPAR Rainfall-Runoff Model Calibration Problem

This problem used a synthetic 200-day rainfall and runoff sequence and the 6-parameter SIXPAR model and has been extensively studied by Duan *et al* (1992). Section 2.7.1 gives more details of that study. The SIXPAR model (Figure 4.5) is a simplified research version of the Sacramento soil moisture accounting (SAC-SMA) model of the National Weather Service River Forecasting System (NWSRFS) of the USA. Parameters *UM* and *BM* have units of length and are thresholds of the upper and lower zone storages respectively. Parameters *UK* and *BK* (units of time $^{-1}$) control the rates of recession. *A* and *X* are dimensionless parameters applied in modelling the percolation process. *Pt* represents the rainfall, *Rt* the overland flow, *It* the interflow and *Bt* the baseflow in period *t*. *USt* and *BSt* represent the upper and lower storage volumes in period *t* respectively. The 'true' parameter set used to generate the synthetic 200-day runoff sequence was; *UM*=10, *BM*=20, *UK*=0.5, *BK*=0.2, *A*=0.31, and *X*=3. The following search space was applied in the optimizations; *UM*=(0,50), *BM*=(0,50), *UK*=(0,1), *BK*=(0,1), *A*=(0,1), and *X*=(0,10). The 200-day rainfall and runoff series is plotted in Figure 4.6. Over the 200 day period, the rainfall and runoff volumes are equal as evapotranspiration losses are not modelled in SIXPAR. In spite of the seemingly high correlation between the rainfall and runoff, the analysis by Duan *et al* (1992) reveals that the SIXPAR optimization problem included all the features of rainfall-runoff model calibration given in Section 2.7.1.

The SIXPAR problem was used to test the GA improvements and was also applied in the sensitivity analysis of the optimization parameters listed in Table 4.1. For the optimizations made for comparison of the GA with the other optimization methods 100 runs were used as Duan *et al* (1993) had done. To save on time, 30 runs, were used for all other purposes.

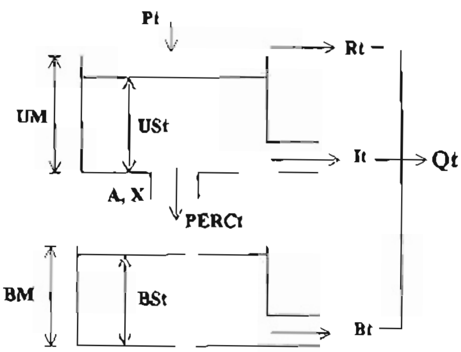


Figure 4.5 A schematic of the SIXPAR Model

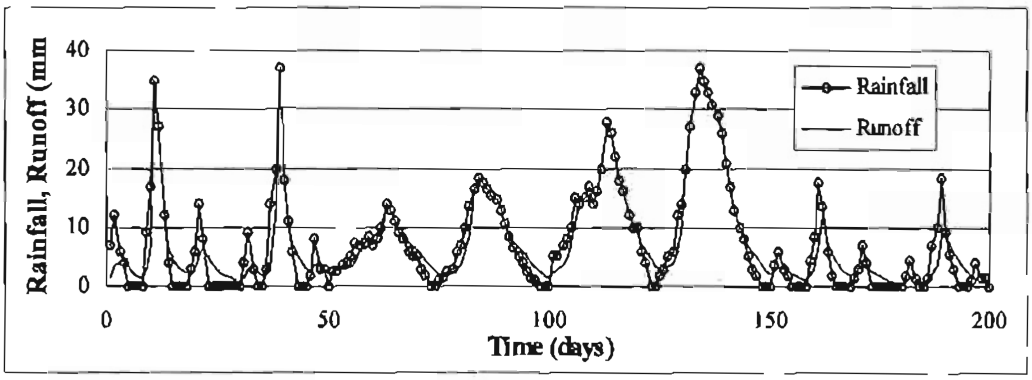


Figure 4.6 Synthetic Rainfall and Runoff series of the SIXPAR Model Optimization Problem

4.4.2 The Hartman Function Optimization Problem

Equation 4.13 describes the Hartman function and the values of the coefficients $\alpha_{i,j}$, c_i and $p_{i,j}$ are given in Table 4.2. The global optimum of the Hartman function is 0 and is located at $[x]$=(0.201, 0.150, 0.477, 0.275, 0.311, 0.657).

$$minimize \quad h[x] = 3.32 - \sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{6} \alpha_{i,j} \left(x_j - p_{i,j} \right)^2 \right) \qquad (4.13)$$

$[x] = (x_1, \ldots\ldots, x_6)^T \qquad 0 \le x_i \le 1$

The GA modifications were tested with the Hartman function using optimization parameters obtained from the sensitivity analysis with the SIXPAR problem.

Table 4.2 Coefficients of the Hartman Function (from Duan *et al* (1993))

Values of α_{ij} and c_j							
j	α_{1j}	α_{2j}	α_{3j}	α_{4j}	α_{5j}	α_{6j}	c_j
1	10	3	17	3.5	1.7	8	1
2	0.05	10	17	0.1	8	14	1.2
3	3	3.5	1.7	10	17	8	3
4	17	8	0.05	10	0.1	14	3.3
Values of p_{ij}							
j	p_{1j}	p_{2j}	p_{3j}	p_{4j}	p_{5j}	p_{6j}	
1	0.1312	0.1696	0.5569	0.0124	0.8283	0.5886	
2	0.2329	0.4135	0.8307	0.3736	0.1004	0.9991	
3	0.2348	0.1451	0.3522	0.2883	0.3047	0.665	
4	0.4047	0.8828	0.8732	0.5743	0.1091	0.0381	

4.4.3 The Griewank Function Optimization Problem

The Griewank function is given by equation 4.14 and has the global optimum at x_i=0, i=1, ... , 10. The function possesses thousands of local minima (Duan *et al* (1993)).

$$g[x] = \left(\sum_{i=1}^{10} x_i^2 \Big/ 4000 \right) - \prod_{i=1}^{10} \cos\left(x_i/\sqrt{i}\right) + 1 \qquad (4.14)$$

$[x] = (x_1, \ldots\ldots, x_{10})^T \qquad -600 \le x_i \le 600$

The Griewank function is considered one of the difficult optimization problems in the global optimization literature (Törn, and Zilinškas (1989)) and has also been tested using parallel GAs (Mühlenbein *et al* (1991), Tomassini (1993)). Applying the criteria used by Duan *et al*

(1993) which specified a maximum of 25000 evaluations, the fully modified GA obtained success rates lower than 10% applying up to 10 subpopulations of 20 individuals each. A further investigation was carried out to find whether the modified GA could perform better allowing more function evaluations. This was a reasonable step as the tests by Mühlenbein *et al* (1991) and Tomassini (1993) had allowed for more function evaluations and achieved 100 percent success. An upper limit of 200000 evaluations was set and the number of runs per test set to 30. Twenty nine of the 30 tests successfully located the global optimum as reported in Section 5.2.3. Other tests with the improved GA developed in this research (Ndiritu and Daniell (1997) achieved 100 percent success in the optimization of the Griewank function. As for the Hartman function, no sensitivity analysis was applied with the Griewank function.

4.5 Rainfall-Runoff Model Development

The objective function and performance criteria, the data collection and preparation and the stepwise development of the models is presented in this Section. Although more models were experimented with, the five described here give an adequate representation. All the models were first tested with the Scott Creek catchment data. Among the five, two of them were considered to be of acceptable performance. The better performing of the two was then tested further using data from the five other catchments. To explain the model development process, qualitative descriptions of the model performances are used. The quantitative results are given in Chapter 5.

4.5.1 Objective Function and Performance Evaluation

An objective function adapted from Diskin and Simon (1977) was applied in all the calibrations and is given as equation 4.15.

$$\text{minimize}\ \frac{Const.}{(tm-pl)}\left(\sum_{i=pl+1}^{tm}\frac{(run_i-arun_i)^{in}}{(run_i+arun_i)^{1/in}}\right) \qquad (4.15)$$

In equation 4.15:

Const. is a constant for maintaining the objective function values within a reasonable range;

tm the length of the hydrological series;

run_t and $arun_t$ is the simulated and historical runoff respectively (mm); and

in an index for varying the relative importance assigned to high and low flows with higher values of *in* favouring higher flows. A value of 1 gives equal importance to all flows while higher values give more importance to higher flows. After a series of trials, a value of 1.2 was selected.

p1 is a model parameter optimized to determine to which period in the past the current runoff depends. After a series of tests, the values of *in* and *Const* selected for all the optimizations were 1.2 and 0.01 respectively. *p1* is included in the summation because the simulated runoffs are only determined for times *t* greater than *p1*. The denominator *(tm-p1)* includes *p1* to ensure that the objective function values for different calibrations receive the same level of factoring, independent of the value of *p1*.

To evaluate simulation performance, the following seven coefficients were initially applied:

- the coefficient of efficiency (*ce*), a measure of the variance;
- the correlation coefficient (*cc*), a measure of correlation;
- the bias (*bias*), a measure of the ability to predict the volume of discharge;
- the absolute deviation (*ade*), a measure of the average departure of the predictions at every time step; and
- three forms of the residual mass curve coefficient (*rmcc*1, *rmcc*2, and *rmcc*3), measures of systematic errors in the simulations.

Equations 4.16 to 4.22 describe the coefficients.

$$ce = 1 - \left(\sum_{t=p1+1}^{tm} (run_t - arun_t)^2 \Big/ \sum_{t=p1+1}^{tm} (run_t + arun_t)^2 \right) \tag{4.16}$$

$$cc = \sum_{t=p1+1}^{tm} \left(run_t - \overline{run}\right)\left(arun_t - \overline{arun}\right) \Big/ \left(\sum_{t=p1+1}^{tm} \left(run_t - \overline{run}\right)^2 \sum_{t=p1+1}^{tm} \left(arun_t - \overline{arun}\right)^2 \right)^{0.5} \tag{4.17}$$

$$bias = \sum_{t=p1+1}^{tm}(run_t - arun_t) \Big/ \sum_{t=p1+1}^{tm} arun_t \tag{4.18}$$

$$ade = \sum_{t=p1+1}^{tm}|run_t - arun_t| \Big/ \sum_{t=p1+1}^{tm} arun_t \tag{4.19}$$

$$rmcc1 = 1 - \sum_{t=p1+1}^{tm}|rmsim_t - rmact_t| \Big/ \sum_{t=P1+1}^{tm}|rmact_t| \tag{4.20}$$

$$rmcc2 = 1 - \sum_{t=p1+1}^{tm}(rmsim_t - rmact_t)^2 \Big/ \sum_{t=p1+1}^{tm}\left(rmact_t - \overline{rmact}\right)^2 \tag{4.21}$$

$$rmcc3 = 1 - \sum_{t=p1+1}^{tm}\left|(rmsim_t - rmact_t)/rmact_t\right| \tag{4.22}$$

Equations 4.16 to 4.19 use the same notation as equation 4.15. In equations 4.20 to 4.22 $rmsim_t$ and $rmact_t$ are the residual mass curve values for the simulated and actual flow at time t respectively. $\overline{rmact}$ is the mean of the residual mass curve values of the actual flow series. The coefficient of efficiency, originally proposed and used by Nash and Sutcliffe (1970), is commonly used (Wang *et al* (1995), Wang (1991), Yapo *et al* (1996), Gan and Biftu (1996), Refsgaard and Knudsen (1996), Franchini *et al* (1996), Gan and Burges (1990)). The bias measure has also been used by Sorooshian *et al* (1993), Yapo *et al* (1996), Chiew and McMahon (1994), Gan and Biftu (1996) and Refsgaard and Knudsen (1996). Boughton (1993) used the correlation coefficient while Aitken (1973) used a residual mass curve coefficient given as *rmcc2* (equation 4.21). As Aitken (1973) points out, the residual mass curve coefficient is more sensitive to systematic errors in the simulated flows than the other coefficients. The coefficient of efficiency, the correlation coefficient and the residual mass curve coefficients take on a maximum value of unity in the case of a perfect fit. The bias and absolute deviation take perfect fit values of zero. The correlation coefficient and the absolute deviation take on a minimum value of zero but the other coefficients could take negative values. The results obtained revealed no advantage in using all the seven as there was the tendency for the trends to be similar. The coefficient of efficiency (*ce*), the bias, the absolute deviation (*ade*) and one of the residual mass curve coefficients (*rmcc*3) were selected for performance evaluation.

4.5.2 Data Collection and Preparation

A total of six catchments, three Australian and three Kenyan were used in the model development and testing. The Australian catchments were selected from a set of 28 unregulated catchments whose average daily rainfall, potential evapotranspiration and runoff had been prepared by Chiew and McMahon (1993b) and made available for teaching and research purposes. The selection was based on the length of the data, the quality of the data as given by Chiew and McMahon (1993b) and the need for the selected catchments to have considerably variable characteristics. Most of the rainfall and climate data was obtained from the Australian Bureau of Meteorology. The runoff data was obtained from the respective State and Territory Water Agencies. To obtain average catchment rainfalls, the Theissen polygon approach was applied. Potential evapotranspiration was derived by Morton's (1983) model using drybulb and wetbulb temperatures and sunshine hours data. Table 4.3 provides some physical and climatic characteristics of the three catchments selected for this research. Chiew and McMahon (1993b) provide more details on the data set preparation and the characteristics of the catchments.

The initial modelling experiments were performed using the Australian catchments more so the Scott Creek catchment, in South Australia, whose rainfall and potential evapotranspiration data quality had been classified as excellent by Chiew and McMahon (1993b). A daily, a pseudoweekly, and a monthly time interval were tried out in the initial stages of the modelling. The daily time interval was found too time consuming as the modelling included summations of past net rainfalls to optimized past periods mostly exceeding 100 at every time step. Intuitively, the number of daily past periods would be expected to be large and the modelling experiments revealed this. The monthly time interval was considered too coarse as the modelling was not entirely empirical. The pseudoweekly duration gave a better balance between time of simulation and precision and was therefore adopted. The data was summed into 6 day and a few 7 day durations so that each month contained five durations. In leap years, the months were assumed to alternately consist of 30 days (five 6 day periods) and 31 days (four 6 day and one 7 day period). In other years, the 12th month was assumed to consist of 30 and not 31 days. Plots of the pseudoweekly series for the three Australian catchments are given in Appendix A4. The Australian data was obtained almost ready for modelling.

The inclusion of Kenyan data provided a chance to obtain and process raw data and thereby experience some of the data collection and preparation challenges of practical hydrological modelling. This helped to get a real 'feel' of the problem especially regarding the forms and extents of explicit and implicit lumping of data. Initially, there was the aim of obtaining data from each of the five drainage basins in Kenya. Raw runoff data was requested from the Kenyan Ministry of Land Reclamation, Regional and Water Development. Following this, staff gauge heights and the corresponding rating curves were obtained for a total of seven catchments located in four of the five drainage basins. Rainfall and pan evaporation data for the catchments was then requested from the Kenya Meteorological Department. The rainfall computer database of the Kenyan Meteorological Department was non-functional at the time. Computer rainfall records were therefore requested from the Kenyan Drought Monitoring Centre. A search of the Drought Monitoring Centre database gave rainfall records for 23 stations for five of the seven catchments. Pan evaporation data was obtained from hard copy records as the evaporation computer database at the Kenyan Meteorological Department was also non-functional. Daily pan evaporation records were obtained for eight stations close to or within six of the seven catchments.

There were therefore five catchments with rainfall, evaporation and runoff records out of the initial seven. One of the five catchments was however found to be highly regulated and was consequently discarded. A check on the other catchments revealed there was no significant regulation. In general, the data was available for varying periods within which some records were missing. Within some periods, the gauge height records exhibited a trend with two records out of a week consistently missing; most likely a reflection of the five-day working week. For some periods, two gauge height readings per day were available. Daily runoff in cubic metres per second was computed using the respective rating equations. For the days with two gauge height records, runoff was computed for each height and a simple averaging used to obtain the daily runoff. Pseudoweekly values of runoff, rainfall and pan evaporation were then obtained by averaging the available daily values within each period leading to mm/day units. For the Australian catchments, the sum of the daily values were obtained throughout and units of mm/pseudoweek were therefore used. After this averaging, the runoff data for one of the four catchments still exhibited considerable discontinuities. As the discontinuities could not be explained or easily filled in, the data from this catchment was not considered for further use.

The Theissen polygon method was used to compute average catchment rainfall and pan evaporation where applicable. Suitable periods from which to obtain modelling data were then selected. Some of the discontinuities (periods with missing data) formed suitable points to split the samples into calibration and validation sets and were used as such. The filling in of runoffs for periods with less than five data points missing was done by hand plots judging from the rainfall and evaporation in the period and from other 'similar' nearby periods. For all the catchments, these periods constituted less than 4% of the total period.

About 10 percent of pseudoweekly evaporation data for one of the catchments was missing. These values were estimated from corresponding values from the other years with an adjustment made for the observed annual trend. This approach was adopted as the pan evaporation series was seasonal with no considerable variations among years and the rainfall-evaporation correlations (Figure A4-7 of Appendix A4) were poorer than correlations between evaporation values of corresponding periods (Figure A4-6 of Appendix A4). Additional details of the data processing and estimations are presented in Appendix A4. Table 4.4 gives some characteristics of the three Kenyan catchments used in the model testing. Figure 4.7 shows the locations of the three Australian and the three Kenyan catchments.

Table 4.3 Some characteristics of the three Australian catchments used in Modelling.

Catchment Name	Babinda Creek at the Boulders	Scott Creek at Scott Bottom	Canning River at Glen Eagle
RGS Number	111105	503502	616065
Location	17° 21′ S 145° 52′ E Queensland 60 km S of Cairns	35° 06′ S 138° 41′ E South Australia 20 km S of Adelaide	32° 14′ S 116° 10′ E Western Australia 50 km SE of Perth
Period of Record	1974-1987	1970-1985	1977-1987
Catchment Area (Km^2)	39	27	544
Annual Runoff (mm)	4700	130	20
Annual Rainfall (mm)	5400	950	800
Annual PET (mm)	1600	1080	1245
Soil Type	Clay	Duplex	Duplex
Catchment Cover	Forest	Grass	Forest

Figure 4.4 Some Characteristics of the three Kenyan Catchments used in Modelling

Catchment	Noigameget	Nyasara	Chania
RGS Number	1BC01	1KA05	4CA02
Location	00° 55′ 40″ S 35° 08′ 00″ E Near Kitale Town	00° 01′ 25″ S 35° 47′ 00″ E Near Kisii Town	00° 38′ 08″ S 37° 03′ 47″ E Near Thika Town
Catchment Area (Km^2)	718	4.1	529
Description	Thicket, forest, woodland, swampy valleys	Periurban	Thick forest, forest, woodland, agriculture
Period of record	1975-1987	1978-1987	1963-1973
Annual Rainfall (mm)	987	2180	1363
Annual PEV (mm)	1489	1565	1322
Annual runoff (mm)	261	1120	525

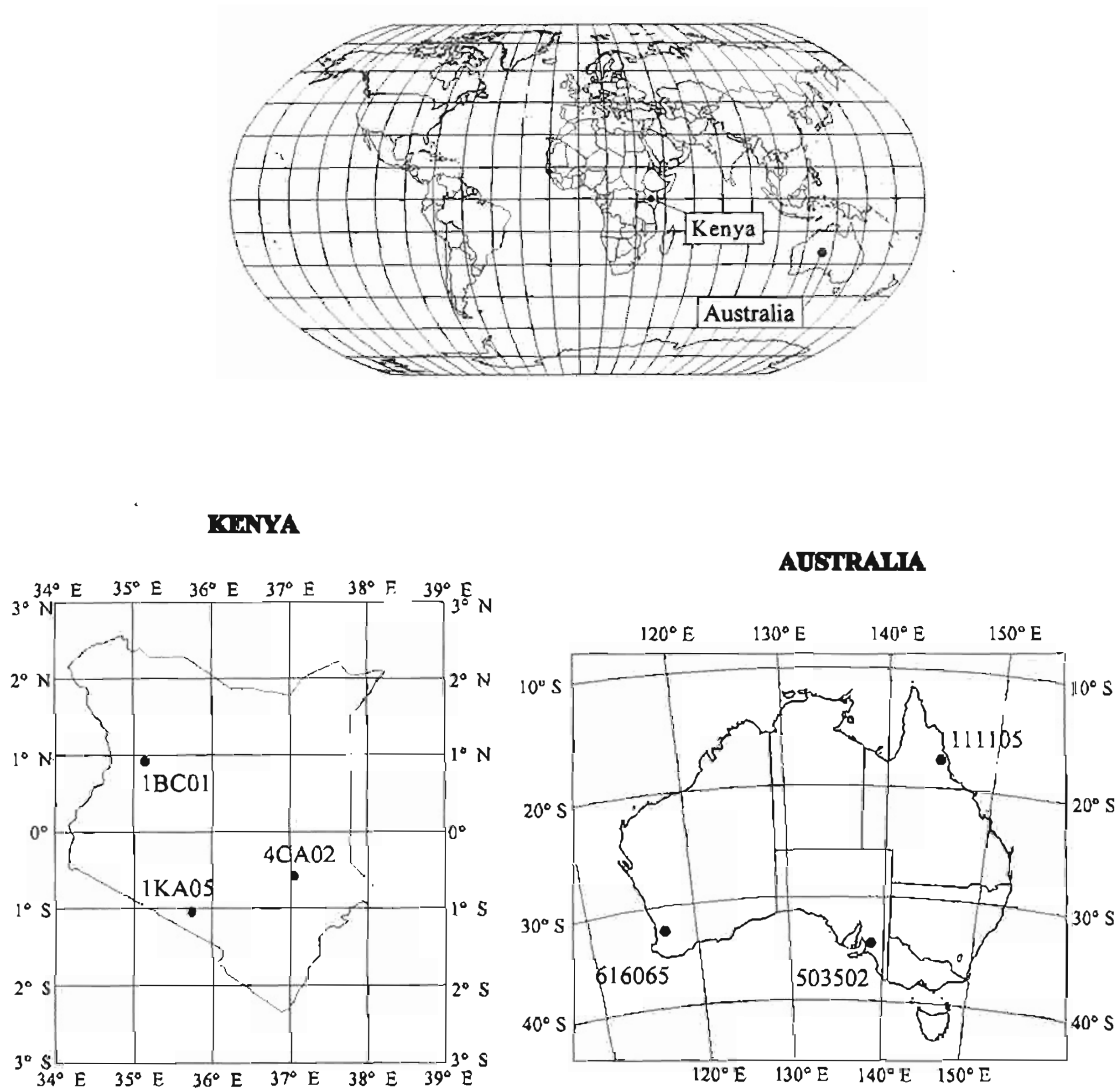


Figure 4.7 Location of the Six Catchments used in Model Development and Testing

4.5.3 The Simple Empirical (SEMP) Model

To begin the model development, a simple empirical (SEMP) model given as equation 4.23-4.24 was tried out first. This model was a modified version of one of the multiple regression models used by Tsykin (1985). An evapotranspiration component was added to Tsykin's model in an attempt to get closer to reality. Tests on the model revealed that it could not handle evapotranspiration as the optimized evapotranspiration coefficient *p1* in equation 4.23 consistently reduced to a negligible value. The model was also poor in modelling both low and high flows. For the analysis and discussion of this model, the second component of equation 4.24 is regarded as the slow flow component.

$$rn_t = r_t - p1.pet_t \qquad rn_t \geq 0 \tag{4.23}$$

$$run_t = p2.rn_t^{p3}.rn_{t-1}^{p4} + p5.rn_{t-1}^{p6}.rn_{t-2}^{p7} \qquad run_t \geq 0 \tag{4.24}$$

where rn_t is the net rainfall, r_t the rainfall, pet_t the potential evapotranspiration, run_t the runoff in period t and $p1$ to $p7$ model parameters.

4.5.4 The Simple Time Domain Tuned Model 1 (STDT1 Model)

An attempt to improve the slow flow component of the SEMP model was made by including a summation of the past net rainfalls to a past period determined through optimization. This gave the first of the simple time-domain tuned (STDT) models, referred to hereafter as the STDT1 model. Some of the multiple regression models used by Tsykin (1985) applied summations of rainfall to specific past periods. In Tsykin's models compared to the STDT models, the past periods over which to sum were not obtained by automatic calibration and evapotranspiration was also not included. Equations 4.25 to 4.27 describe the STDT1 model.

$$sl_t = \sum_{j=t-p1}^{t-1} \left(rn_j / p1 \right) \qquad sl_t \geq 0 \tag{4.25}$$

$$rn_t = r_t - p2.pet_t \qquad rn_t \geq 0 \tag{4.26}$$

$$run_t = p3.rn_t^{p4}.rn_{t-1}^{p5} + p6.rn_{t-1}^{p7}.rn_{t-2}^{p8} + p9.sl_t \qquad run_t \geq 0 \tag{4.27}$$

Model STDT1 was found not to improve the simulations significantly. A major conceptualization limitation of this model was considered to be the equal weight given to all past net rainfalls in determining the slow flow component $p9.sl_t$. This resulted in very low values of parameter $p9$. Earlier rainfalls are expected to have a lower impact on the current runoff than more recent ones. The second and the third component of this model both represented a slow flow component and this was considered unnecessary.

4.5.5 The Simple Time Domain Tuned Model 2 (STDT2 Model)

A variable weight of the past net rainfalls in obtaining the slow flow component sl_t and the omission of the second component of model STDT1 (equation 4.27) resulted in the STDT2 model given by equations 4. 26, 4.28 and 4.29.

$$sl_t = \sum_{j=t-p1}^{t-1}\left(rn_j/(t-j)\right) \qquad sl_t \geq 0 \tag{4.28}$$

$$run_t = p3.rn_t^{p4}.rn_{t-1}^{p5} + p6.sl_t \qquad run_t \geq 0 \tag{4.29}$$

Model STDT2 performed considerably better than STDT1. The hydrograph plots however revealed a weakness in the simulation of high flows. A probable reason for this was thought to be the non-consideration of the antecedent catchment wetness in obtaining the quick flow, the first component of equation 4.29. The runoff generated from a given volume of rainfall depends on the antecedent catchment wetness with a wetter catchment producing more runoff than a drier one.

4.5.6 The Simple Time Domain Tuned Model 3 (STDT3 Model)

The slow flow component sl_t was used as an indicator of catchment wetness and a parameter determined through optimization used to differentiate between the wet and the dry catchment states. Different coefficients for obtaining the current runoff component were then used for the wet and the dry state. An additional modification was the omission of rn_{t-1} from the computation of the quick flow as the contribution of rn_{t-1} was the largest component of slow flow component sl_t. This gave a more distinct delineation of the quick and the slow flow. The STDT3 model is given by equations 4.26 and 4.30 to 4.32.

$$sl_t = \sum_{j=t-p1}^{t-1} \left(rn_j / (t-j) \right) \qquad sl_t \geq 0 \tag{4.30}$$

If $sl_t \geq p3$ *then*

$$run_t = p4.rn_t^{p5} + p6.sl_t \qquad run_t \geq 0 \tag{4.31}$$

Elseif $sl_t \leq p3$ *then*

$$run_t = (p2/p7)rn_t^{p3} + p6.sl_t \qquad run_t \geq 0 \tag{4.32}$$

Model STDT3 gave better simulations than STDT2 and separated the slow and quickflows more satisfactorily. In the search of further improvements to model STDT3, several other models were tried out and the publication by Ndiritu and Daniell (1996a) presents the application of a 12 parameter STDT model to the Babinda Creek catchment and the stepwise model development described more comprehensively in this Section. Model STDT4 was selected as being representative of the many versions tested.

4.5.7 The Simple Time Domain Tuned Model 4 (STDT4 Model)

Model STDT4 was obtained with the following additions to model STDT3.

- The use of indices to allow further for the nonlinear nature of the rainfall-runoff process. A total of four such indices were included.
- The inclusion of range limits to the past net rainfalls in the determination of the slow flow. It was felt that setting these limits could improve the slow flow evaluation as high rainfalls would have drained away in previous periods and high evapotranspiration rates dry a catchment to a limit. Two parameters were included to confine the past net rainfalls.
- The inclusion of an additional wetness state to give a total of three states; a very wet, a wet and a dry state. The dry state results in only slow flow. Thus an additional parameter was added.

The 14 parameter STDT4 Model is described by equations 4.33 to 4.41.

$$sl_t = \sum_{j=t-p1}^{t-1} \left(\frac{(nr_j)^{p5}}{(t-j+1)^{p6}} \right) \qquad sl_t \geq 0 \tag{4.33}$$

$$p4 \leq (nr_j = r_j - p2.pet_j) \leq p3 \tag{4.34}$$

$$If \qquad p7.(sl_t)^{p8} \geq p9 \tag{4.35}$$

$$run_t = p7.(sl_t)^{p8} + p10.p7.(nrc_t)^{p11} \tag{4.36}$$

$$where \qquad nrc_t = r_t - p2.pet_t \tag{4.37}$$

$$Elseif \qquad p12 \leq p7.(sl_t)^{p8} < p9 \tag{4.38}$$

$$run_t = p7.(sl_t)^{p8} + \left(\frac{p10}{p13}\right).p7.(nrc_t)^{p11} \tag{4.39}$$

$$Else \qquad run_t = p14.p7.(sl_t)^{p8} \tag{4.40}$$

$$For\ all \quad t \qquad run_t \geq 0 \tag{4.41}$$

The weighted sum of past net rainfalls sl_t is converted to slow flow using parameters $p7$ and $p8$ to give $p7.sl_t^{p8}$ as the slow flow component in equations 4.36, 4.39 and 4.40. Parameters $p3$ and $p4$ (equation 4.34) restrict the past net rainfalls nr_j. The current net rainfalls nrc_t are not restricted as equation 4.37 indicates. The quick flows in the very wet and the wet conditions are given by $p10.p7.rnc_t^{p11}$ (equation 4.36) and $(p10.p7/p13).rnc_t^{p11}$ (equation 4.39) respectively. The total flow in the dry state is given by equation 4.40. In equation 4.36, parameter $p7$ is included so that a direct comparison of the relative contributions of slow and quick flow can be judged from the value of $p10$. For making direct quantitative comparison of the quickflow contributions in the very wet and the wet states, parameters $p7$ and $p10$ is included in equation 4.39.

Model STDT4 contains four physically realistic parameters. These are:

- $p1$, which determines up to which period in the past the current runoff depends;

- *p2*, an evaporation coefficient or the ratio of actual to potential evapotranspiration; and
- *p9* and *p12* which relate the catchment wetness to slow flow.

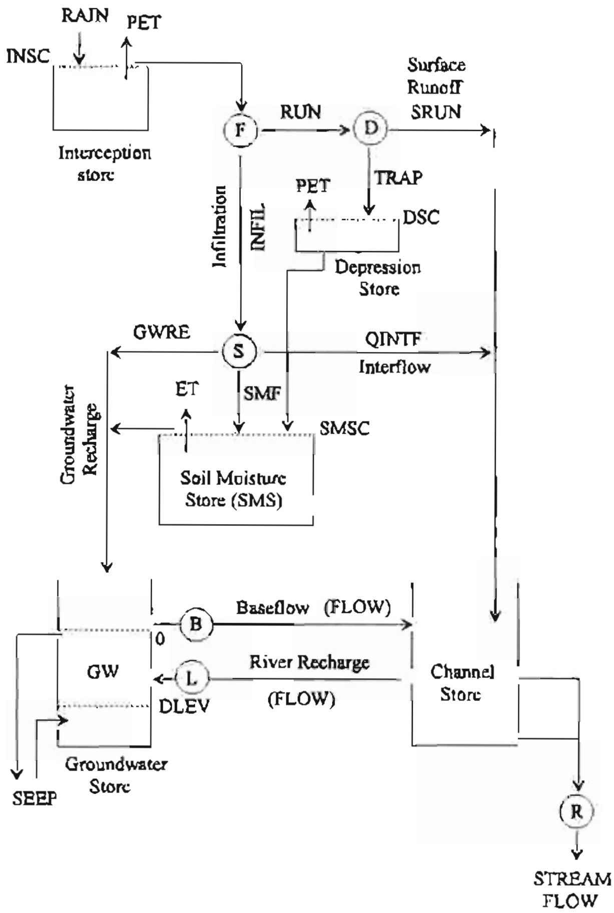
The model attempts to mimic the catchment processes more than traditional empirical models and also includes a number of empirical parameters. By the model classification method used by Wheater *et al* (1993) given in Section 2.1, it could therefore be classified as a conceptual - empirical model.

4.6 Comparative Study of Models

The daily rainfall-runoff model MODHYDROLOG was chosen as a commonly used model for the comparative study and a monthly time step was selected for the comparisons. The monthly time step was preferred to the pseudoweekly time step as it is more commonly used. It was also an opportunity to test the STDT model performances at a different time step. Data from the three Australian catchments was applied in the tests and the split sample calibration - validation approach was adopted. Section 4.6.1 gives a description of the MODHYDROLOG model. In Chapter 7, more details on the comparative study, the results and discussion are provided.

4.6.1 The MODHYDROLOG Model

The structure and the equations representing the hydrological processes as modelled by MODHYDROLOG are presented in Figure 4 8. In Table 4.5, the model parameters are listed. The MODHYDROLOG model can use up to 19 parameters but was used with 10 parameters with the 9 others set to values suggested by Chiew and McMahon (1994).



F Infitration Function
D Depression Flow Function
S Soil Moisture Function
B Baseflow Function
L River Recharge Function
R Nonlinear Routing Function

RAIN = Rainfall
PET = Potential Evapotranspiration
INFIL = Lesser of { **COEFF** exp(-**SQ**.SMS/**SMSC**), RAIN-**INSC**}
RUN = RAIN-**INSC**-INFIL
TRAP = (**DSC**-**ADS**·ARGD) exp(-**MD**·**DSC**/RUN)
SRUN = RUN-TRAP
QINTF= **SUB**·(SMS/**SMSC**)·INFIL
GWRE= **CRAK**·(SMS/**SMSC**).(INFIL-QINTF)
SMF = INFIL-QINTF-GWRE
ET = lesser of {**EM**·(SMS/**SMSC**), PET}
FLOW = **K1**.|GW|+**K2**·[1-exp(-**K3** |GW|)
SEEP = **VCOND**·(GW-**DLEV**)

Figure 4.8 Model Structure of MODHYDROLOG (adapted from Chiew and McMahon (1994))

Parameter	Description
ADS	Fraction of total area which is depressional
CO	Routing coefficient
COEFF	Maximum infiltration loss parameter
CRAK	Constant of proportionality in the determination of groundwater recharge
DLEV	Parameter used in deep seepage equation
DSC	Depression storage capacity
EM	Maximum plant controlled rate of evapotranspiration
INSC	Interception store capacity
K1	Constant of proportionality in linear part of aquifer-stream flow equation
K2	Constant of proportionality in exponential part of aquifer-stream flow equation
K3	Exponent in exponential part of aquifer-stream flow equation
LOCATE	Parameter to fix the origin of the seasonal cycle of COEFF, CRAK and SUB
MD	Exponent in depression flow equation
POWER	Routing exponent
SEAS	Parameter to fix the amplitude in the seasonal fluctuation of COEFF, CRAK and SUB
SMSC	Soil moisture store capacity
SQ	Exponent in infiltration capacity equation
SUB	Constant of proportionality in the calculation of interflow
VCOND	Constant of proportionality in deep seepage equation

Table 4.5 Parameters of the MODHYDROLOG Model

These parameter settings are given in Table 4.6. More details on the MODHYDROLOG can be obtained from Chiew and McMahon (1994). An objective function that uses the square roots of the observed and predicted values given as equation 2.11 was applied in the MODHYDROLOG model calibrations.

Table 4.6 MODHYDROLOG Model Parameters set to Constant Values

Process	Parameter	Set Value
Depression Flow	ADS	0
Depression Flow	MD	1
Depression Storage	DSC	0
Monthly Fluctuations	LOCATE	1
Monthly Fluctuations	SEAS	0
Routing	POWER	0
Baseflow	K2	0
Baseflow	K3	0
Deep Seepage	DLEV	-0.1

4.7 Concluding Remarks

This chapter has presented the methodology and the experimentation followed in the research. Some results have been given, mostly qualitatively, in order to explain some of the steps taken in the research. The quantative results and more specific details of the experimentation are reported in Chapters 5, 6 and 7.

Chapter Five

Results, Analysis and Discussion of Genetic Algorithm Modifications

5.1 Summary

Five problems were applied in the tests of the modifications to the genetic algorithm (GA). These are the SIXPAR rainfall-runoff model calibration, the Hartman function optimization, the Griewank function optimization, the STDT3 and the STDT4 rainfall-runoff model calibration. Section 4.4 describes the first three while Sections 4.5.6 and 4.5.7 describe the STDT models. As stated in Section 4.4, the SIXPAR, the Hartman and the Griewank problems were also used to compare the GA with four other optimization methods; the multisimplex (MSX), two versions of the shuffled complex evolution, (SCE-1 and SCE-2) and the comparative random search (CRS-2). The performance of the four methods was obtained from a previous study by Duan *et al* (1993). Sensitivity analyses of GA performance were also carried out using the SIXPAR and the STDT3 model.

This Chapter consists of six Sections. Section 5.2 mainly reports and discusses the comparison of the traditional GA and the modified GAs with the four other optimization methods. In Section 5.3, the sensitivity analysis of the GA performance using the SIXPAR model is presented. Section 5.4 covers the GA performance and sensitivity using the STDT3 model. The analysis with the STDT3 model was based on objective function values and data from one of the Australian catchments, Scott Creek. Section 5.5 presents the tests carried out to investigate the effect of the GA modifications on the validation performance of the STDT4 model. The tests used the STDT4 model and applied data from the three Australian catchments; Babinda Creek, Scott Creek and Canning River. In Section 5.6, some typical features of the fully modified GA are demonstrated using the calibration of the STDT3 model as an example. A discussion is then given in Section 5.7.

For brevity, the terms introduced in Section 4.3 to describe the three versions of the modified GA are applied in this Section. These are the fully modified GA, the range varying GA and the shuffled GA. The term modified GAs is a general term for the three versions. Unless where stated otherwise, Duan's shuffling method (Section 4.2.4) was applied in all the optimizations.

5.2 Comparison of the Genetic Algorithm with other Optimization Methods

The SIXPAR model calibration, the Hartman function and the Griewank function optimization were used to compare the traditional and the modified GAs with the other four optimization methods. The methodology of the tests is described in Section 4.4. Although a sensitivity analysis of the GA with the SIXPAR model was done, it was decided that these comparisons be carried out before the systematic sensitivity analysis. This avoided giving the GA the undue advantage of being applied optimally while the same process may not have been applied with the other optimization methods. The publication by Duan *et al* (1993) from which the performance of the other optimization procedures was obtained did not indicate whether or not the methods had been applied optimally. The choice of the GA optimization parameters used was therefore based on experience, intuition and a few tests but not a comprehensive sensitivity analysis. The multiple point crossover was applied in all the tests with the modified GAs. Table 5.1. gives the optimization parameter values applied in the modified GA tests where applicable. The settings for the other optimization parameters are as given in Table 4.1. The traditional GA was applied with a two-point crossover and various population sizes. These are given within the text where the traditional GA performances are reported. The rest of the parameters applied with the traditional GA were as for the modified GAs.

Table 5.1 Genetic Algorithm Optimization Parameters used in SIXPAR Model Calibration, Hartman Function Optimization and Griewank Function Optimization.

Parameter	Symbol	Value		
		SIXPAR	Hartman	Griewank
Subpopulation size	p_s	12	12	20
Bit length of parameter substring	l	20	20	20
Probability of crossover	c	1.0	1.0	1.0
Number of crossover positions	n_{cross}	6	6	10
Probability of mutation	m	0.05	0.05	0.05
Fitness scaling index	f_{scale}	3	3	3
Convergence parameter	*cheperf*	0.9999	0.9999	0.9999

5.2.1 SIXPAR Rainfall-Runoff Model Calibration

The results for the MSX, SCE-1, SCE-2 and the CRS-2 obtained from Duan *et al* (1993) and those of the fully modified GA are given in Table 5.2 and Figure 5.1. The meanings of the symbols used in Table 5.2 and in the other tables comparing the optimization methods (Table 5.3, and 5.4) are as follows:

- *M-GA*: the fully modified GA;
- *nst*: the number of starts of the MSX method;
- *np*: the population size of the SCE-1 and the CRS-2 method;
- *nc*: the number of complexes of the SCE-2 method;
- *ns*: the number of subpopulations of the fully modified GA;
- *nf*: the number of times the optimization method failed to locate the global optimum out of the 100 times used in each test; and
- *a-eval*: the average number of function evaluations used for the trials in which the runs were successful.

The fully modified GA performed as effectively as the SCE-1, SCE-2 and the CSR-2 but at a lower level of efficiency using about three times the number of function evaluations at success rates greater than 95 percent. For the high success rates, the modified GA performed better than the MSX method. Duan *et al* (1992) reported that the MSX took an average of 10500 function evaluations to achieve 99 percent success.

Table 5.2 Comparison of Five Methods in SIXPAR Model Calibration

MSX			SCE-1			SCE-2			CRS-2			M-GA		
nst	nf	a-eval	np	nf	a-eval	nc	nf	a-eval	np	nf	a-eval	ns	nf	a-eval
1	65	903	10	98	628	1	91	629	30	93	1179	1	67	2462
2	56	1507	30	29	1107	2	21	1104	40	51	1673	2	34	4392
3	51	1764	40	22	1341	3	15	1359	50	11	2208	3	17	5306
4	46	1999	50	12	1611	4	5	1697	60	5	2000	4	9	5872
5	40	2292	60	12	1826	6	2	2397	90	4	2269	5	4	6227
6	29	3282	90	4	2570	8	1	3133	120	4	2745	6	5	6193
7	19	4259	120	1	3293							7	5	6432
8	11	5249										8	2	6384
9	8	6263												
10	7	7189												

The traditional GA with a population size of 96 failed in all 100 attempts to obtain the global optimum. The same population size (8 subpopulations with 12 individuals each) gave 98 percent success with the fully modified GA. The range varying GA was tested using 30 runs as part of the sensitivity analysis of Section 5.3 and gave 21 successes; a 70 percent success rate. One hundred runs of the shuffled GA with 8 subpopulations did not yield even a single success.

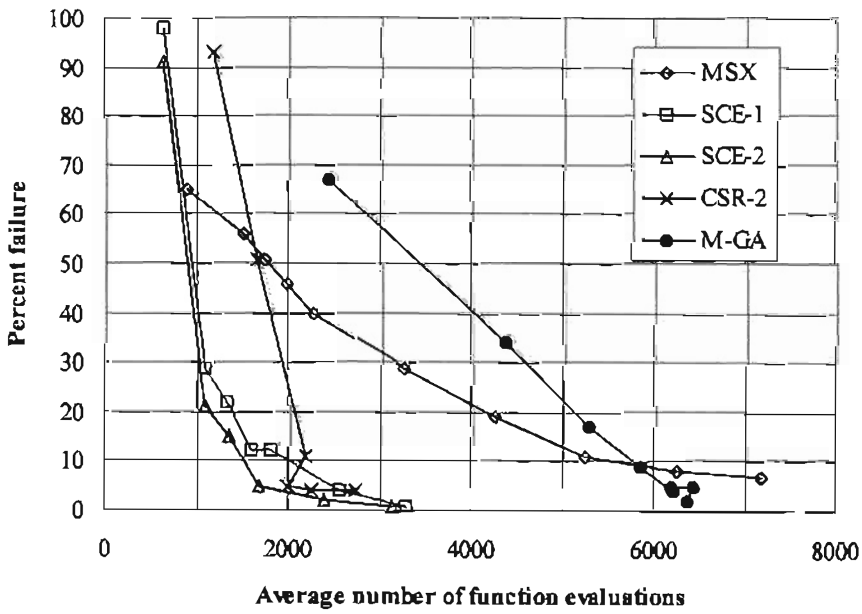


Figure 5.1 Comparative Performance of Five Optimization Methods in SIXPAR Model Calibration

5.2.2 Hartman Function Optimization

Table 5.3 and Figure 5.2 give a comparison of the fully modified GA with the MSX, the SCE-1, the SCE-2 and the CRS-2. The modified GA performed better than the other four methods and achieved 100% success with four subpopulations. The traditional GA with a population size of 48, the population that gave 100 percent success with the fully modified GA, achieved 11 percent success. In the Hartman function optimizations, the overlapping shuffling approach (Section 4.2.4) was applied.

Table 5.3 Comparison of Five Methods in Hartman Function Optimization

MSX			SCE-1			SCE-2			CRS-2			M-GA		
nst	nf	a-eval	np	nf	a-eval	nc	nf	a-eval	np	nf	a-eval	ns	nf	a-eval
1	25	307	10	54	334	1	32	329	10	98	404	1	36	830
2	4	812	20	36	354	2	45	415	20	81	646	2	13	1187
3	3	1258	30	44	433	3	41	608	30	45	901	3	5	1374
4	2	1730	40	50	525	4	40	756	40	31	999	4	0	1564
5	0	2204	50	45	612	5	41	971	50	31	940			
			60	41	693	6	43	1125	60	29	1041			
			70	48	801	7	26	1329	70	23	1157			
			80	44	879	8	20	1603	80	21	1212			
			90	46	994	10	22	1982	90	21	1332			
			100	51	1088	12	16	2306	100	22	1520			
			110	40	1186	15	16	2946	110	22	1627			
			120	40	1300	20	8	3984	120	26	1950			
			150	50	1587	25	4	4989	150	28	2634			
			200	46	2126				200	31	4608			
			350	30	3979				350	31	6944			
			500	18	6173				500					

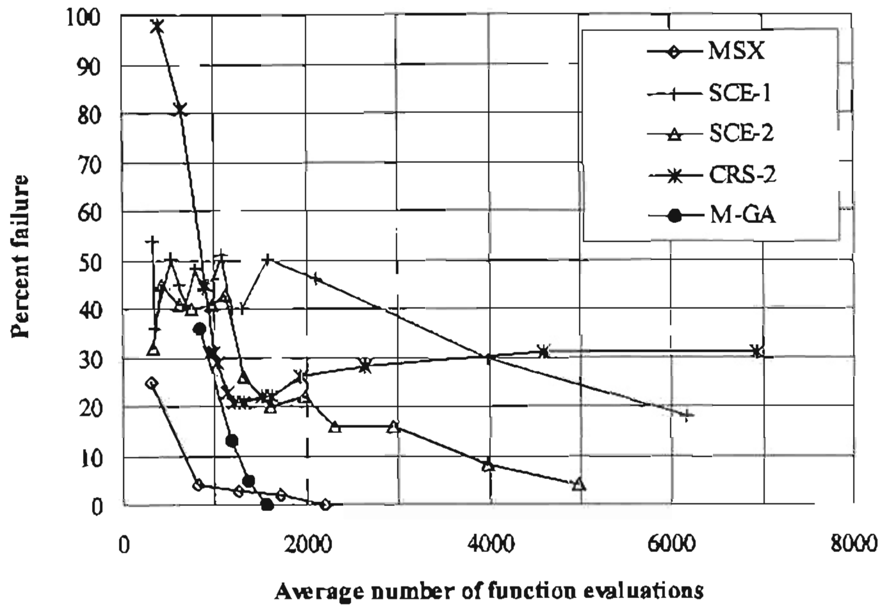


Figure 5.2. Comparative performance of five methods in the Optimization of the Hartman function.

5.2.3 Griewank Function Optimization

The results of the Griewank function optimization are presented in Table 5.4 and Figure 5.3. Compared to the SCE-1, SCE-2 and the CRS-2, the fully modified GA was effective but far less efficient. Compared with the SCE-2 method which obtained 100 percent success with an average of 3070 evaluations, the fully modified GA obtained 97 percent success (1 failure in 30 runs) with an average of 74504 function evaluations. As reported by Duan *et al* (1993), the MSX method failed totally to locate the global optimum with an allowance of up to 25000 function evaluations. In a publication by the author and his supervisor Ndiritu and Daniell (1997), 100 percent success was obtained with an average of 101096 function evaluations applying the fully modified GA with overlapping shuffling. Mühlenbein *et al* (1991) obtained an average of 59520 function evaluations for 100 percent success with 50 runs of the Griewank function using a parallel GA. Tomassini (1993) also achieved 100 percent success with 30 runs applying a massively parallel GA that used 122880 function evaluations. In all 100 optimizations using the traditional GA with population sizes varying from 20 to 200, the global optimum was not located. Tomassini (1993) also reported the total failure of the traditional GA in the optimization of the Griewank function.

Table 5.4 Comparative Results of Four Methods in the Optimization of the Griewank Function

SCE-1			SCE-2			CRS2			M-GA			M-GA *		
np	nf	a-eval	nc	nf	a-eval	np	nf	a-eval	ns	nf	a-eval	ns	nf *	a-eval
15	100	-	2	14	1977	15	11	684	1	100	-	1	100	-
20	91	1484	3	1	2465	20	16	1029	2	99	4450	2	97	4450
30	45	2242	4	0	3070	30	30	1684	3	100	-	3	100	-
40	11	2465				40	33	2430	4	97	14887	4	90	14887
50	31	2601				50	27	3099	5	92	8008	5	67	22388
60	1	2940				60	32	3698				6	53	30513
70	1	3230				70	44	4211				7	30	47705
80	0	3569				80	34	4564				8	23	62497
						90	24	5261				9	3	74504
						100	22	5580						
						110	15	6006						
						120	28	6652						
						130	15	6861						
						140	21	7376						
						150	8	7732						
						200	10	9131						

M-GA* M-GA with up to 200000 function evaluations allowed
nf* obtained as a percent from 30 runs

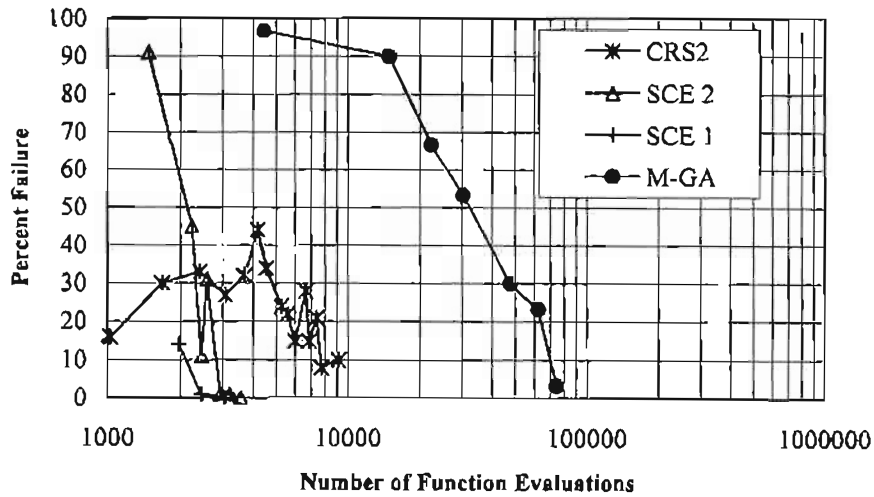


Figure 5.3 Comparative Results of Four Methods in the Optimization of the Griewank Function

5.3 Sensitivity of Genetic Algorithm Performance using the SIXPAR Model

A total of twelve sensitivity analysis tests were carried out; eight on the fully modified and four on the range varying GA. The optimization parameters and the settings applied in the tests are given in Table 5.5. The notations used in Table 5.5 are not given as it was considered convenient to contain the whole Table on the same page. The notations can be obtained from Table 4.1. The parameter ranges applied in the tests are highlighted with bold face in Table 5.5.

Table 5.6 to 5.8 and Figure 5.4 to 5.6 present the results of the sensitivity analysis. In Tables 5.6 to 5.8, the symbol s denotes the number or the percent of successful runs. As stated in Section 4.4.1, 30 calibration runs were made in each of the sensitivity analysis tests. The result of the comparison of the fully modified GA with the four other optimization methods (Section 5.2) was included as a test of the sensitivity of the fully modified GA to the number of subpopulations (n_s). As indicated in Table 5.6, this test involved 100 runs. Table 5.5 indicates the specific part of Figures 5.4 to 5.6 that the particular settings apply.

The effectiveness of the calibration was quantified by the proportion of successes in locating the global optimum. The effectiveness of the fully modified GA was highly sensitive to the following parameters; the number of subpopulations n_s (Figure 5.4b), the bit length of the parameter substrings l (Figure 5.4c), the probability of crossover c (Figure 5.4d), the probability of mutation m (Figure 5.6a) and the objective function-based convergence parameter *cheperf* (Figure 5.6d). There was a lower but considerable sensitivity to the rate of uniform crossover u_{cross} (Figure 5.5d) and the fitness scaling index f_{scale} (Figure 5.6c). The effectiveness of the fully modified GA was relatively insensitive to the number of crossover positions n_{cross} (Figure 5.5a).

The efficiency was quantified by the average number of function evaluations of the successful calibrations. The efficiency of the fully modified GA was highly sensitive to the number of subpopulations n_s (Figure 5.4b), the parameter substring bit length l (Figure 5.4c), the probability of crossover c (Figure 5.4d), the mutation probability m (Figure 5.6a) and the convergence parameter *cheperf* (Figure 5.6d). There was a lower although significant level of sensitivity to the number of crossover positions n_{cross} (Figure 5.5a) and the rate of uniform crossover u_{cross} (Figure 5.5d).

Table 5.5 Optimization Parameters for Genetic Algorithm Sensitivity Analysis with the SIXPAR Model

Parameter Figure	p 5.4a	n_s 5.4b	l 5.4c	c 5.4d
		Values		
p	**12 - 96**	12 - 96	96	96
p_s	12 - 96	12	12	12
n_s	1	**1 - 8**	8	8
l	20	20	**5 - 20**	20
c	1.0	1.0	1.0	**0.0 - 1.0**
n_{cross}	6	6	6	6
u_{cross}	-	-	-	-
m	0.05	0.05	0.05	0.05
f_{scale}	3	3	3	3
cheperf	0.999	0.999	0.999	0.999

Parameter Figure	n_{cross} 5.5a	n_{cross} 5.5b	u_{cross} 5.5c	u_{cross} 5.5d
		Values		
p	96	96	96	96
p_s	12	96	96	12
n_s	8	1	1	8
l	20	20	20	20
c	1.0	1.0	1.0	1.0
n_{cross}	**2 - 18**	**2 - 18**	-	-
u_{cross}	-	-	**0.0 - 0.6**	**0.0 - 0.6**
m	0.05	0.05	0.05	0.05
f_{scale}	3	3	3	3
cheperf	0.999	0.999	0.999	0.999

Parameter Figure	m 5.6a	m 5.6b	f_{scale} 5.6c	cheperf 5.6d
		Values		
p	96	96	96	96
p_s	12	96	12	12
n_s	8	1	8	8
l	20	20	20	20
c	1.0	1.0	1.0	1.0
n_{cross}	6	-	2	6
u_{cross}	-	0.5	-	-
m	**0.0 - 0.10**	**0.0 - 0.10**	0.05	0.05
f_{scale}	3	3	**0.05 - 3.0**	3
cheperf	0.999	0.999	0.999	**0.9 - 0.99998**

Table 5.6 Sensitivity Analysis of the Genetic Algorithm using the SIXPAR Model (Tests 1 to 4)

Test 1

p	a-eval	s/30	s (%)
12	2910	6	20.0
24	4512	9	30.0
36	6228	11	36.7
48	5718	15	50.0
60	9136	11	36.7
72	8902	14	46.7
84	10952	13	43.3
96	14950	11	36.7

Test 2

ns	a-eval	s/100	s (%)
1	2462	33	33.0
2	4392	66	66.0
3	5306	83	83.0
4	5872	91	91.0
5	6227	96	96.0
6	6193	95	95.0
7	6432	95	95.0
8	6384	98	98.0

Test 3

l	a-eval	s/30	s (%)
5	16140	2	6.7
6	15862	15	50.0
7	14132	23	76.7
8	13267	25	83.3
9	9428	28	93.3
10	8081	30	100
20	7118	30	100

Test 4

c	a-eval	s/30	s (%)
0	-	0	0.0
0.2	15816	1	3.3
0.4	19378	7	23.3
0.6	15638	21	70.0
0.8	9537	29	96.7
1	7118	30	100

Table 5.7 Sensitivity Analysis Results of the Genetic Algorithm using the SIXPAR Model (Tests 5 to 8)

Test 5

ncross	a-eval	s/30	s (%)
2	5842	30	100
6	7118	30	100
10	8295	29	96.7
14	9747	28	93.3
18	10791	29	96.7

Test 6

ncross	a-eval	s/30	s (%)
2	14632	12	40.0
6	14950	11	36.7
10	14313	11	36.7
14	14576	12	40.0
18	16128	14	46.7

Test 7

ucross	a-eval	s/30	s (%)
0.1	15264	12	40.0
0.2	15856	12	40.0
0.3	16475	13	43.3
0.4	16687	11	36.7
0.5	15992	12	40.0
0.6	17162	13	43.3

Test 8

ucross	a-eval	s/30	s (%)
0	8152	28	93.3
0.1	8655	26	86.7
0.2	9671	27	90.0
0.3	10414	22	73.3
0.4	10070	22	73.3
0.5	9964	18	60.0
0.6	14456	23	76.7

Table 5.8 Sensitivity Analysis Results of the Genetic Algorithm using the SIXPAR Model (Tests 9 to 12)

Test 9

m	a-eval	s/30	s (%)
0		0	0.0
0.02	7976	24	80.0
0.04	4980	28	93.3
0.05	7118	30	100
0.06	8670	27	90.0
0.08	10898	27	90.0
0.1	16145	16	53.3

Test 10

m	a-eval	s/30	s (%)
0		0	0.0
0.02	11465	20	66.7
0.04	13141	21	70.0
0.06	12927	18	60.0
0.08	15656	8	26.7
0.1		0	0.0

Test 11

fscale	a-eval	s/30	s (%)
0.05	5548	27	90.0
0.1	4983	26	86.7
0.15	6457	30	100
0.2	6816	30	100
0.25	4661	28	93.3
0.3	6418	30	100
0.35	5576	30	100
0.4	6712	28	93.3
0.45	5970	29	96.7
0.5	7304	30	100
1	4581	28	93.3
3	5462	30	100

Test 12

cheperf	a-eval	s/30	s (%)
0.9	20572	19	63.3
0.92	22149	19	63.3
0.94	20023	20	66.7
0.96	17802	14	46.7
0.98	16343	19	63.3
0.98	16343	19	63.3
0.983	14900	28	93.3
0.986	15779	26	86.7
0.989	11501	29	96.7
0.992	9706	29	96.7
0.995	9621	30	100
0.998	6901	29	96.7
0.999	7118	30	100
0.9993	8056	30	100
0.9996	6744	29	96.7
0.9999	5869	30	100
0.99994	5948	27	90.0
0.99998	6537	29	96.7

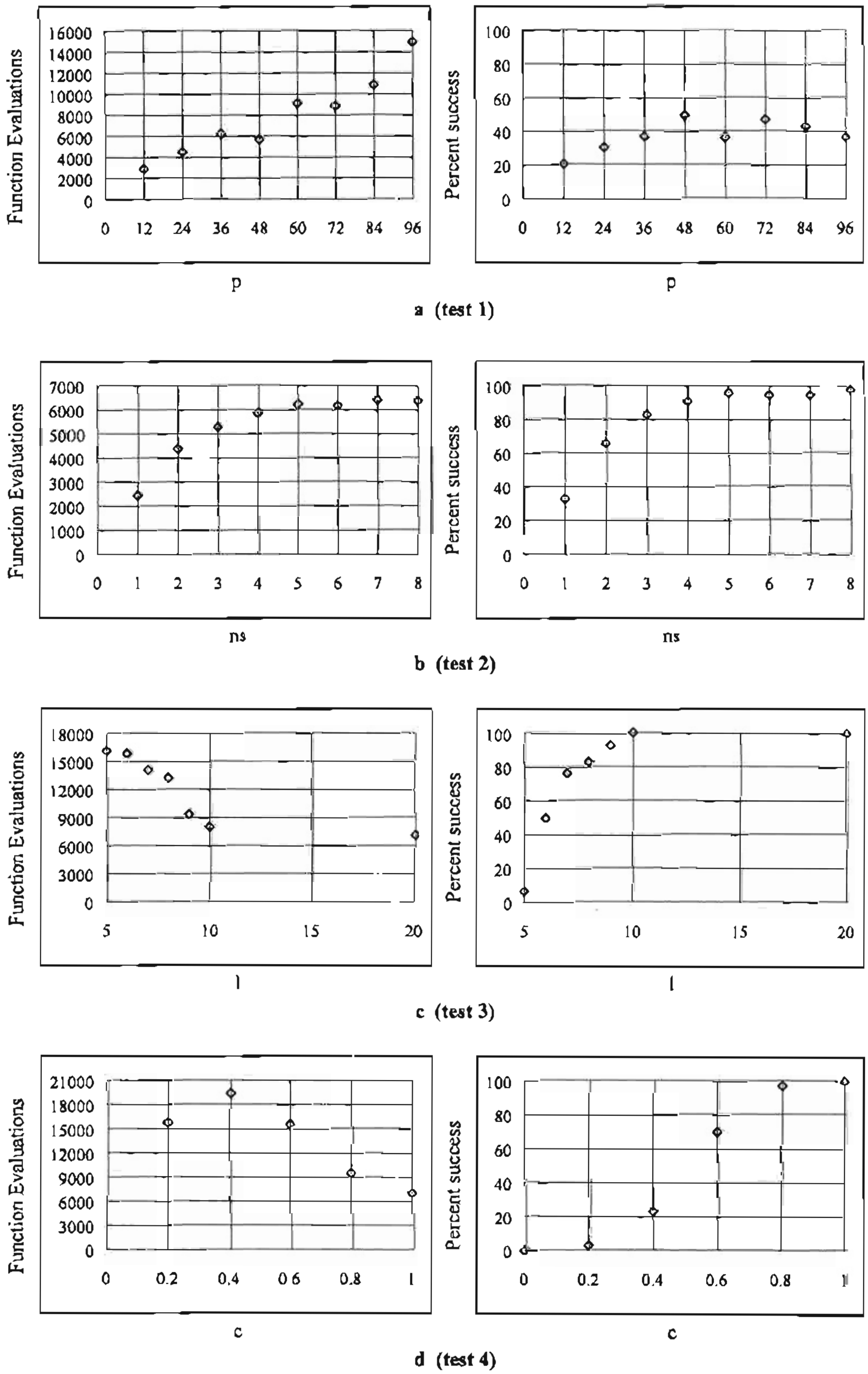


Figure 5.4 Sensitivity Analysis of the Genetic Algorithm using the SIXPAR Model (Tests 1 to 4)

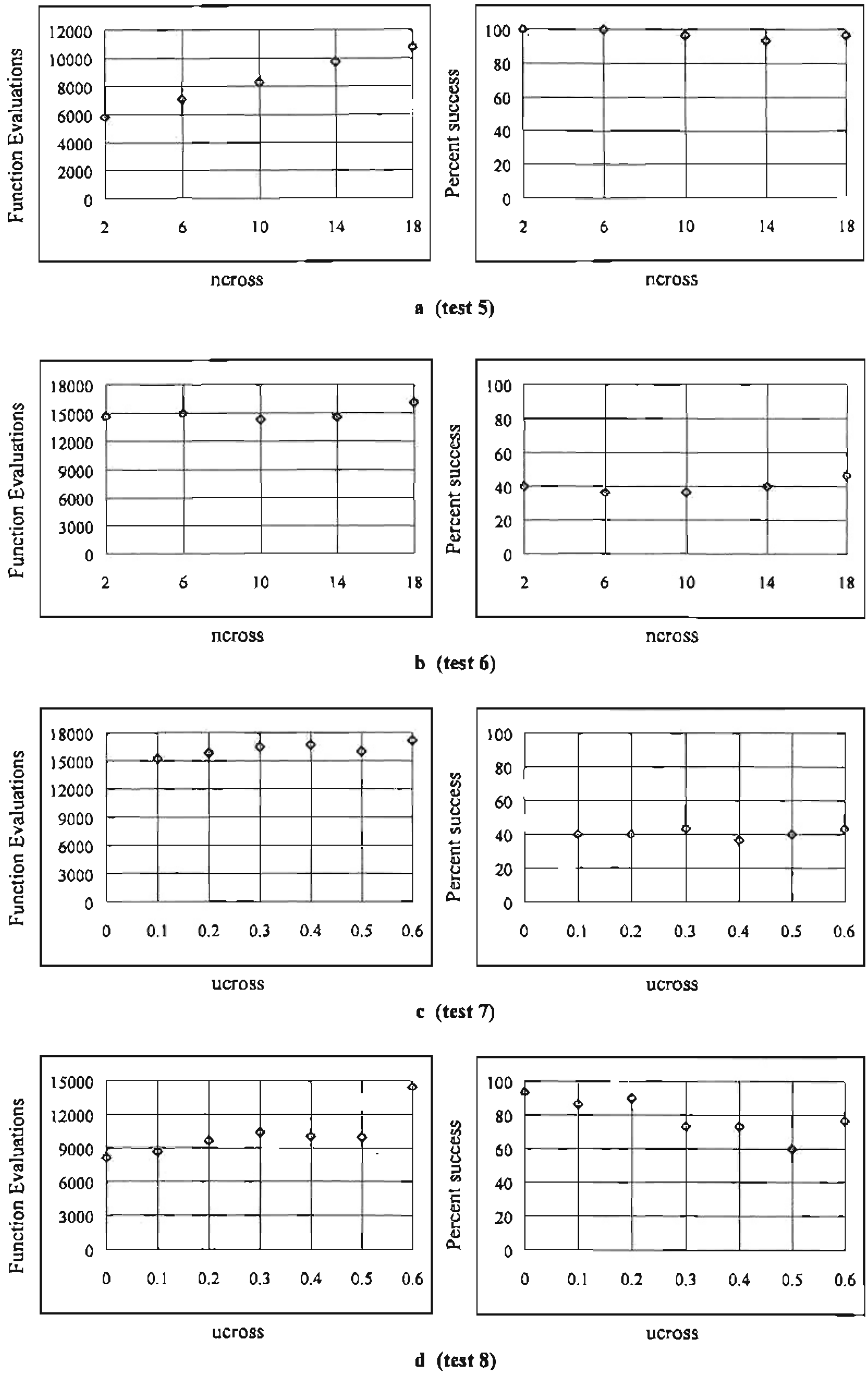


Figure 5.5 Sensitivity Analysis of the Genetic Algorithm using the SIXPAR Model (Tests 5 to 8)

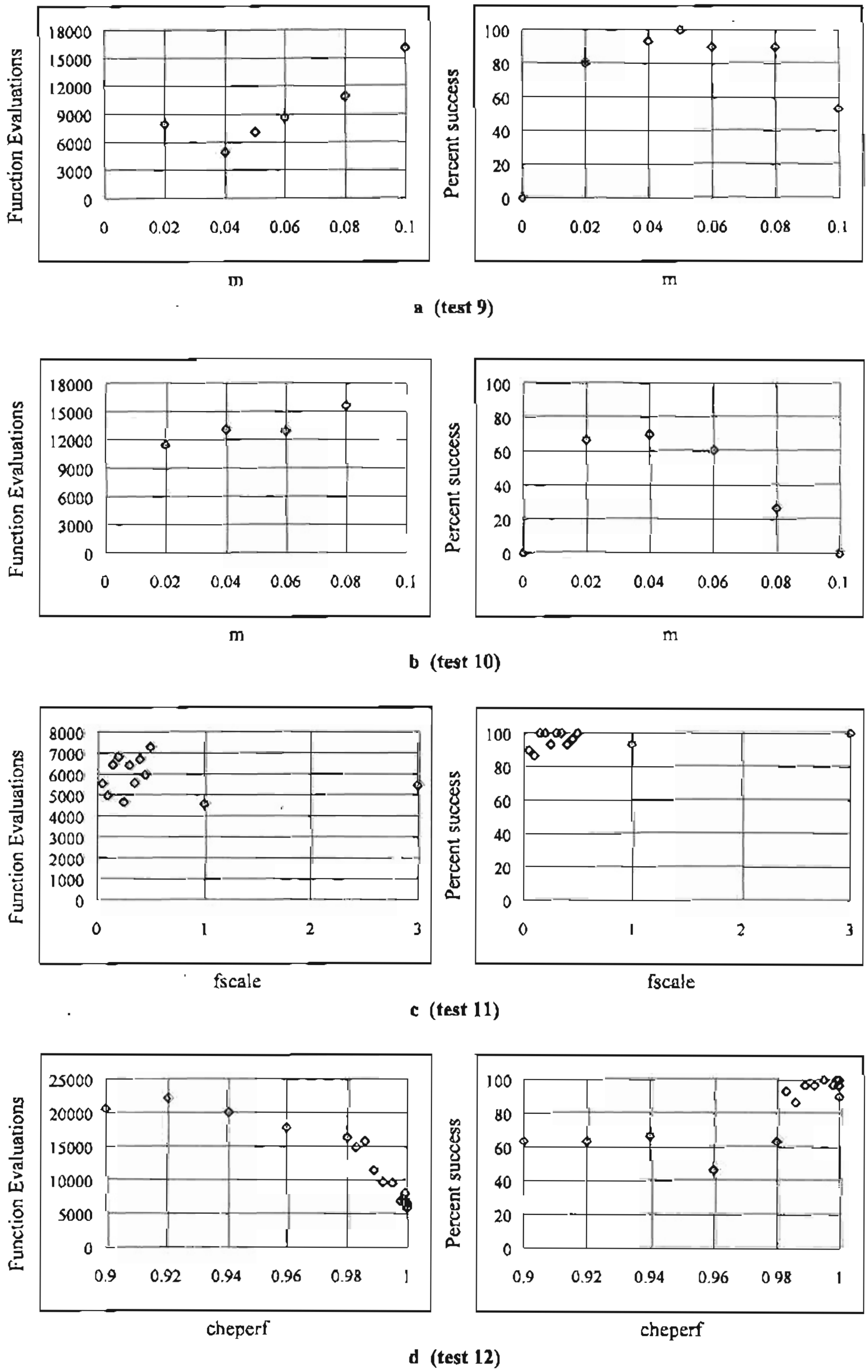


Figure 5.6 Sensitivity Analysis of the Genetic Algorithm using the SIXPAR Model (Tests 9 to 12)

Although the sensitivity analysis was not exhaustive, the values given in Table 5.9 can be taken as reasonable optimization parameter values of the SIXPAR model calibration.

Table 5.9 Satisfactory Parameter Values for SIXPAR Model Calibration using the Fully Modified Genetic Algorithm

Parameter	Symbol	Value
Population size	P	96
Number of subpopulations	n_s	8
Bit length of parameter substring	l	10 - 20
Probability of crossover	c	1.0
Number of crossover positions	n_{cross}	2
Rate of uniform crossover	u_{cross}	0.0
Probability of mutation	m	0.05
Fitness scaling index	f_{scale}	3
Convergence parameter	*cheperf*	0.9999

The effectiveness of the range varying GA was highly sensitive to the mutation probability (Figure 5.6b) and to a lesser extent the population size (Figure 5.4a). The effectiveness however exhibited a much lower sensitivity to the number of crossover positions (Figure 5.5b) and the rate of uniform crossover (Figure 5.5c). The efficiency of the range varying GA was highly sensitive to the population size as Figure 5.4a shows and less sensitive to the probability of mutation (Figure 5.6b). The number of crossover positions (Figure 5.5b) and the rate of uniform crossover (Figure 5.5c) did not seem to have any significant effect on the efficiency of the range varying GA.

The sensitivity of the fully modified GA to the number of subpopulations was expected as the chance of locating the global optimum increases as the number of subpopulations increases. The use of more subpopulations however increases the number of runs that have to be made to locate the global optimum. The large effect of the parameter substring length on the performance of the modified GA was considered to result from the lower rate of convergence of an optimization with a smaller substring length. A smaller substring length gives a smaller discretization of the search space and the GA therefore takes more evaluations to close in to the optima whether local or global even with the use of finetuning and hillclimbing. It is possible that different results of the GA sensitivity to l could have been obtained with other values of the finetuning and hillclimbing parameters. Constant values of the finetuning and hillclimbing parameters were however adopted in this study (Table 4.1).

The observed sensitivity of the fully modified GA to the probability of crossover means there is considerable importance of the exchange of information among individuals in the search. When this exchange is slow, at low probabilities of crossover, then the convergence to the global optimum will, on the average take a greater number of function evaluations implying a lower efficiency. In optimizations like the SIXPAR model calibration in which an upper limit of the number of function evaluations was set, a lower level of global optimum locations is achieved with lower crossover rates.

The optimal probability of mutation was around 0.05 (Figure 5.6a). This result is justifiable from the expected effects of mutation. These are:

- the creation of new genetic material that results in a more robust search; and
- the disruption effect of mutation that destroys useful genetic material if applied at a high probability.

When the two are balanced with the choice of the appropriate probability of mutation, then better performances are achieved. For the SIXPAR problem, 0.05 was a balanced mutation probability.

The fully modified GA attained a better efficiency and effectiveness at high levels of the convergence parameter *cheperf*. This implies that at low levels of *cheperf*, the GA had the tendency not to close in adequately to the global optimum to achieve the 0.001 objective function value set for a successful global optimum location (Section 4.4). At lower *cheperf* levels the subpopulation searches more often attained the termination criteria before achieving the 0.001 level of precision in the objective function value.

5.4 STDT3 Model Calibration and Sensitivity Analysis

The seven-parameter STDT3 model was used for an evaluation of the modifications to the GA on the basis of the objective function value. Section 4.5.6 describes the model and equation 4.15 the objective function. The performance evaluation was part of the twelve sensitivity analysis tests done; seven on the fully modified GA, two on the shuffled GA, one on the range varying GA and two on the traditional GA. For each sensitivity analysis test, ten runs using two sets of historical data from the Scott Creek catchment; 1970-77 and 1978-85 were applied giving a total of 20 runs. Table 5.10 and 5.11 present the optimization parameter values and the settings applied in the calibrations. The parameter ranges applied in the individual tests are highlighted with bold face in the two Tables. The results of the twelve sensitivity analysis tests are presented graphically in Figures 5.7 to 5.18. Table 5.10 and 5.11 give the parameter settings for each of the 12 tests.

The respective optimization parameter values and settings for each of the Figures are indicated in Table 5.10. and 5.11. The actual objective function values are given as Tables A5-1 to A5-12 in Appendix A5. The two historical data sets gave two objective function values that could practically be regarded as the global optima. These were 237.1 and 251.0 for 1970-77 and 1978-85 data set respectively. For the tests with the fully modified GA convergence towards the two values was evident (Figure 5.7-5.10, 5.14, 5.17 and 5.18). As lower objective functions were not obtained with more than 200 randomly initialized runs, the two values were considered as global optima. The traditional, the range varying and the shuffled GA occasionally gave objective function values close to the two global optima.

The fully modified GA performed better than the shuffled and the range varying GA thus highlighting the value of both modifications; the range variation procedures and the independent subpopulation searches coupled with shuffling. As with the SIXPAR model calibration, the range varying GA (Figure 5.12) was found to perform better than the shuffled GA (Figure 5.13). The traditional GA (Figure 5.13) and the shuffled GA (Figure 5.11) exhibited the same level of performance.

Table 5.10 Parameter Values and Settings for STDT3 Model Calibration and Sensitivity Analysis (Tests 1 to 6)

Parameter	ev_{max}	c	ncross	ucross	ucross	ucross
P	98	98	98	98	98	98
p_s	14	14	14	14	14	98
n_s	7	7	7	7	7	1
l	20	20	20	20	20	20
c	1.0	**0 - 1.0**	1.0	1.0	1.0	1.0
n_{cross}	7	7	**2 - 18**	-	-	-
u_{cross}	-	-	-	**0. - 0.6**	**0. - 0.6**	**0. - 0.6**
m	0.05	0.05	0.05	0.05	0.05	0.05
f_{scale}	3	3	3	3	3	3
cheperf	0.95	0.95	0.95	0.95	0.95	0.95
ev_{max}	**2000-10000**	10000	10000	10000	10000	10000
Test	1	2	3	4	5	6
Range variation ?	yes	yes	yes	yes	no	yes
Figure of Results	5.7	5.8	5.9	5.10	5.11	5.12
Table of Results	A5-1	A5-2	A5-3	A5-4	A5-5	A5-6

Table 5.11 Parameter Values and Settings for STDT3 Model Calibration and Sensitivity Analysis (Tests 7 to 12)

Parameter	ucross	m	m	m	fscale	cheperf
P	98	98	98	98	98	98
p_s	98	14	14	98	14	14
n_s	1	7	7	1	7	7
l	20	20	20	20	20	20
c	1.0	1.0	1.0	1.0	1.0	1.0
n_{cross}	-	7	7	-7	-7	-7
u_{cross}	**0. - 0.6**	-	-	-	-	-
m	0.05	**0 - 0.1**	**0 - 0.1**	**0 - 0.1**	0.05	0.05
f_{scale}	3	3	3	3	**0.01-3**	3
cheperf	0.95	0.95	0.95	0.95	0.95	**0.9-0.99**
ev_{max}	10000	10000	10000	10000	10000	10000
Test	7	8	9	10	11	12
Range variation ?	no	yes	no	no	yes	yes
Figure of Results	5.13	5.14	5.15	5.16	5.17	5.18
Table of Results	A5-7	A5-8	A5-9	A5-10	A5-11	A5-12

The following observations were made from the sensitivity analysis:

- A maximum number of function evaluations of about 10000 was required for adequate convergence to the global optima in all the ten runs (Figure 5.7). After this test, it was decided to set an upper limit of 10000 runs for the rest of the sensitivity analysis. The approach used allowed the epoch at which 10000 evaluations were reached to complete. Most of the runs therefore exceeded 10000 function evaluations by small amounts mostly not exceeding 100 as Table A5-2 to A5-12 of Appendix A5 indicate.
- For the fully modified GA, a crossover probability of 0.8 to 1.0 gave a better solution than lower crossover probabilities (Figure 5.8)
- The fully modified GA was insensitive to the number of crossover points (Figure 5.9)
- All the GA types were relatively insensitive to the uniform crossover rate as Figures 5.10 to 5.13 show. This contrasted with the results reported by Eshelman *et al* (1989) given in Section 3.2.3. Eshelman *et al* found the GA to be sensitive to the uniform crossover rate.
- The fully modified GA was insensitive to the probability of mutation although there was the tendency for lower values of mutation probability to give slightly better convergence to the global optima. (Figure 5.14). Probabilities of mutation of 0.1 gave better solutions than lower mutation probabilities for the shuffled GA (Figure 5.15) and for the traditional GA (Figure 5.16).
- The fully modified GA was insensitive to the fitness scaling factor (Figure 5.17) and the convergence parameter (Figure 5.18).

The sensitivity of the performance of the fully modified GA to crossover probability could be explained in the same way as for the SIXPAR model. A lower crossover gives a slower exchange of information and consequently more function evaluations to achieve the global optimum. When an upper limit on the number of function evaluations is set, as in the STDT3 model calibration, a poorer performance results with a lower probability of crossover. The insensitivity of the fully modified GA to the probability of mutation was an indication that the finetuning and hillclimbing operations gave the required level of robustness in search and the mutation therefore did not play a significant role. With the shuffled and the traditional GA, mutation played the role of increasing the robustness of the search up to the maximum mutation probability of 0.1 applied in the sensitivity analysis tests.

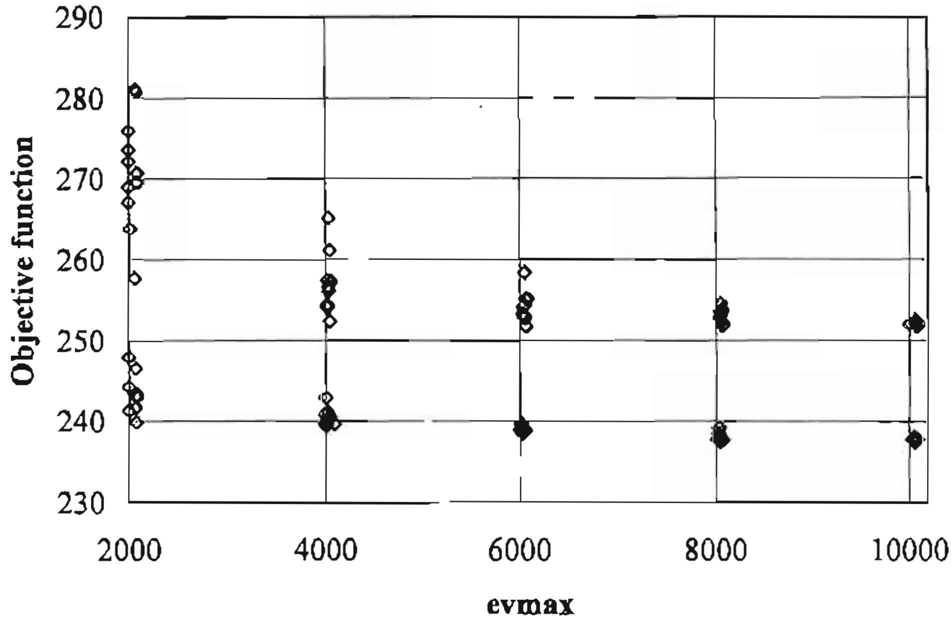


Figure 5.7 Sensitivity of Genetic Algorithm Performance to the Number of Function Evaluations using the STDT3 Model (test 1)

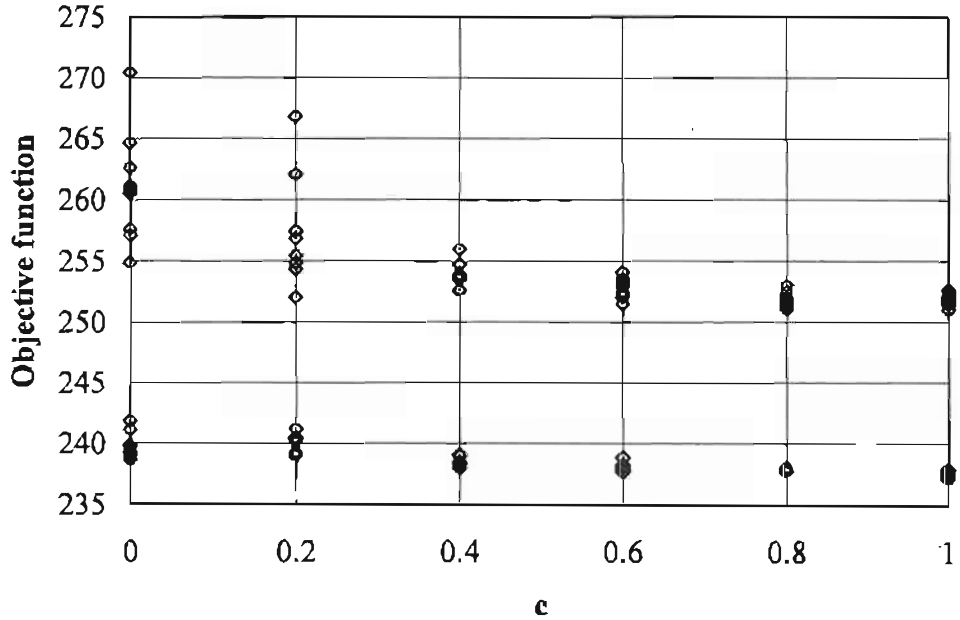


Figure 5.8 Sensitivity of Genetic Algorithm Performance to the Probability of Crossover using the STDT3 Model (test 2)

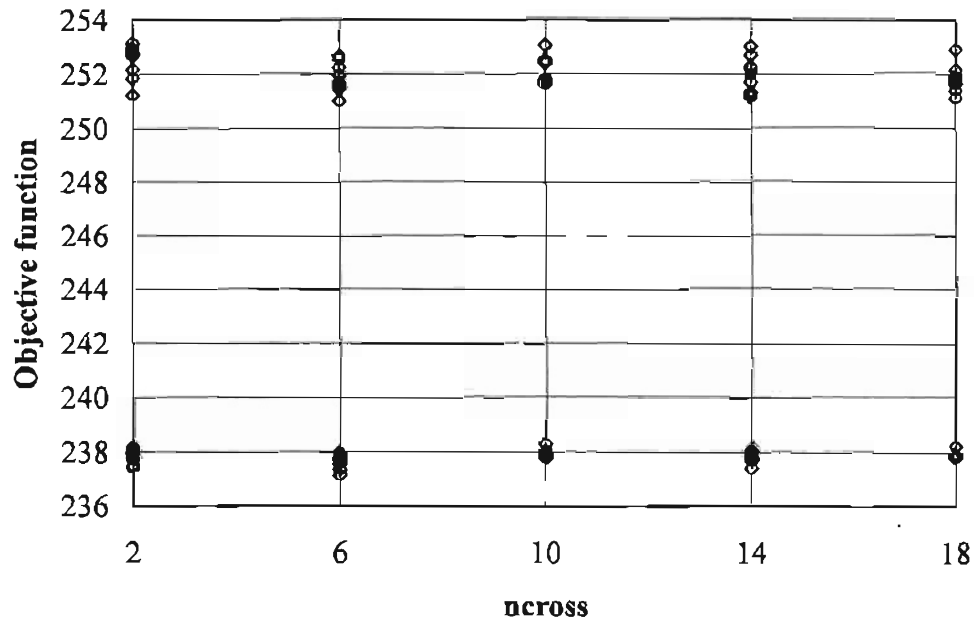


Figure 5.9 Sensitivity of Genetic Algorithm Performance to the Number of Crossover Positions using the STDT3 Model (test 3)

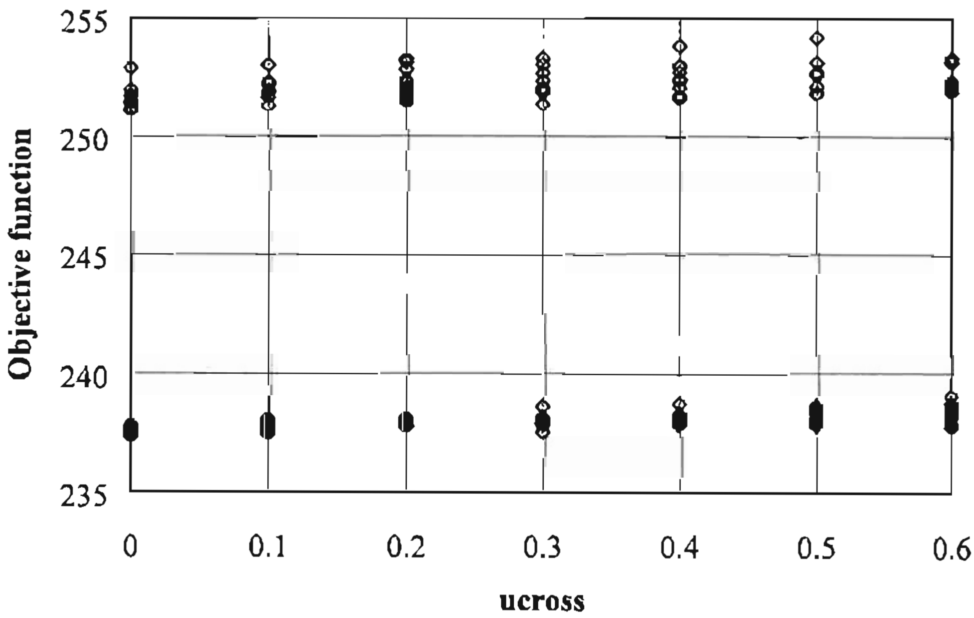


Figure 5.10 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 4)

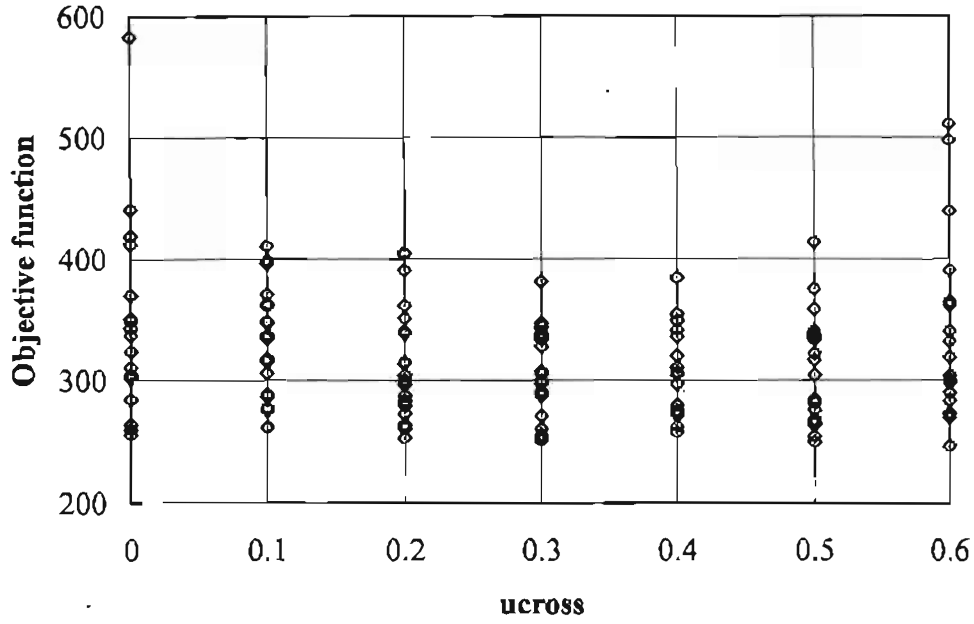


Figure 5.11 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 5)

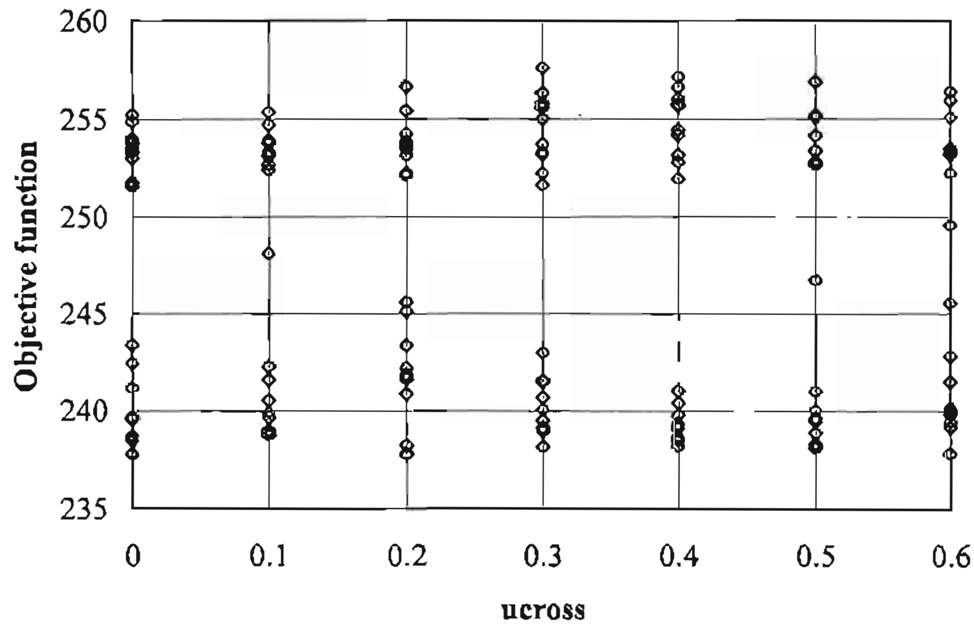


Figure 5.12 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 6)

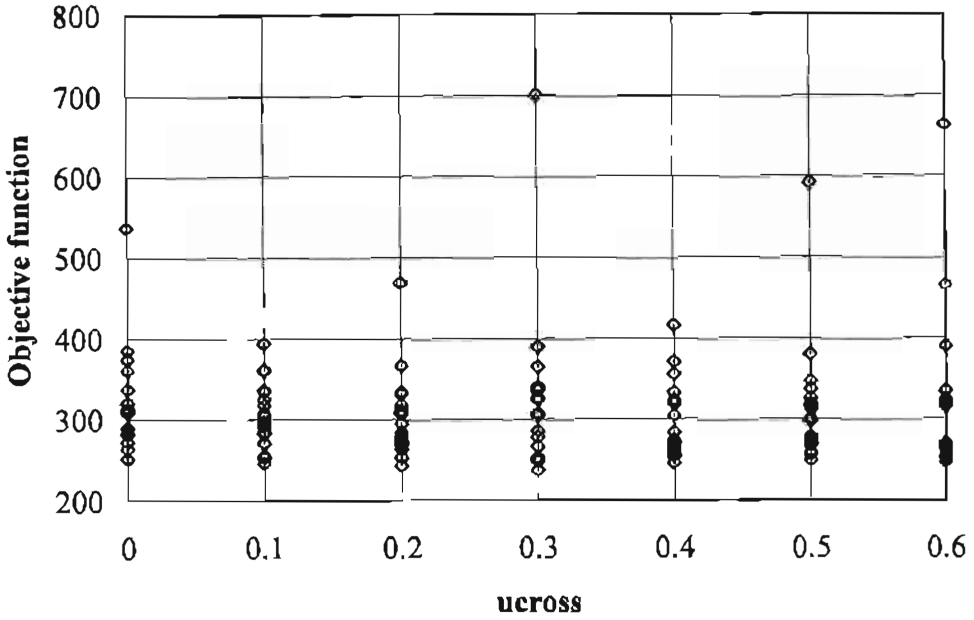


Figure 5.13 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 7)

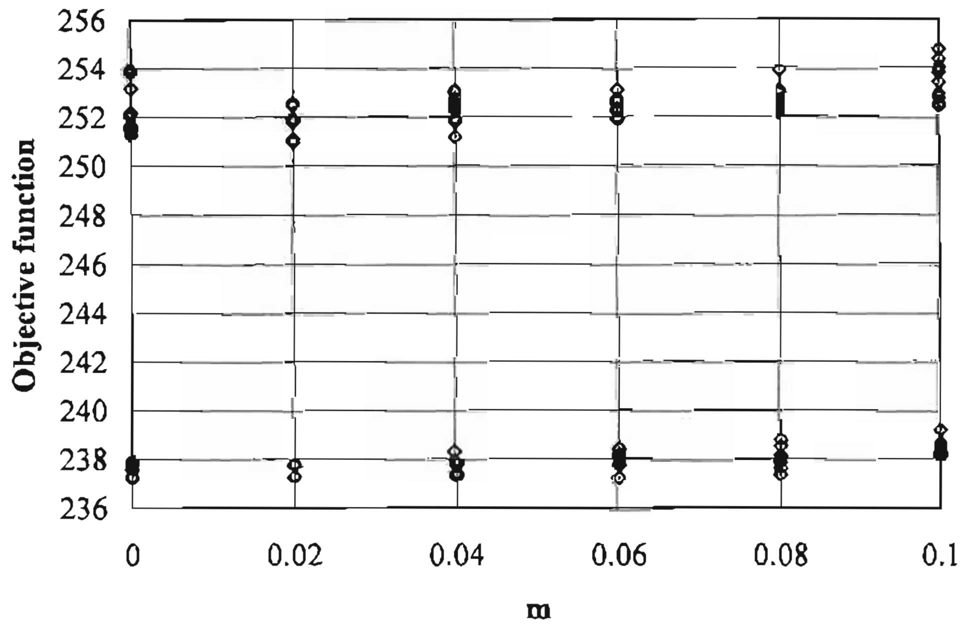


Figure 5.14 Sensitivity of Genetic Algorithm Performance to the Probability of Mutation using the STDT3 Model (test 8).

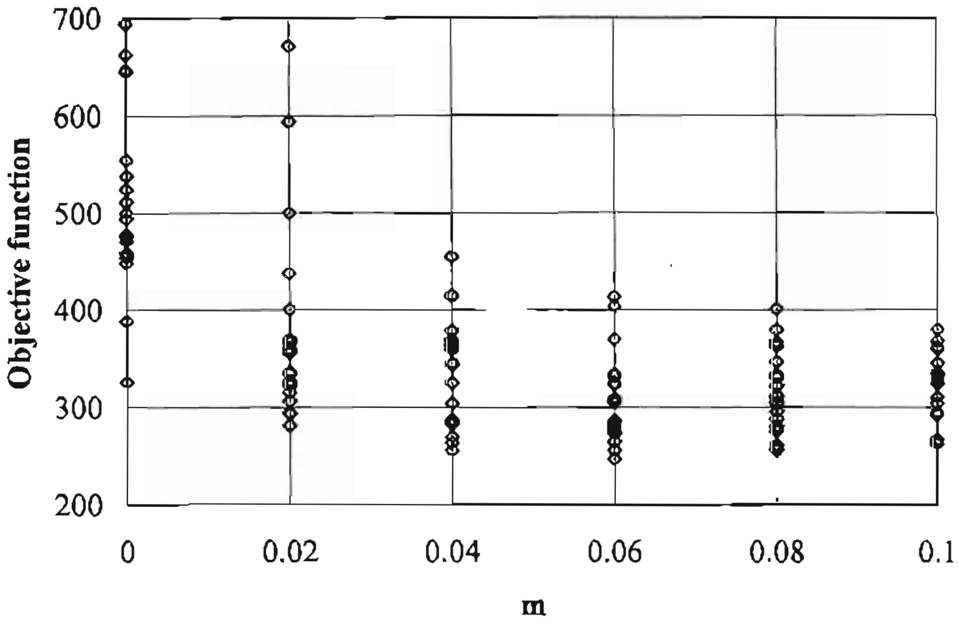


Figure 5.15 Sensitivity of Genetic Algorithm Performance to the Probability of Mutation using the STDT3 Model (test 9)

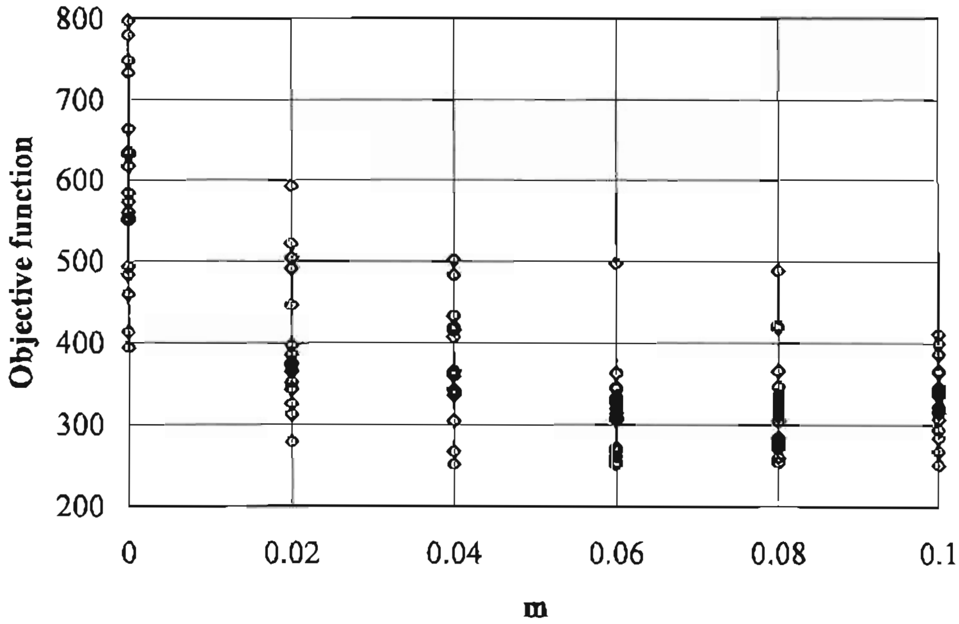


Figure 5.16 Sensitivity of Genetic Algorithm Performance to the Probability of Mutation using the STDT3 Model (test 10)

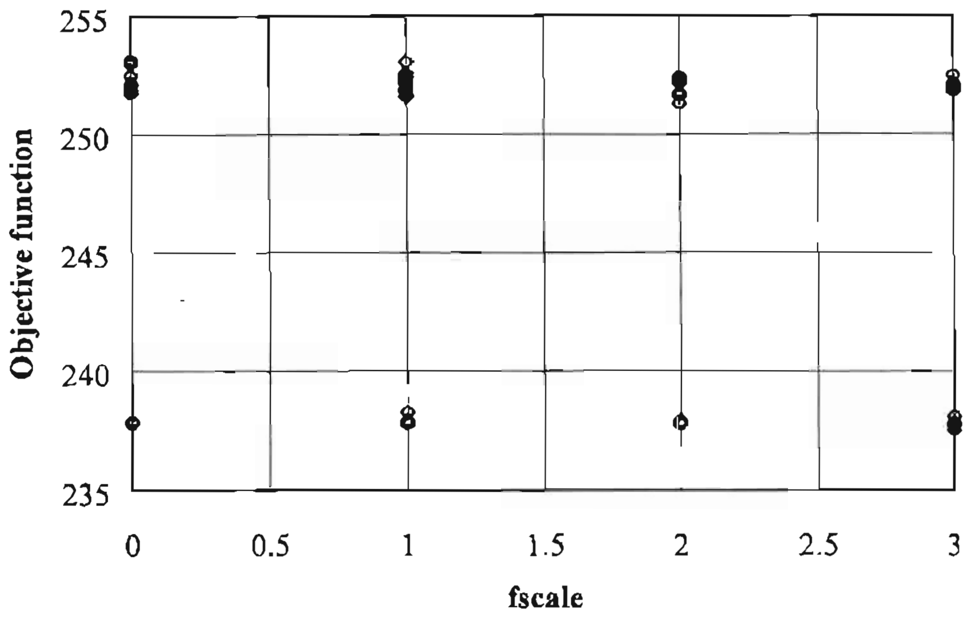


Figure 5.17 Sensitivity of Genetic Algorithm Performance to the Fitness Scaling Parameter using the STDT3 Model (test 11)

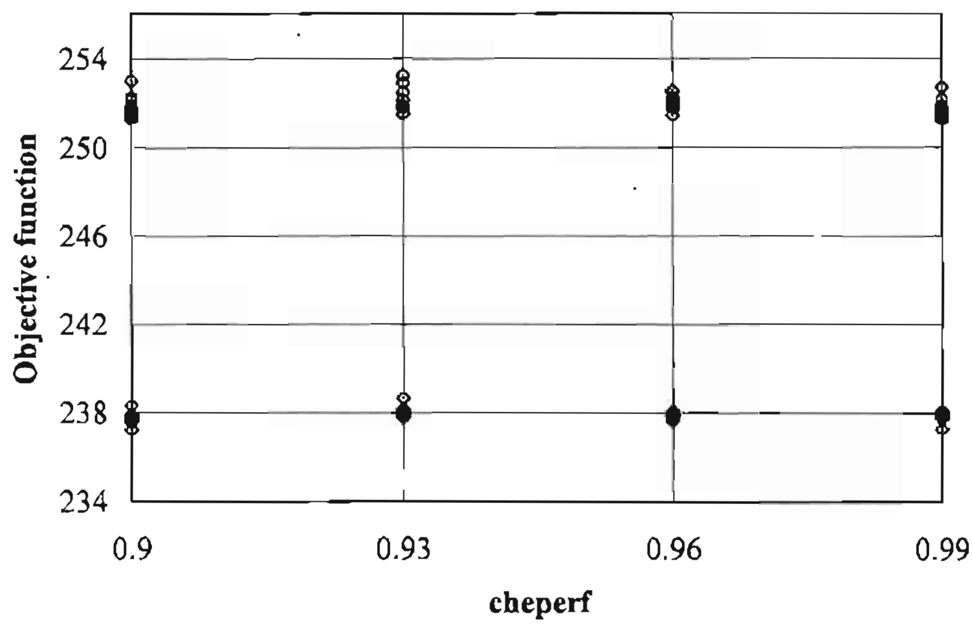


Figure 5.18 Sensitivity of Genetic Algorithm Performance to a Convergence Parameter using the STDT3 Model (test 12)

5.5 Effect of Modifications to the Genetic Algorithm on the Validation Performance of the STDT4 Model

A common application of conceptual and empirical rainfall-runoff models is the extension and filling in missing runoff data. In such situations, the model is usually calibrated using the concurrently available rainfall, runoff and evapotranspiration data. The model is then applied with parameters obtained from the calibration to generate the missing runoff data. A test of the significance of the modifications to the GA on the quality of validation results is therefore a more direct indicator of the practical value of the modifications to catchment modelling than the tests of Sections 5.2 to 5.4. To carry out such an investigation, the STDT4 model and data from the three Australian catchments were used. The STDT4 model was selected on the basis of its better performance compared to the other STDT models. The difficulty of calibrating the 14 parameter STDT4 was also considered more representative of what is likely to be encountered in typical conceptual modelling.

For each data set, twenty split-sample calibration-validations were done; ten with the earlier data series used in calibration and the later data series used in validation and viceversa for the other ten runs. The results for the three catchments obtained with the fully modified GA are presented in Table 6.18 to 6.20 of Section 6.3.1 which presents the performance of the STDT4 model. The corresponding results obtained with the traditional GA are presented in Appendix A5. In Appendix A5, the parameter settings used with the traditional GA are also presented. A graphical comparison of the validation performances obtained with the traditional and with the fully modified GA is given in Figure 5.19 to 5.21.

The validations obtained with the fully modified GA were found to give better coefficients of efficiency and absolute deviations than the validations obtained with the traditional GA. The consistency of the performances was also better with the fully modified GA than with the traditional GA. An exception to these trends was the 1974-80 coefficients of efficiency for Babinda Creek where very close values were obtained with the two types of the GA. The bias and residual mass curve coefficients however were not sensitive to the GA modifications as no considerable differences were observed between the two types of the GA. The inadequate duration of the 1984-87 Canning River data gave the notably poor validations of the 1978-84 flows (Figure 5.21).

Even then, the fully modified GA still gave better validation results than the traditional GA. The parameter identification plots obtained with the improved GA are plotted in Figures 6.11 to 6.13 of Section 6.3.1. Compared to those obtained with the traditional GA (Figure A5-1 to A5-3 of Appendix 5), the superior parameter identification with the use of the fully modified GA is evident.

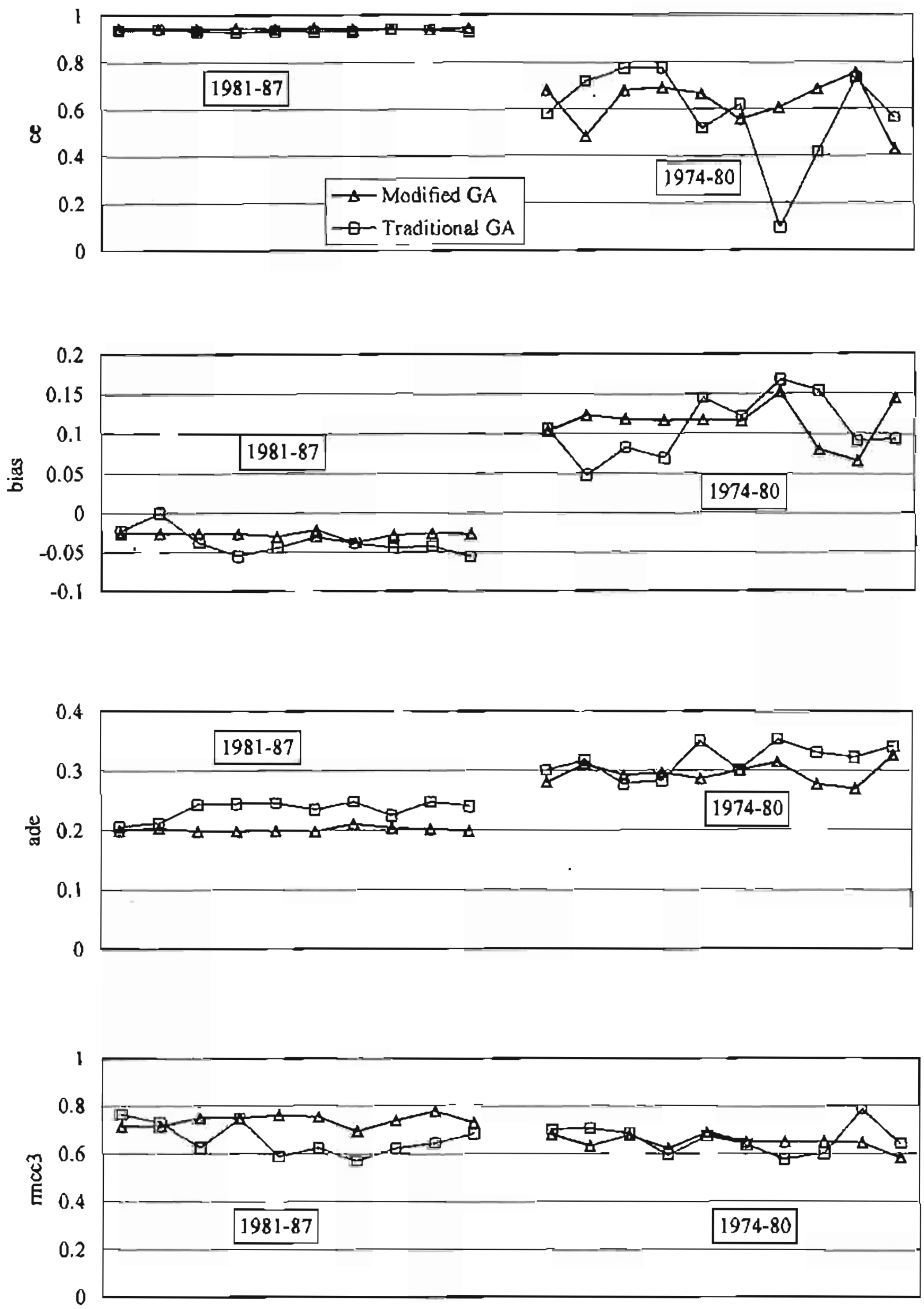


Figure 5.19 STDT4 Model Babinda Creek Validation Performances using the Traditional and the fully Modified Genetic Algorithm

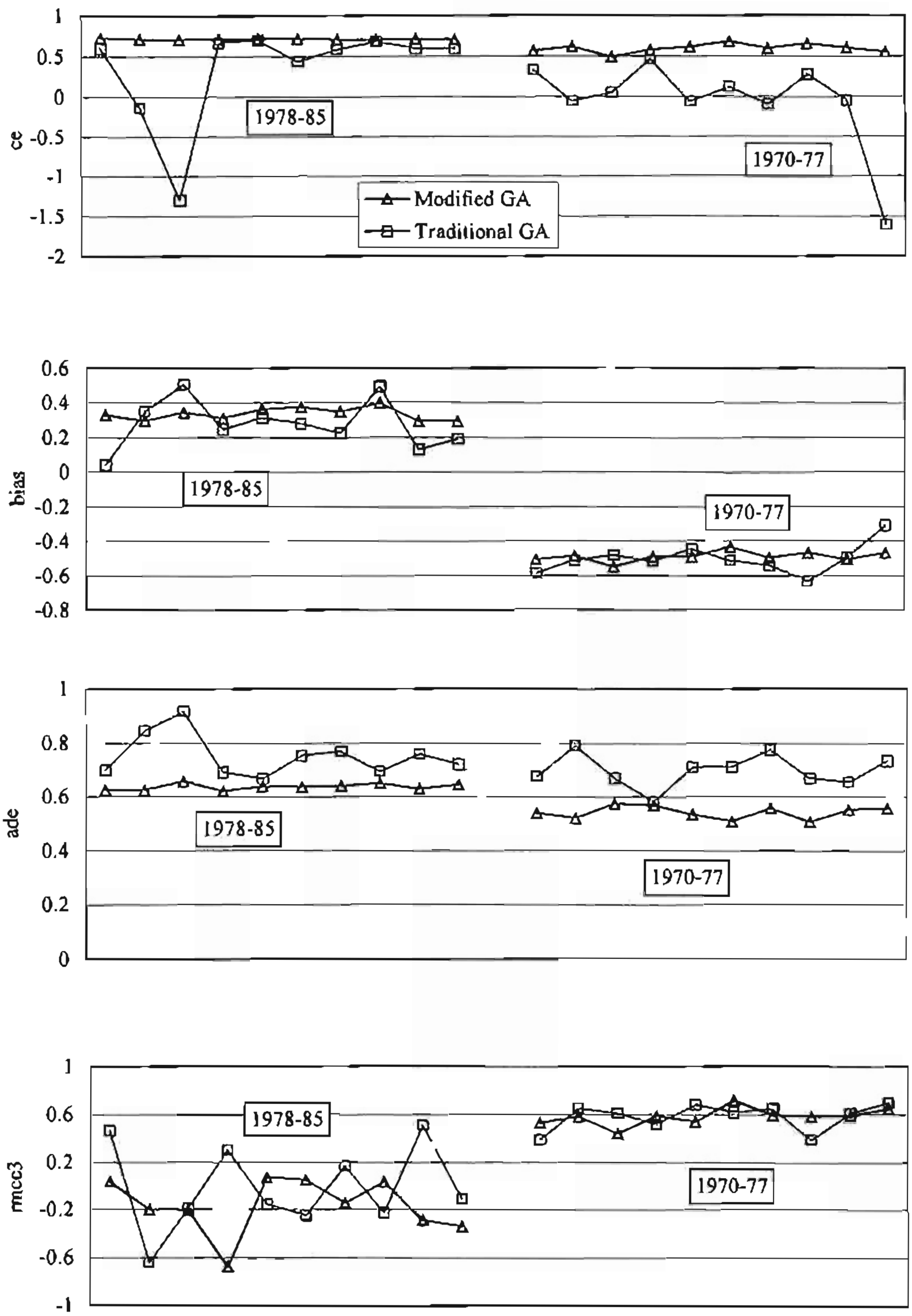


Figure 5.20 STDT4 Model Scott Creek Validation Performances using the Traditional and the fully Modified Genetic Algorithm

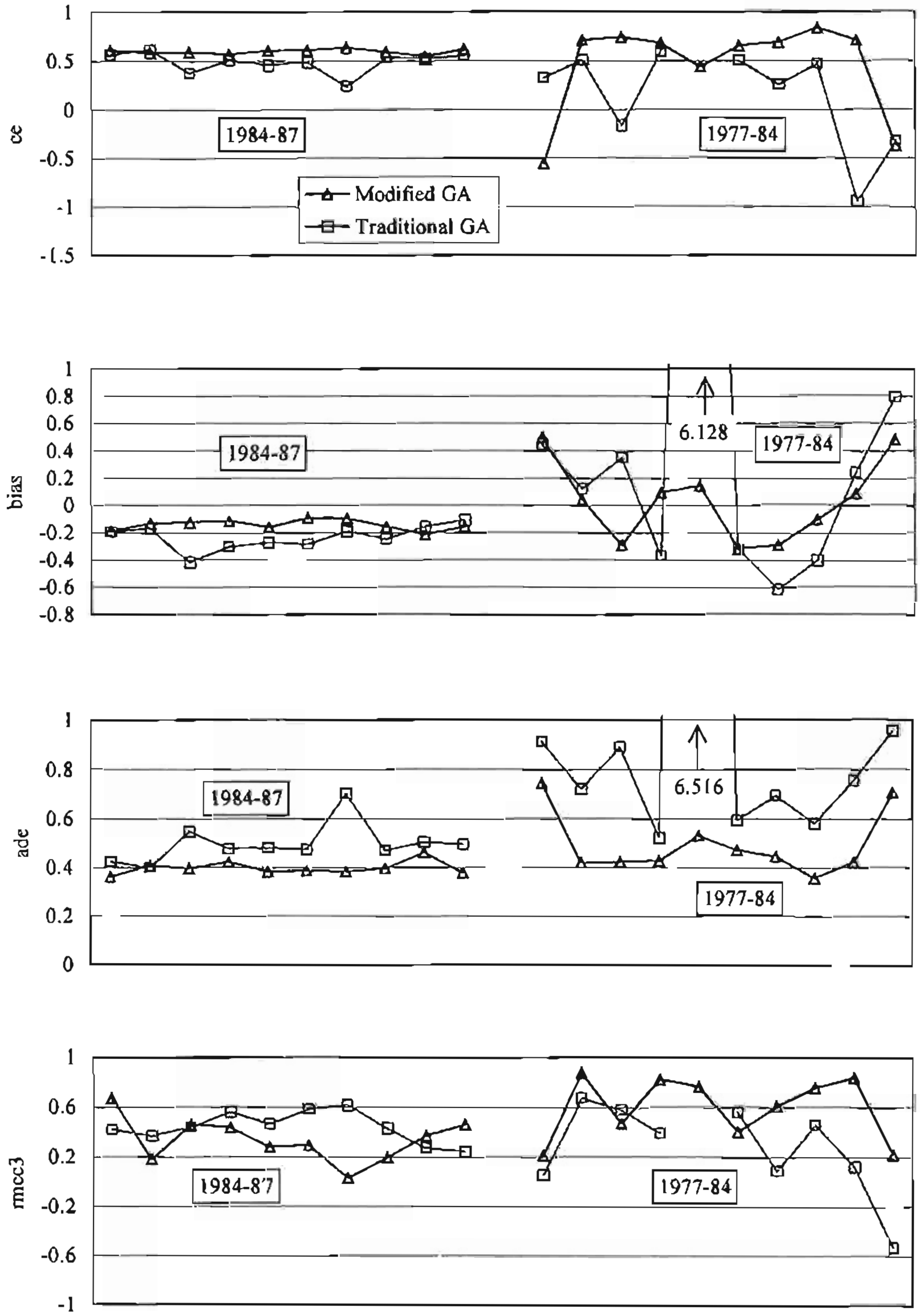


Figure 5.21 STDT4 Model Canning River Validation Performances using the Traditional and the fully Modified Genetic Algorithm

5.6 Typical Features of an Optimization using the Modified Genetic Algorithm

This section demonstrates the working of some features of the GA modifications with a calibration of the STDT3 model using the fully modified GA and the 1970-77 Scott Creek data set. The calibration uses the optimization parameters given in test 1 (first column) of Table 5.10 allowing a maximum of 10000 function evaluations. As stated in Section 5.4, this calibration was considered as having obtained the global optimum, having an objective function value of 237.5.

Figure 5.22 shows the optimized objective function (*obf*) values obtained with the seven subpopulations at each epoch. In Figure 5.23 and 5.24, the optimizations of each of the subpopulations for the first epoch (1) and the last epoch (9) are presented. In the two Figures, *obf* denotes the least objective function value obtained at each generation. To illustrate the effects of the finetuning and the hillclimbing operations, three quantities were computed for the fourth subpopulation (subpopulation-4) for the generations where the two operations were performed out during the calibration. As stated in Section 4.2.2 and 4.2.3, the finetuning and hillclimbing operations were performed after every 5 generations with hillclimbing being undertaken 2 generations after every finetuning. These are the range reduction *rr*, the range shift *rs*, and the relative range shift *rrs*. Equation 5.1 to 5.3 show how the three quantities were computed and Figure 5.25 to 5.27 present their values graphically. $Pmax_i^{\,g}$ and $pmin_i^{g}$ denote the upper and lower parameter search range limits for parameter i in generation g. $Xmax_{Ii}$ and $Xmin_{Ii}$ are the upper and the lower initial search range limits for parameter i in the first epoch.

$$rr = \left(p\,max_i^{\,g} - p\,min_i^{\,g}\right) \Big/ \left(X\,max_{Ii} - X\,min_{Ii}\right) \tag{5.1}$$

$$rs = \left(\left(\frac{p\,max_i^{\,g} + p\,min_i^{\,g}}{2}\right) - \left(\frac{X\,max_{Ii} + X\,min_{Ii}}{2}\right)\right) \Big/ \left(X\,max_{Ii} - X\,min_{Ii}\right) \tag{5.2}$$

$$rrs = \frac{\left(\dfrac{pmax_i^{\,g} + pmin_i^{\,g}}{2}\right) - \left(\dfrac{pmax_i^{\,g-1} + pmin_i^{\,g-1}}{2}\right)}{pmax_i^{\,g-1} - pmin_i^{\,g-1}} \tag{5.3}$$

The range reduction *rr* was obtained as the ratio of the current search range to the initial search range of the first epoch and the range shift *rs* as the ratio of the shift in range to the initial search range of the first epoch. The middle of the search range was taken as its position in computing the range shifts. The relative search range shifts *rrs* were computed as ratios of the current search range shift to the search range of the previous generation.

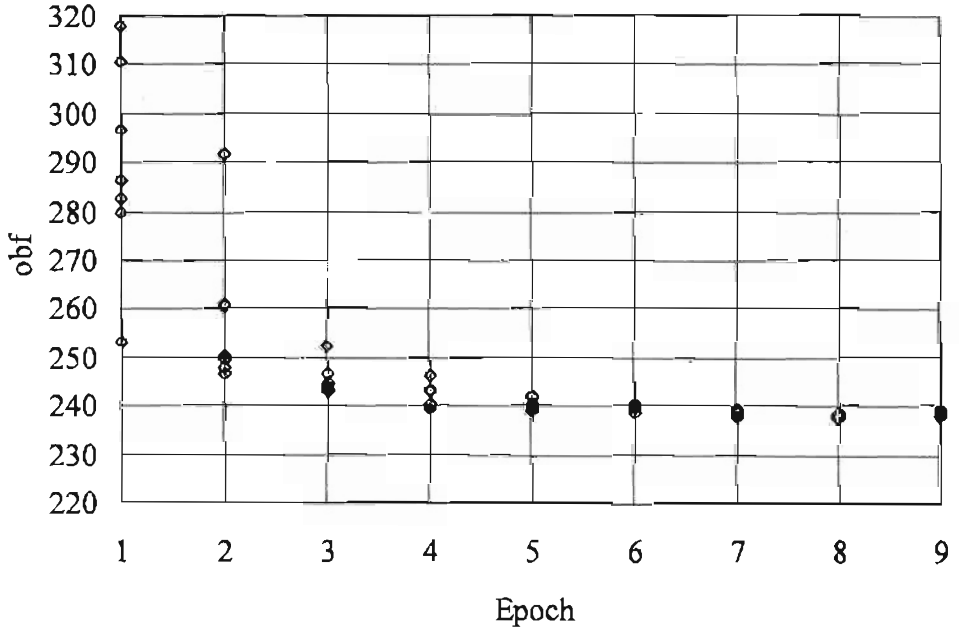


Figure 5.22 Subpopulation Objective Function Values for a Typical Calibration of the STDT3 Model

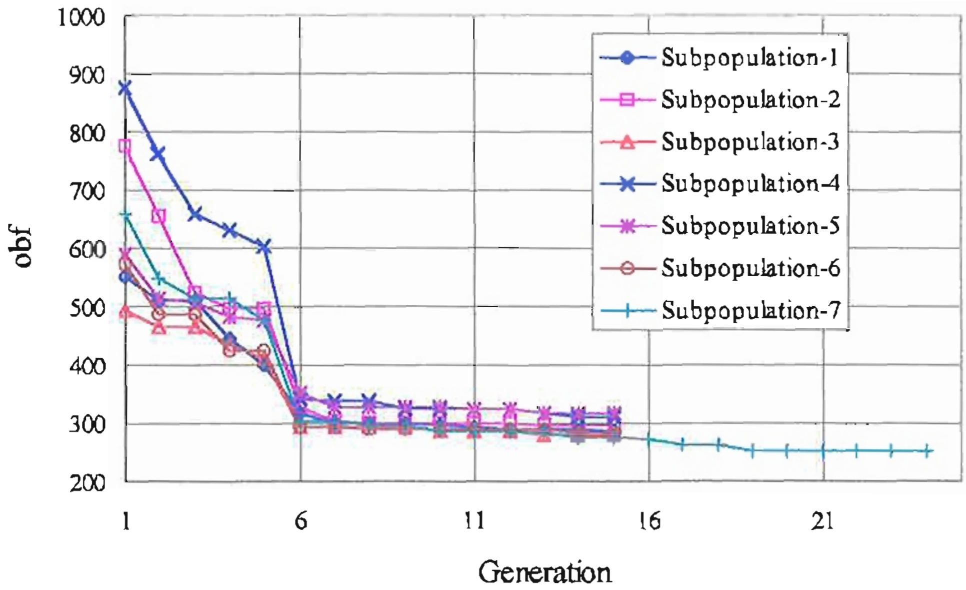


Figure 5.23 Optimizations of individual Subpopulations in the first Epoch of a typical STDT3 Model Calibration

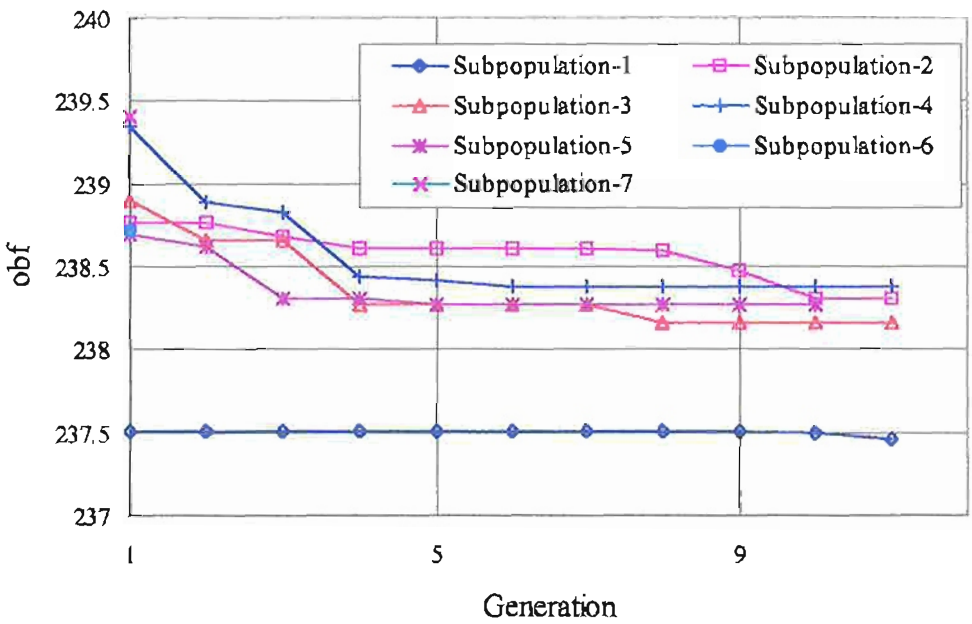


Figure 5.24 Optimizations of individual Subpopulations in the last Epoch a typical STDT3 Model Calibration

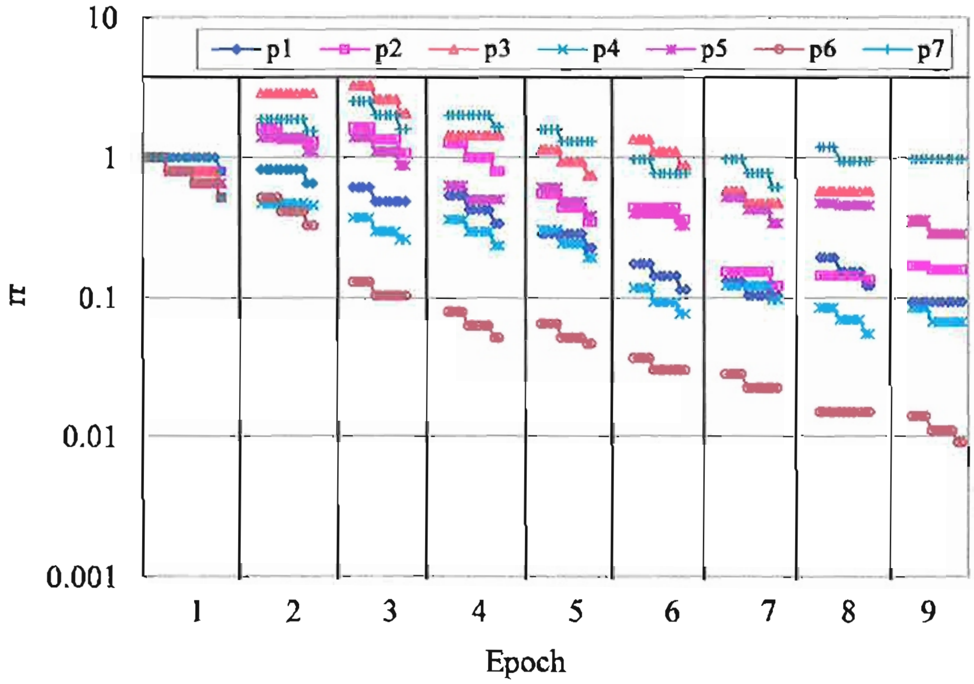


Figure 5.25 Range Reductions of a typical STDT3 Model Calibration

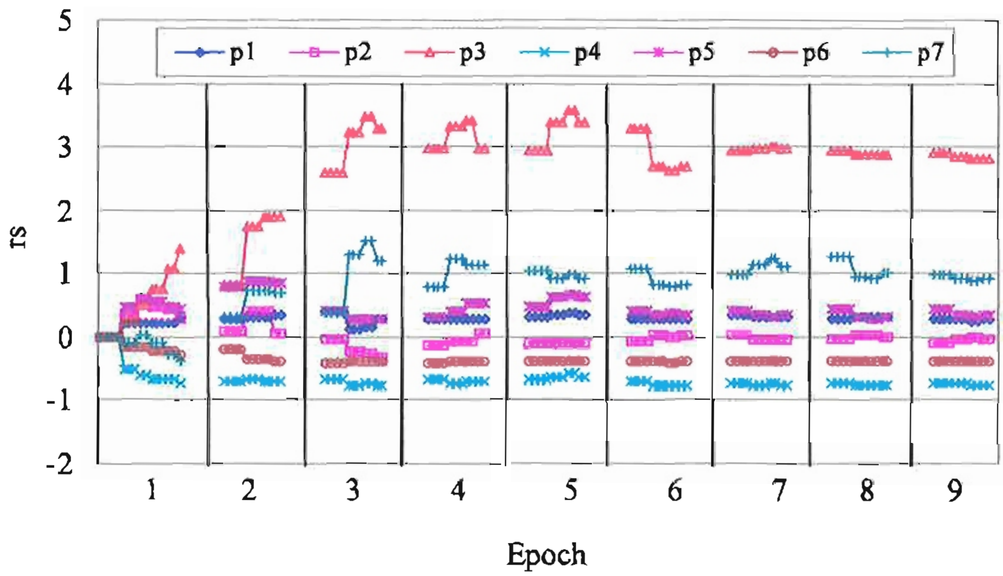


Figure 5.26 Range Shifts of a typical STDT3 Model Calibration

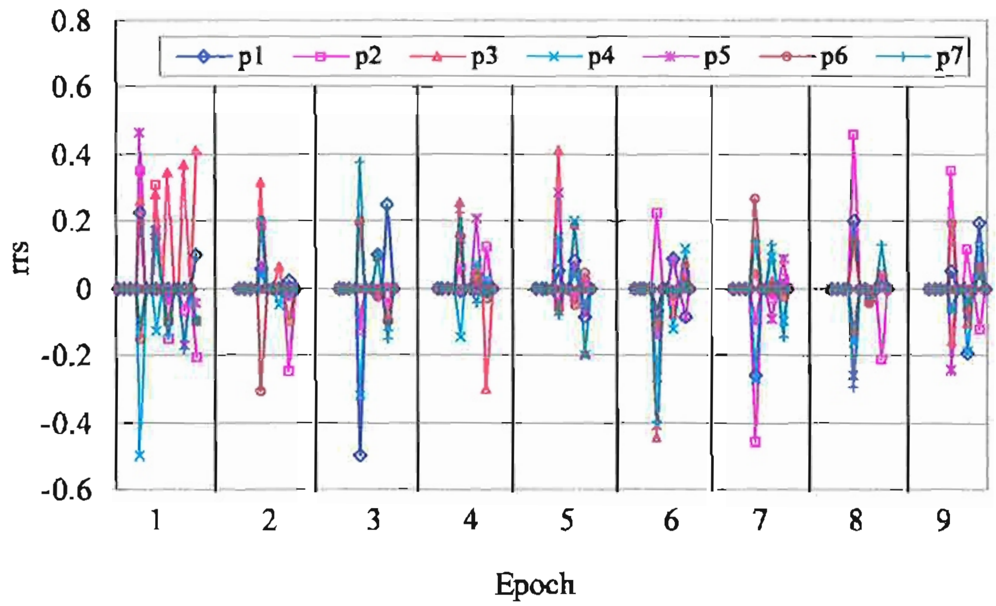


Figure 5.27 Relative Range Shifts of a typical STDT3 Model Calibration

A number of features of the fully modified GA were observed. The gradual convergence of the subpopulation searches towards the global optimum is observed in Figure 5.22. The subpopulations initially terminate at local optimums and gradually converge towards the global optimum. Figures 5.23 and 5.24 show the higher variability of the subpopulation searches of the first as compared to the last epoch. Both Figures demonstrate the application of elitism; the inclusion of the best individual in the current generation as one of the individuals of the next generation. The least objective function values do not therefore increase as the optimization proceeds. Figure 5.24 also demonstrates the better initial start (lower objective function value) in the optimization of the first subpopulation (subpopulation-1). The first subpopulation uses the individuals of the previous epoch to initiate the search whilst the other subpopulations use randomly generated individuals. Section 4.2.4 gives the details of the shuffling operation.

In Figure 5.25 to 5.27, the variable manner in which the GA handles each parameter in finetuning and hillclimbing is evident. The expected overall reduction of the search range as the optimization proceeds (Figure 5.25) is observed. Figure 5.26 shows the expected reduction of the absolute shifts in the parameter search ranges in the later epochs as the search converges to the optimum. Search range shifting however still happens actively even in the later stages of the optimization as the relative search ranges plotted in Figure 5.27 indicate. Some of the range reductions plotted in Figure 5.25 are greater than unity indicating an increase in the search range. This is not undesirable and could be considered as an indirect indication of the robustness of the search. The increase in the search range results from the initialization of the subpopulation search ranges at the beginning of each epoch.

5.7 Discussion

The investigations carried out with all the five optimization problems namely the SIXPAR rainfall-runoff model calibration, the Hartman function optimization, the Griewank function optimization, the STDT3 and the STDT4 rainfall-runoff model calibration all indicate that the modifications to the traditional genetic algorithm (GA) were effective in improving the performance of the GA. The modifications were found to:

- improve the location of the known global optima of the SIXPAR, the Hartman and the Griewank problems;
- improve the values of the objective functions in the STDT3 model calibration; and
- improve the performance of the validation results of the STDT4 model.

The result of the STDT4 model validation underlines the importance of effective model calibration in practical applications of rainfall-runoff models such as runoff data generation. This study however confirmed and made practical the suggestion by Kuczera (1997) that the traditional GA can be improved for rainfall-runoff model calibration.

In the SIXPAR and the STDT3 model calibrations, the range varying GA gave better performance than the shuffled GA. This suggested that operations of finetuning and hillclimbing had a bigger impact than the use of independent subpopulations coupled with shuffling. However both range variation and the use of independent subpopulations with shuffling were useful because the GA incorporating all of them consistently performed better than the range varying or the shuffled GA.

Compared with the four other methods of optimization; the multisimplex (MSX), the two versions of the shuffled complex evolution, (SCE-1 and SCE-2) and the comparative random search (CRS-2), the performance of the fully modified GA was varied. The fully modified GA was as effective in locating the known global optima as the SCE-1, and the SCE-2. Compared to the SCE-2, the method found to perform best among the four in the previous study by Duan *et al* (1993), the modified GA was about two times less efficient with the SIXPAR problem, about three times more efficient with the Hartman problem and about twenty five times less efficient with the Griewank problem. It is therefore appropriate that further improvements of the GA should focus on improving the efficiency.

The sensitivity analysis revealed the high sensitivity of the performance of the fully modified GA to the probability of crossover, the number of subpopulations and the allowed maximum number of function evaluations. With the SIXPAR problem the performance of the fully modified GA was sensitive to the probability of mutation. This was however found not to be the case with the STDT3 problem. The fully modified GA was also more sensitive to variations in the convergence parameter *cheperf* with the SIXPAR than with the STDT3 problem. The dependence of the sensitivity of the GA on the problem points to the need for trials to obtain suitable optimization parameter values when applying the GA method.

Chapter Six

Results and Discussion of Model Development and Testing

6.1 Summary

This Chapter presents the results and discusses the stepwise development of the simple conceptual-empirical models described in Sections 4.5.3 to 4.5.7. The five models are:

- the seven-parameter simple empirical (SEMP) model;
- the nine-parameter simple time-domain tuned model 1 (STDT1);
- the six-parameter simple time-domain tuned model 2 (STDT2);
- the seven-parameter simple time-domain tuned model 3 (STDT3); and
- the fourteen-parameter simple time-domain tuned model 1 (STDT4).

The model development used data from the Scott Creek catchment. The 16-year long data set was split into two samples of 8 years each for the customary split-sample calibration-validation. Figure A4-2 of Appendix A4 gives plots of the split samples. Section 6.2 presents the results of the application of the five models to the Scott Creek data. In Section 6.3, a more comprehensive testing of the STDT4, which performed better than the other models is presented. In addition to Scott Creek, data from two other Australian and three Kenyan catchments was used to test the STDT4 model. Section 4.5.2 and Appendix A4 give details pertaining to the data acquisition and preparation. With each model and each split calibration-validation data series, ten calibrations were done. The genetic algorithm (GA) optimization parameters given in Tables 6.1 and 6.2 were applied in the optimizations. The selection of some of the optimization parameter values was based on the expected difficulty of the optimization in proportion to the number of model parameters.

Table 6.1 Genetic Algorithm Optimization Parameters used in the SEMP, the STDT, the STDT2 and the STDT3 Model Calibrations

Optimization Parameter	Symbol	Parameter Value		
		SEMP	STDT1	STDT2/3
Population size	P	98	126	84
Subpopulation size	p_s	14	18	12
Number of subpopulations	n_s	7	7	7
Bit length of parameter substring	l	20	20	20
Maximum number of generations per optimization	g_{max}	1000	1000	1000
Maximum number of function evaluations	ev_{max}	10000	10000	10000
Probability of crossover	c	1.0	1.0	1.0
Number of crossover positions	n_{cross}	7	9	6
Probability of mutation	m	0.05	0.05	0.05
Tournament size	t_o	4	5	4
Fitness scaling index	f_{scale}	3	3	3
Convergence parameter	$cheperf$	0.95	0.95	0.95
Maximum number of epochs	ep_{max}	50	50	50

Table 6.2 Genetic Algorithm Optimization Parameters used in the STDT4 Model Calibrations

Optimization Parameter	Symbol	Parameter Value
Population size	P	196
Subpopulation size	p_s	28
Number of subpopulations	n_s	14
Bit length of parameter substring	l	20
Maximum number of generations per optimization	g_{max}	1000
Maximum number of function evaluations	ev_{max}	25000
Probability of crossover	c	1.0
Number of crossover positions	n_{cross}	7
Probability of mutation	m	0.05
Tournament size	t_o	8
Fitness scaling index	f_{scale}	3
Convergence parameter	$cheperf$	0.95
Maximum number of epochs	ep_{max}	50

6.2 Development of the Simple Time Domain Tuned Models: Results and Discussion

6.2.1 Results of the SEMP Model

The SEMP model is described in Section 4.5.3. The optimized parameter values and the performance coefficients of the SEMP model simulations are given in Tables 6.3 and 6.4 respectively. In Table 6.3, the number of function evaluations (*eval*) and the objective function (*obf*) values are included. The same is done in Tables 6.5, 6.7, 6.9 and 6.13 which give the optimized parameter values of the other models. In Table 6.4, 6.6, 6.8, 6.10 and 6.19 which present performance coefficients, *ce* denotes the coefficient of efficiency, *ade* the absolute deviation and *rmcc3* the residual mass curve coefficient. In Table 6.4, 6.6, 6.8, 6.10 and 6.19, each row represents the results of a single calibration using one split sample and the accompanying validation with the other split sample. Figure 6.1 is a sample of the SEMP model calibration hydrograph for a four-year period.

Table 6.3 SEMP Model parameter and Objective Function Values for Scott Creek

Data	eval	p1	p2	p3	p4
	10010	0.000344	0.08350	0.452	0.620
	10010	0.000079	0.08535	0.453	0.641
	10010	0.000076	0.08437	0.463	0.620
	10024	0.000044	0.08617	0.464	0.615
1970-77	10094	0.000195	0.09021	0.471	0.644
	10094	0.000085	0.08354	0.462	0.612
	10010	0.000018	0.08151	0.451	0.607
	10010	0.000126	0.07760	0.433	0.610
	10010	0.000225	0.08876	0.481	0.617
	10010	0.000177	0.08451	0.465	0.613
	10094	0.000066	0.00631	0.152	0.236
	10066	0.000236	0.00889	0.229	0.257
	10010	0.000140	0.00821	0.164	0.322
	10052	0.000073	0.00963	0.195	0.329
1978-85	10066	0.000183	0.00701	0.159	0.238
	10066	0.000590	0.00734	0.173	0.259
	10052	0.000406	0.00748	0.178	0.250
	10066	0.000102	0.00949	0.195	0.317
	10052	0.000972	0.00898	0.249	0.208
	10094	0.000101	0.00955	0.223	0.275

Data	p5	p6	p7	obf
	0.255	1.506	0.323	424.0
	0.242	1.484	0.310	424.0
	0.236	1.459	0.322	423.9
	0.226	1.458	0.306	423.9
1970-77	0.220	1.443	0.304	423.9
	0.223	1.380	0.345	423.9
	0.238	1.414	0.357	423.9
	0.243	1.390	0.375	424.0
	0.214	1.459	0.282	423.9
	0.212	1.430	0.300	423.9
	0.548	1.674	0.848	361.5
	0.510	1.665	0.833	361.5
	0.565	1.685	0.919	362.3
	0.548	1.758	0.806	361.5
1978-85	0.527	1.733	0.811	361.6
	0.510	1.632	0.821	361.2
	0.532	1.656	0.853	361.1
	0.511	1.756	0.774	361.5
	0.620	2.062	0.719	364.5
	0.496	1.771	0.766	361.6

Table 6.4 SEMP Model Performance Coefficients for Scott Creek

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.543	-0.166	0.586	0.494		0.642	0.107	0.742	0.204
	0.546	-0.175	0.586	0.482		0.636	0.096	0.744	0.202
	0.548	-0.184	0.584	0.473		0.631	0.084	0.742	0.203
	0.548	-0.182	0.584	0.466		0.626	0.086	0.748	0.203
Calibration	0.546	-0.190	0.584	0.463		0.623	0.076	0.746	0.202
1970-77	0.552	-0.193	0.581	0.455	Validation	0.620	0.071	0.746	0.205
	0.553	-0.185	0.581	0.469	1978-85	0.629	0.082	0.744	0.205
	0.555	-0.186	0.580	0.469		0.629	0.080	0.743	0.206
	0.545	-0.192	0.585	0.456		0.619	0.074	0.748	0.201
	0.545	-0.203	0.583	0.446		0.614	0.059	0.746	0.202
	0.641	-0.269	0.615	0.130		0.202	-0.445	0.722	0.555
	0.636	-0.281	0.613	0.141		0.257	-0.454	0.713	0.530
	0.640	-0.290	0.612	0.124		0.166	-0.459	0.730	0.559
	0.645	-0.261	0.612	0.132		0.169	-0.436	0.721	0.563
Calibration	0.635	-0.284	0.615	0.137	Validation	0.205	-0.456	0.723	0.540
1978-85	0.638	-0.268	0.614	0.141	1970-77	0.269	-0.446	0.710	0.532
	0.640	-0.271	0.613	0.135		0.231	-0.447	0.717	0.544
	0.637	-0.279	0.614	0.142		0.218	-0.451	0.717	0.537
	0.640	-0.253	0.619	0.119		-0.273	-0.417	0.759	0.629
	0.630	-0.294	0.618	0.145		0.228	-0.462	0.717	0.523

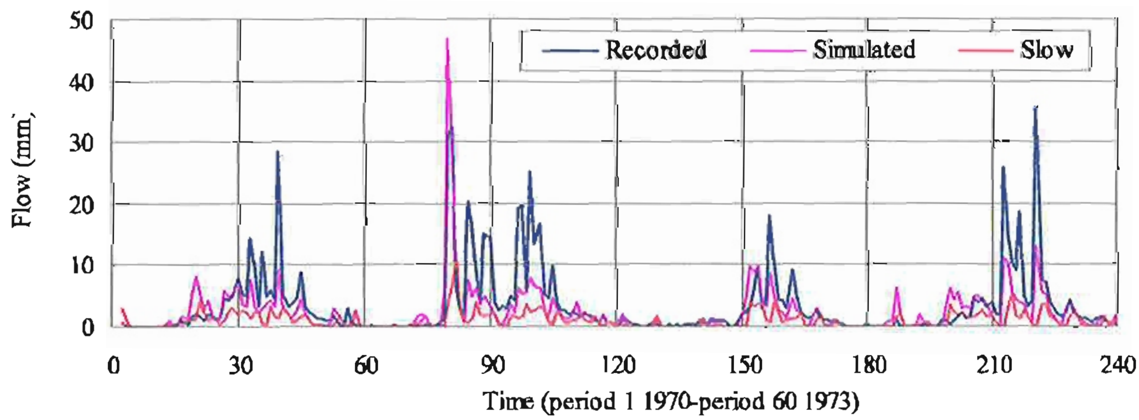


Figure 6.1 Sample of SEMP Model Calibration Hydrograph for Scott Creek

Parameter $p1$, the evapotranspiration coefficient optimized to negligible values indicating the model was not simulating evapotranspiration losses. Figure 6.1 reveals the inadequacy of the model in simulating both low and high flows. The model did not include an effective slow flow simulation as it based the slow flow on the net rainfalls of the past two periods only. The first modification was the inclusion of a slow flow component obtained from the summation of the past net rainfalls to a period obtained by calibration. This gave the STDT1 model.

6.2.2 Results of the STDT1 Model

Section 4.5.4 gives a description of the STDT1 model. The STDT1 model optimized parameter values and performance coefficients are presented in Tables 6.5 and 6.6 respectively.

Figure 6.2 is a sample of the STDT1 calibration hydrographs. The results indicate no improvement over the SEMP model. The slow flow component turned out to be negligible as the hydrograph shows. Parameter *p9*, the coefficient for obtaining slow flow from the summation of the past net rainfalls, optimized to zero and near zero values. The objective function values of the STDT1 were not better than those of the SEMP model and the validation results were poorer than those of the SEMP model. This is attributed to the absence of weighting of the past net rainfalls in the determination of the slow flow. More recent net rainfalls are expected to have a larger effect on the current runoff than those further in the past.

Table 6.5 STDT1 Model parameter and Objective Function Values for Scott Creek

Data	eval	p1	p2	p3	p4	p5
	10116	22	0.002	0.265	1.387	0.547
	10116	59	0.002	0.594	1.623	0.619
	10008	3	0.000	0.416	1.370	0.778
	10026	3	0.002	0.270	1.121	0.645
1970-77	10026	5	0.002	0.111	1.328	0.164
	10008	2	0.013	0.288	1.273	0.733
	10062	5	0.005	0.294	1.292	0.580
	10080	4	0.000	0.371	1.302	0.653
	10026	4	0.003	0.181	1.266	0.403
	10044	2	0.005	0.389	1.972	0.328
	10080	4	0.001	0.435	1.454	0.789
	10080	2	0.000	0.486	1.804	0.764
	10044	9	0.001	0.697	2.193	0.898
	10080	2	0.000	0.476	1.899	0.771
1978-85	10026	8	0.002	0.553	2.569	0.391
	10080	6	0.001	1.020	2.654	0.801
	10098	6	0.002	0.834	2.535	0.704
	10062	7	0.000	0.687	2.403	0.630
	10080	51	0.012	0.816	4.023	0.470
	10008	1	0.000	0.422	1.754	0.555

Data	p6	p7	p8	p9	obf
	0.126	0.552	0.688	0.000008	422.4
	0.057	0.353	0.600	0.000002	420.0
	0.073	0.251	0.729	0.000001	420.2
	0.053	0.389	0.549	0.000001	418.2
1970-77	0.204	0.982	0.526	0	430.9
	0.080	0.366	0.525	0.000001	425.5
	0.064	0.279	0.655	0	417.3
	0.056	0.165	0.810	0	420.1
	0.079	0.405	0.611	0	420.4
	0.073	0.497	0.341	0	430.4
	0.008	0.185	0.367	0	356.4
	0.023	0.374	0.410	0	356.6
	0.018	0.336	0.419	0	358.0
	0.023	0.354	0.502	0	353.8
1978-85	0.042	0.504	0.413	0	374.4
	0.058	0.779	0.434	0	371.4
	0.039	0.519	0.528	0	363.3
	0.011	0.244	0.195	0	357.9
	0.038	0.439	0.501	0	387.0
	0.012	0.162	0.397	0	359.4

Table 6.6 STDT1 Model Performance Coefficients for Scott Creek

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.534	-0.146	0.576	0.507		0.643	0.155	0.768	-0.027
	0.062	0.020	0.653	0.803		0.659	0.277	0.731	0.024
	0.479	-0.113	0.603	0.592		0.677	0.184	0.750	0.146
	0.547	-0.224	0.575	0.434		0.614	0.032	0.742	0.225
Calibration	0.491	-0.171	0.594	0.456		0.585	0.107	0.794	0.180
1970-77	0.540	-0.142	0.583	0.492	Validation	0.623	0.142	0.795	0.248
	0.553	-0.161	0.578	0.479	1978-85	0.634	0.121	0.764	0.209
	0.530	-0.141	0.594	0.541		0.664	0.152	0.750	0.181
	0.528	-0.213	0.583	0.383		0.562	0.052	0.791	0.225
	0.170	-0.032	0.633	0.617		0.657	0.271	0.775	0.250
	0.629	-0.256	0.628	0.148		0.387	-0.439	0.680	0.484
	0.646	-0.244	0.612	0.162		0.242	-0.422	0.695	0.534
	0.635	-0.299	0.612	0.067		-0.518	-0.441	0.786	0.654
	0.629	-0.307	0.615	0.160		0.198	-0.467	0.713	0.517
Calibration	0.653	-0.083	0.623	0.118	Validation	-1.700	-0.249	0.746	0.727
1978-85	0.578	-0.058	0.648	-0.091	1970-77	-4.538	-0.188	0.857	0.642
	0.634	-0.142	0.618	-0.005		-2.644	-0.278	0.819	0.719
	0.628	-0.212	0.627	0.078		-1.376	-0.360	0.799	0.703
	0.564	-0.320	0.643	0.073		-32.51	-0.011	1.222	-0.372
	0.632	-0.204	0.636	0.172		0.309	-0.398	0.680	0.501

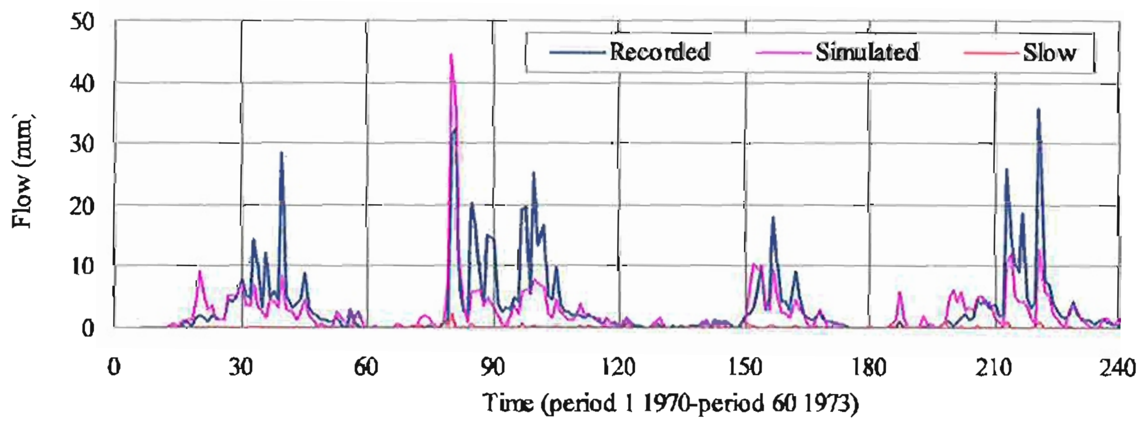


Figure 6.2 Sample of STDT1 Model Calibration Hydrograph for Scott Creek

6.2.3 Results of the STDT2 Model

Changes to the STDT1 model included weighting of the past net rainfalls to obtain the slow flow to give model STDT2 (Section 4.5.5). The optimized parameter values of this model are given in Table 6.7 and the performance coefficients in Table 6.8. A sample plot of the hydrograph obtained from the STDT2 is given as Figure 6.3.

Table 6.7 STDT2 Model parameter and Objective Function Values for Scott Creek

Data	eval	p1	p2	p3	p4	p5	p6	obf
	10068	21	0.4398	0.315	1.492	0.537	0.0372	315.4
	10068	21	0.4399	0.323	1.503	0.533	0.0371	315.4
	10056	21	0.4399	0.322	1.499	0.535	0.0371	315.4
	10056	21	0.4399	0.320	1.499	0.533	0.0371	315.4
1970-77	10056	21	0.4399	0.324	1.504	0.534	0.0371	315.4
	10056	21	0.4399	0.324	1.505	0.534	0.0371	315.4
	10068	21	0.4399	0.318	1.501	0.528	0.0371	315.4
	10044	21	0.4399	0.320	1.497	0.536	0.0371	315.4
	10056	21	0.4399	0.322	1.503	0.533	0.0371	315.4
	10032	21	0.4399	0.324	1.503	0.534	0.0371	315.4
	10080	15	0.0198	0.758	2.168	0.889	0.0070	299.8
	10008	15	0.0193	0.759	2.163	0.893	0.0070	299.8
	10008	15	0.0194	0.751	2.168	0.885	0.0070	299.8
	10068	15	0.0194	0.760	2.168	0.891	0.0070	299.8
1978-85	10032	15	0.0199	0.760	2.168	0.891	0.0070	299.8
	10080	15	0.0199	0.758	2.167	0.890	0.0070	299.8
	10008	15	0.0198	0.754	2.168	0.888	0.0070	299.8
	10080	15	0.0195	0.758	2.163	0.893	0.0070	299.8
	10032	15	0.0194	0.765	2.154	0.904	0.0070	299.8
	10080	15	0.0195	0.759	2.163	0.894	0.0070	299.8

The STDT2 model did not exhibit any marked improvements over the SEMP with regards to the performance coefficients. The STDT2 1970-77 validations also gave lower coefficients of efficiency and higher absolute deviations than the SEMP. The STDT2 model however gave more realistic values of *p2*, the evapotranspiration loss coefficient and also exhibited a more satisfactory slow flow simulation. The simulation of the dry season (low) flows with the STDT2 was also better than that of the STDT1 and the SEMP models. This justifies the lower objective function values obtained in the STDT2 model calibrations. The STDT2 simulation of high flows was however poor.

Table 6.8 STDT2 Model Performance Coefficients for Scott Creek

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.627	-0.187	0.460	0.564		0.664	0.152	0.726	0.250
	0.625	-0.182	0.461	0.572		0.666	0.160	0.725	0.241
	0.623	-0.176	0.465	0.589		0.663	0.168	0.733	0.163
	0.622	-0.175	0.468	0.596		0.661	0.170	0.737	0.120
Calibration	0.625	-0.178	0.463	0.583		0.667	0.165	0.729	0.202
1970-77	0.625	-0.179	0.463	0.582	Validation	0.667	0.164	0.729	0.203
	0.627	-0.181	0.461	0.575	1978-85	0.666	0.160	0.729	0.220
	0.622	-0.175	0.467	0.595		0.661	0.169	0.737	0.134
	0.624	-0.179	0.464	0.582		0.665	0.164	0.730	0.197
	0.625	-0.178	0.463	0.583		0.666	0.165	0.730	0.196
	0.639	-0.237	0.591	0.092		-0.670	-0.397	0.778	0.692
	0.639	-0.236	0.591	0.086		-0.664	-0.396	0.778	0.693
	0.640	-0.239	0.591	0.095		-0.649	-0.399	0.777	0.689
	0.639	-0.236	0.591	0.091		-0.678	-0.396	0.779	0.693
Calibration	0.639	-0.236	0.591	0.092	Validation	-0.676	-0.396	0.778	0.693
1978-85	0.639	-0.236	0.591	0.093	1970-77	-0.671	-0.396	0.778	0.692
	0.640	-0.239	0.591	0.094		-0.658	-0.398	0.778	0.690
	0.640	-0.237	0.591	0.092		-0.661	-0.397	0.778	0.692
	0.639	-0.234	0.591	0.090		-0.664	-0.395	0.778	0.694
	0.639	-0.236	0.591	0.093		-0.664	-0.396	0.778	0.692

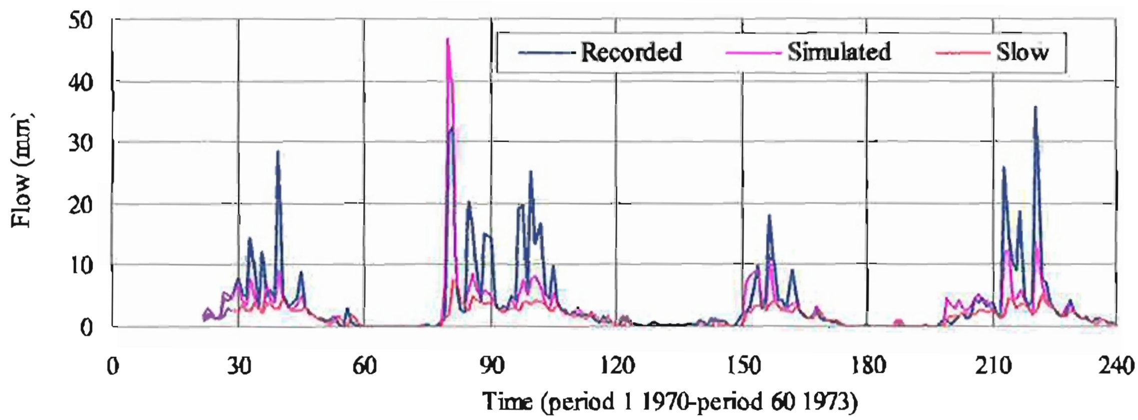


Figure 6.3 Sample of STDT2 Model Calibration Hydrograph for Scott Creek

6.2.4 Results of the STDT3 Model

A possible improvement to the STDT2 model was considered to be the inclusion of an antecedent wetness component and the variation of the current net rainfall contributions to runoff according to the antecedent catchment wetness. The full details of this modification, which resulted in the STDT3 model are given in Section 4.5.6. The optimized parameter values and performance coefficients for this model are given in Table 6.9 and 6.10 respectively. Figure 6.4 presents a four-year sample hydrograph of the STDT3 model. The STDT3 model gave better performance coefficients in both calibration and validation than the STDT1, the STDT2 and the SEMP. The STDT3 model objective functions were also considerably lower than those of the three other models. The simulation of the high flows was also considerably better. The validation performance of STDT3 (Table 6.10) was however considered unsatisfactory.

Table 6.9 STDT3 Model parameter and Objective Function Values for Scott Creek

Data	eval	p1	p2	p3	p4	p5	p6	p7	obf
	10038	21	0.399	1.657	0.283	1.387	0.029	7.313	237.5
	10066	19	0.381	1.624	0.234	1.304	0.030	7.038	237.9
	10052	19	0.382	1.604	0.258	1.352	0.029	7.811	237.9
	10066	21	0.381	1.687	0.307	1.506	0.029	7.848	237.9
1970-77	10038	19	0.380	1.629	0.258	1.375	0.030	8.174	237.9
	10052	19	0.380	1.588	0.241	1.306	0.029	8.071	237.8
	10052	19	0.366	1.567	0.243	1.319	0.029	7.893	237.7
	10052	19	0.366	1.566	0.258	1.360	0.028	7.904	237.8
	10038	19	0.381	1.602	0.233	1.280	0.029	7.820	237.8
	10066	21	0.398	1.678	0.305	1.456	0.029	7.829	237.2
	10080	27	0.119	0.389	0.333	1.881	0.006	21.34	252.5
	10080	26	0.109	0.376	0.291	1.804	0.006	18.78	251.7
	10010	26	0.096	0.355	0.263	1.665	0.005	20.67	251.5
	10066	27	0.122	0.385	0.262	1.762	0.006	18.65	252.8
1978-85	10024	27	0.119	0.375	0.278	1.693	0.006	18.71	252.3
	10066	27	0.101	0.348	0.271	1.700	0.005	20.56	251.8
	10010	18	0.034	0.435	0.340	1.860	0.006	26.20	252.8
	10066	27	0.111	0.371	0.293	1.778	0.006	22.16	251.7
	10080	19	0.045	0.406	0.340	1.865	0.006	26.61	252.9
	10080	26	0.106	0.389	0.280	1.809	0.006	21.77	251.8

Table 6.10 STDT3 Model Performance Coefficients for Scott Creek

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.773	-0.119	0.354	0.679		0.659	0.297	0.699	0.265
	0.758	-0.091	0.365	0.733		0.661	0.283	0.695	0.516
	0.743	-0.076	0.367	0.776		0.651	0.276	0.706	0.279
	0.779	-0.125	0.353	0.680		0.661	0.295	0.691	0.233
Calibration	0.738	-0.082	0.367	0.774		0.653	0.268	0.702	0.274
1970-77	0.756	-0.089	0.366	0.756	Validation	0.660	0.286	0.694	0.498
	0.753	-0.090	0.367	0.752	1978-85	0.661	0.283	0.692	0.499
	0.739	-0.081	0.370	0.776		0.662	0.296	0.694	0.483
	0.761	-0.095	0.366	0.741		0.646	0.252	0.705	0.303
	0.780	-0.115	0.352	0.691		0.657	0.308	0.698	0.250
	0.616	-0.178	0.536	0.327		0.219	-0.372	0.595	0.733
	0.604	-0.219	0.543	0.259		0.373	-0.408	0.600	0.689
	0.601	-0.225	0.545	0.277		0.485	-0.412	0.589	0.658
	0.597	-0.272	0.535	0.356		0.436	-0.448	0.603	0.607
Calibration	0.606	-0.196	0.545	0.261	Validation	0.459	-0.391	0.585	0.687
1978-85	0.607	-0.237	0.535	0.359	1970-77	0.462	-0.420	0.591	0.642
	0.611	-0.208	0.534	0.099		0.130	-0.409	0.629	0.743
	0.612	-0.219	0.533	0.352		0.388	-0.405	0.595	0.676
	0.609	-0.224	0.534	0.103		0.123	-0.426	0.634	0.738
	0.604	-0.252	0.532	0.360		0.389	-0.431	0.604	0.639

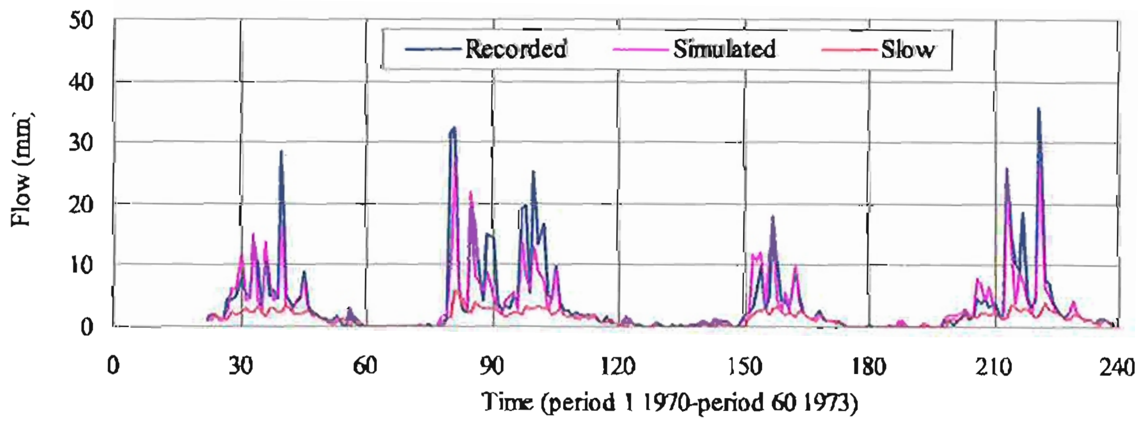


Figure 6.4 Sample of STDT3 Model Calibration Hydrograph for Scott Creek

6.2.5 Results of the STDT4 Model

The search for further model improvements as reported in Section 4.5.7, resulted in the STDT4 model. The results of a more comprehensive study of the STDT4 model including five other catchments is presented in Section 6.3. The results of the STDT4 modelling of

Scott Creek are therefore presented together with those of the other catchments in Section 6.3. The optimized parameter values and performance coefficients of the STDT4 are given in Table 6.13 and Table 6.19 respectively for Scott Creek. A sample four-year calibration hydrograph is given within this Section as Figure 6.5. The STDT4 model gave considerably better performance coefficients than the STDT3 in calibration with an exception of the residual mass curve coefficients for the 1978-85 data series. In validation, STDT4 gave better coefficients of efficiency and absolute deviations but poorer bias and residual mass curve coefficients than STDT3. A comparison of the respective hydrographs, Figure 6.4 and 6.5 also reveals a better matching of the recorded and the simulated flows with the STDT4. The objective function values of the STDT4 (Table 6.13) were also lower than those of the STDT3 (Table 6.9).

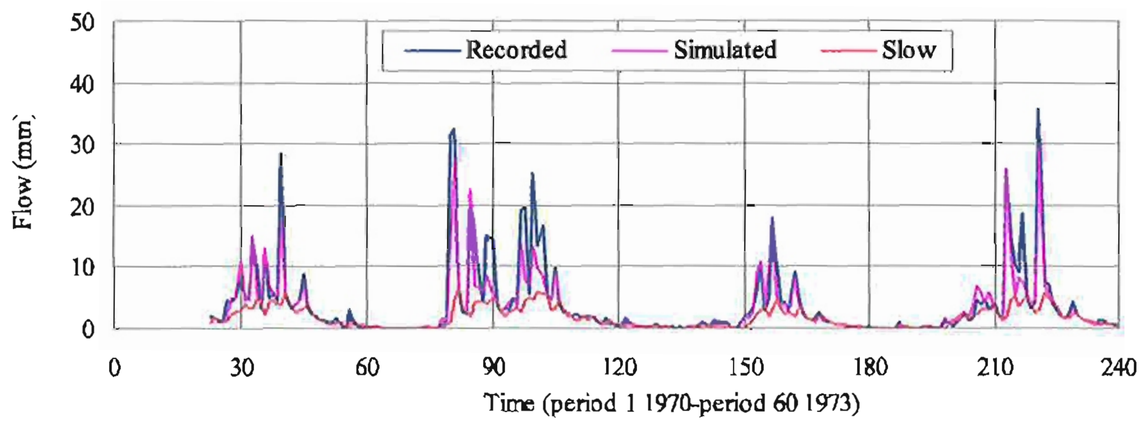


Figure 6.5 Sample of STDT4 Model Calibration Hydrograph

6.2.6 Discussion

The results of the stepwise development of a set of conceptual-empirical models has been presented. The models being partly empirical necessarily meant that calibration would play an important role in guiding the model development. Among the models, the 14 parameter STDT4 performed the best. This was at the expense of more effort in calibration and of dealing with a higher number of parameters. Further improvements of this model could consider the possibility of reducing the number of model parameters. Some suggestions have been given in Section 6.3.4 regarding this. Among the five models, the STDT3 and the STDT4 seem to have an acceptable performance for the simulation of pseudo weekly flows.

The other models; the SEMP, the STDT1 and the STDT2 are regarded as experimental and not acceptable for practical applications. The STDT4 gave the best overall performance and was therefore selected for a more comprehensive analysis presented in Section 6.3. It is worthwhile to mention that the model development was based on data from a single catchment, one type of objective function and the pseudo weekly time interval. Chapter 7 presents the comparison of three models including the STDT3 and the STDT4 in the simulation of monthly flows from three Australian catchments.

6.3 The Application of the STDT4 Model to Australian and Kenyan Catchments

The data from the three Australian and the three Kenyan catchments was each split into two samples as presented in the data plots of Appendix A4. For each catchment, twenty split-sample calibrations and validations were done and the performance coefficients of both calibrations and validations evaluated. Ten of the runs used the earlier sample for calibration and the later one for validation. The samples were swapped for the other ten calibration and validation runs. The initial parameter search ranges and range limits used for the six catchments are given in Table 6.11. Table 6.2 of Section 6.1 gives the GA optimization parameters applied in the calibrations. The acquisition and preparation of the data is presented in Section 4.5.2.

The STDT4 model is described in Section 4.5.7 and this section covers three aspects of the application of the model. These aspects are:

- an assessment of the adequacy of the calibration of the model (Section 6.3.1);
- an analysis of the model parameter identification, correlations and consistency of flow separation (Section 6.3.2); and
- an analysis of the performance of the model using the four performance coefficients applied in Section 6.2; the coefficient of efficiency (*ce*), the bias, the absolute deviation (*ade*) and the residual mass curve coefficient (*rmcc3*). This analysis is given in Section 6.3.3.

A discussion of the modelling in Section 6.3.4 gives a summary.

Table 6.11 Parameter Search Ranges for the STDT4 Modelling of Australian and Kenyan Catchments

Parameter	Initial parameter ranges		Parameter range limits	
	lower	upper	lower	upper
1	12	32	3	52
2	0.5	2	0.001	5
3	50	100	10	500
4	-20	0	-100	50
5	0.5	1	0.01	5
6	0.5	1.5	0.01	5
7	0.001	0.2	0.000001	1
8	0.4	1	0.1	5
9	1	5	0.01	10
10	4	10	0.1	30
11	1	2	0.1	5
12	0.2	2	0.0001	5
13	2	10	1	30
14	0.6	1	0.001	5

6.3.1 Adequacy of STDT4 Model Calibrations

Although the modified GA was found to be robust (Chapter 5), an assessment of the adequacy of the calibration was performed. The objective function values obtained from the twenty calibrations and the parameter values are given in Tables 6.12 to 6.17 for the six catchments. Plots of the objective function values for each set of calibrations are given in Figure 6.6.

There were notable differences in the objective function values among the 10 identical runs done for each split sample. This indicates that the precise global optima were hardly ever obtained. However the objective function values from the multiple runs were not highly variable. A search for indications of low performance due to insufficient calibration was done by checking for the occurrence of poor performance and high objective function values in the same simulation.

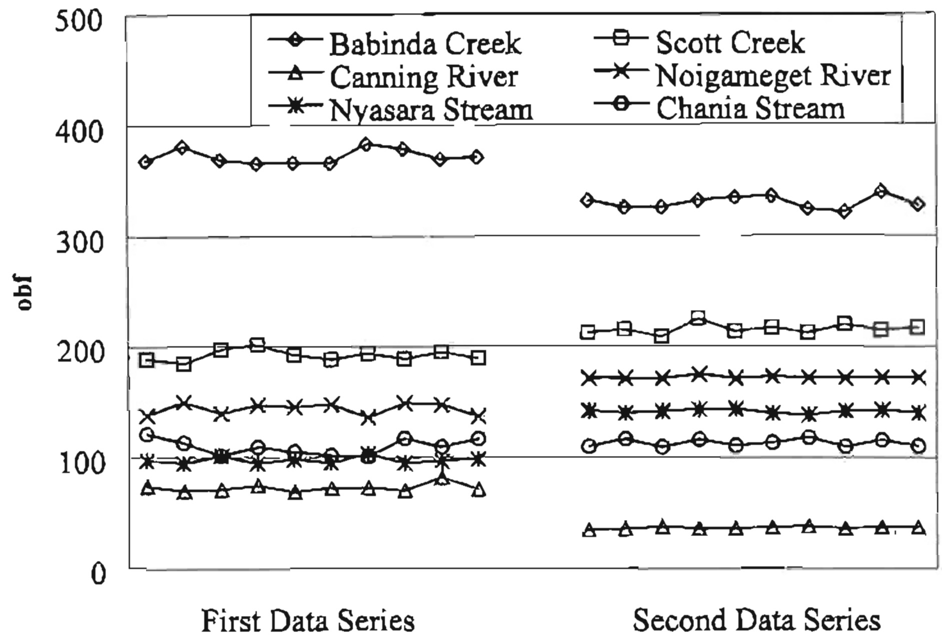


Figure 6.6 Objective Function Values for STDT4 Model Calibrations of Six Catchments

The performance coefficients for the six catchments are presented in Tables 6.18 to 6.23. Out of the total one hundred and twenty calibrations, two cases suggesting inadequate calibration were found. These are:

- Canning River 1977-84 run 9 (Table 6.14 and 6.20): The highest objective function value of 81.85 corresponded to the lowest coefficient of efficiency (0.823) and the highest absolute deviation (0.368). This was also translated to the corresponding 1984-87 validation where the lowest coefficient of efficiency (0.540) and the highest absolute deviation (0.463) were obtained. The calibration and validation for this run also give untypically higher slow flows (Table 6.26 and Figure 6.13 of Section 6.3.2). As Table 6.14 reveals, parameters *p2*, *p5*, *p8*, *p12* and to a lesser extent *p14* for this run were considerably out of the ranges obtained in the other runs.

- Chania River 1963-68 run 1 (Table 6.17 and 6.23): The highest objective function value (121.2) coincided with the lowest coefficient of efficiency (0.697) and the highest absolute deviation (0.279). For this run, parameter *p12* took an untypically high value of 4.250.

The occurrence of the two cases emphasizes further the importance of adequate model calibration, a subject analysed and discussed more fully in Chapter 5.

As Table 6.20 shows, two of the 1978-84 validation runs for Canning River are poor, exhibiting negative coefficients of efficiency and much higher absolute deviations. This set of validations also exhibited a poor consistency of flow separation (Table 6.26 and Figure 6.13). These observations were attributed to inadequate length of the calibration data set (1984 to 1987) and not to insufficient calibration or model deficiencies. The short 1978-81 calibration period also accounts for the poor 1982-87 validations of Nyasara Stream (Table 6.22). The 1982-87 validations of Nyasara Stream also exhibit a poorer consistency of flow separations (Table 6.28 and Figure 6.14).

It is likely that better calibrations would have been obtained with a systematic tuning of the optimization parameters of the fully modified GA or with the SCE-UA method. The calibrations performed here were however considered adequate for a satisfactory evaluation of the model's performance. The two runs with insufficient calibration were removed from the relative parameter location plots and in the computation of parameter correlation coefficients in Section 6.3.2.

Table 6.12 STDT4 Model Parameters and Objective Function Values for Babinda Creek

Data	eval	p1	p2	p3	p4	p5	p6	p7
	25116	33	0.181	400.8	18.27	0.850	1.157	0.123
	25088	31	0.122	489.3	14.00	0.722	1.158	0.121
	25060	29	0.343	496.0	12.64	0.710	1.247	0.219
	25004	34	0.544	468.5	16.34	0.662	1.284	0.199
1974-80	25032	34	0.332	497.0	16.76	0.809	1.230	0.175
	25144	34	0.280	489.9	11.40	0.638	1.259	0.179
	25032	30	0.348	498.4	22.21	0.803	1.377	0.277
	25088	33	0.545	496.5	19.59	0.940	1.332	0.275
	25144	34	0.402	492.9	11.50	0.938	1.359	0.310
	25116	31	0.200	488.7	13.00	0.726	1.307	0.230
	25172	33	0.434	303.7	22.24	0.726	1.185	0.119
	25004	28	0.730	349.7	9.309	0.538	1.171	0.175
	25032	34	0.212	246.0	14.92	0.940	1.106	0.115
	25088	36	0.233	256.9	16.77	1.209	1.118	0.133
1981-87	25116	35	0.557	266.4	19.79	0.748	1.259	0.190
	25004	33	0.352	313.5	13.99	0.702	1.123	0.106
	25088	27	0.523	234.5	26.56	0.833	1.130	0.123
	25144	33	0.413	314.3	17.61	0.724	1.165	0.118
	25032	33	0.292	370.2	18.94	0.815	1.088	0.097
	25004	29	0.557	291.3	13.36	0.772	1.181	0.193
	p8	p9	p10	p11	p12	p13	p14	obf
	1.791	6.538	2.036	1.431	3.771	1.919	2.971	380.3
	1.978	2.870	1.785	1.515	1.712	23.20	4.154	371.0
	1.712	4.617	0.998	1.514	0.576	18.28	1.718	372.6
	2.057	8.774	1.256	1.474	4.001	5.365	1.180	370.4
1974-80	1.733	9.052	1.322	1.506	3.738	2.924	3.460	368.7
	2.011	4.478	1.384	1.428	2.109	28.684	3.806	367.8
	1.700	6.487	0.786	1.503	2.249	4.297	4.291	374.1
	1.419	7.293	0.833	1.496	0.978	9.308	2.108	376.3
	1.352	4.236	0.677	1.517	0.023	20.51	2.583	378.3
	1.750	4.762	1.048	1.445	3.288	15.25	1.360	369.7
	2.238	4.003	2.245	1.577	4.002	11.83	4.448	332.0
	2.076	9.897	1.500	1.625	0.161	3.556	0.862	325.7
	1.850	9.945	2.518	1.546	2.721	2.014	2.134	325.6
	1.483	9.235	2.233	1.532	4.462	2.591	0.543	331.6
1981-87	2.123	4.523	1.416	1.578	2.266	23.65	0.326	334.3
	2.135	1.396	2.414	1.621	0.634	6.417	0.942	335.4
	2.169	9.803	2.309	1.570	1.761	4.235	0.434	323.6
	2.159	9.147	2.195	1.585	4.615	3.691	3.990	321.1
	1.846	9.836	2.748	1.553	3.986	8.457	0.906	338.9
	1.728	9.019	1.470	1.606	0.513	4.279	0.671	327.4

Table 6.13 STDT4 Model Parameters and Objective Function Values for Scott Creek

Data	eval	p1	p2	p3	p4	p5	p6	p7
	25172	20	0.530	411.7	0.605	0.514	0.974	0.0260
	25144	22	0.512	188.3	0.814	0.523	1.004	0.0268
	25116	22	0.457	140.2	-0.291	0.762	1.131	0.0847
	25172	26	0.535	451.2	1.382	0.471	1.167	0.0491
1970-77	25144	22	0.556	221.6	0.707	0.586	1.013	0.0374
	25116	22	0.500	177.1	0.883	0.569	1.013	0.0334
	25060	20	0.388	410.0	0.550	0.651	1.049	0.0478
	25116	20	0.486	154.4	0.641	0.537	1.043	0.0369
	25060	21	0.488	174.4	0.443	0.773	0.877	0.0349
	25060	21	0.501	196.6	1.295	0.522	1.038	0.0314
	25088	19	0.680	129.0	0.604	0.570	1.049	0.0190
	25116	15	0.361	406.9	5.190	0.692	0.956	0.0178
	25116	17	0.788	130.6	1.240	0.485	1.034	0.0170
	25172	23	0.474	114.0	0.187	0.668	1.336	0.0196
1978-85	25116	18	0.334	283.8	2.890	0.848	0.952	0.0226
	25088	18	0.610	154.8	3.773	0.897	0.910	0.0213
	25116	22	0.507	270.3	1.971	0.459	1.219	0.0199
	25144	33	0.395	372.0	0.663	0.468	1.353	0.0288
	25032	15	0.433	220.5	1.488	0.643	0.980	0.0143
	25088	22	0.480	223.1	1.075	0.614	1.218	0.0295

Data	p8	p9	p10	p11	p12	p13	p14	obf
	2.805	1.739	13.01	1.853	0.026	8.448	1.043	188.4
	2.954	1.783	13.60	1.856	0.065	6.995	0.240	184.4
	1.943	1.929	4.188	1.882	0.002	7.526	0.713	197.1
	3.757	1.945	8.522	1.909	0.056	9.688	1.846	201.4
1970-77	2.381	1.817	10.07	1.973	0.071	6.004	0.465	191.9
	2.674	1.706	11.29	1.911	0.038	6.564	2.439	187.9
	2.476	1.577	7.820	1.881	0.006	6.658	0.613	193.4
	2.691	1.701	10.39	1.874	0.006	8.989	4.229	188.5
	2.155	1.779	11.37	1.934	0.025	6.261	0.797	194.5
	2.986	1.862	9.675	1.630	0.061	7.604	1.787	189.0
	1.769	1.496	30.00	1.896	0.849	3.290	0.824	212.4
	3.183	0.772	18.17	1.864	0.196	5.658	1.252	215.2
	2.617	1.736	29.78	1.941	0.763	2.510	0.948	208.3
	0.872	1.174	26.44	1.754	0.804	2.799	0.472	225.3
1978-85	2.597	0.582	13.45	1.921	0.113	10.44	2.473	213.2
	2.120	0.784	21.50	2.000	0.372	3.437	1.252	216.4
	3.191	1.190	24.20	1.929	0.471	2.817	1.139	211.9
	2.399	1.186	12.74	1.629	0.644	2.765	0.830	219.4
	1.860	1.009	27.07	1.790	0.620	2.736	0.971	214.6
	2.187	1.522	18.94	1.869	0.641	2.638	1.054	216.9

Table 6.14 STDT4 Model Parameters and Objective Function Values for Canning River

Data	eval	p1	p2	p3	p4	p5	p6	p7
	25032	43	0.573	334.7	-18.79	0.791	0.869	0.0202
	25116	36	0.655	78.99	-33.33	0.985	0.855	0.0290
	25032	48	0.626	118.4	-19.60	0.837	0.793	0.0210
	25088	47	0.631	111.5	-34.69	0.874	0.853	0.0238
1977-84	25032	36	0.682	81.71	-22.57	0.977	0.854	0.0325
	25060	37	0.601	97.21	-55.34	0.932	0.864	0.0281
	25060	37	0.586	78.18	-74.27	0.981	0.894	0.0368
	25004	36	0.710	77.79	-44.49	1.068	0.853	0.0450
	25116	38	1.061	51.23	-17.24	1.327	0.778	0.0694
	25032	43	0.686	104.3	-17.75	0.899	0.827	0.0283
	25060	31	0.572	309.1	-30.47	0.853	0.829	0.0145
	25144	30	0.659	491.7	-45.34	0.838	0.814	0.0134
	25060	31	0.636	239.6	-83.06	0.736	0.850	0.0118
	25172	31	0.587	170.0	-20.25	0.839	0.814	0.0125
1984-87	25032	30	0.624	148.5	-77.03	0.807	0.840	0.0125
	25172	30	0.656	139.2	-57.18	0.833	0.813	0.0130
	25032	33	0.728	110.8	-91.52	0.952	0.829	0.0231
	25116	32	0.613	191.8	-39.87	0.825	0.862	0.0170
	25060	30	0.584	377.3	-40.56	0.815	0.784	0.0097
	25004	32	0.607	450.7	-49.94	0.912	0.830	0.0211
	p8	p9	p10	p11	p12	p13	p14	obf
	2.972	1.286	8.209	1.865	0.080	8.095	1.459	73.83
	2.559	1.305	5.175	1.431	0.135	9.240	0.780	69.99
	2.450	1.407	6.007	1.289	0.127	8.378	1.065	71.07
	2.103	1.233	5.266	1.279	0.174	8.400	0.801	74.52
1977-84	2.805	1.341	5.302	1.680	0.083	9.878	1.409	69.04
	2.855	2.003	5.820	1.383	0.122	9.962	0.855	72.47
	2.999	1.238	1.943	1.409	0.089	4.670	1.237	72.82
	2.728	1.580	2.880	1.479	0.100	7.477	1.075	70.15
	1.654	3.131	16.631	1.763	1.176	8.055	0.586	81.85
	2.741	1.678	4.242	1.450	0.095	7.444	1.561	71.34
	3.392	0.803	27.72	1.814	0.051	26.73	0.822	34.62
	2.897	0.905	16.20	1.851	0.045	15.56	1.046	35.41
	2.919	0.671	5.632	1.948	0.044	4.398	1.566	37.24
	3.298	0.824	18.55	1.933	0.050	14.50	0.796	35.49
1984-87	2.784	0.793	21.48	1.732	0.064	20.40	0.859	35.55
	2.927	7.429	21.09	1.883	0.055	17.95	1.123	36.81
	2.676	6.080	16.30	1.762	0.053	23.60	1.343	37.58
	3.016	1.049	8.432	1.836	0.067	9.715	1.047	35.49
	3.397	0.825	21.98	1.846	0.038	13.36	0.854	36.99
	3.499	1.119	19.42	1.999	0.046	27.25	0.985	36.68

Table 6.15 STDT4 Model Parameters and Objective Function values for Noigameget River

Data	eval	p1	p2	p3	p4	p5	p6	p7
	25004	58	0.116	412.3	-8.343	1.040	0.062	0.0055
	25060	54	0.235	139.2	-42.79	0.850	0.066	0.0270
	25060	58	0.402	289.6	-42.16	0.837	0.022	0.0076
	25088	55	0.122	204.3	-18.91	0.557	0.062	0.0021
Calibration	25088	54	0.398	158.5	-2.073	1.044	0.038	0.0151
1975-80	25088	54	0.338	95.57	-1.889	0.849	0.132	0.0200
	25004	57	0.246	42.67	-1.436	0.783	0.108	0.0038
	25032	54	0.289	10.511	-1.790	1.157	0.074	0.0458
	25060	58	0.008	12.76	-0.799	1.293	0.227	0.0602
	25116	56	0.205	253.7	-29.70	0.997	0.066	0.0096
	25004	53	4.930	142.6	39.58	1.070	1.745	0.0114
	25172	52	4.926	143.7	13.29	0.854	3.591	0.0272
	25032	54	4.942	158.1	35.71	0.594	2.596	0.0161
	25172	52	2.993	261.6	26.52	1.375	2.075	0.1661
Calibration	25004	54	4.944	150.2	24.46	1.228	1.199	0.0323
1980-87	25144	52	4.385	171.3	46.13	1.445	3.008	0.2194
	25144	52	4.936	224.3	30.86	2.271	2.328	0.0293
	25032	55	4.863	324.2	8.531	0.976	1.526	0.0495
	25144	52	4.638	14.07	45.00	1.981	2.165	0.0280
	25172	52	4.776	129.1	25.68	0.943	0.560	0.0034

Data	p8	p9	p10	p11	p12	p13	p14	obf
	2.485	5.259	28.58	0.843	0.727	9.480	2.079	138.1
	1.162	8.931	8.822	2.487	4.998	2.362	0.265	149.9
	0.751	2.054	8.264	0.492	0.843	10.55	1.577	139.8
	1.850	9.762	1.022	4.511	4.145	19.24	0.358	147.0
Calibration	0.716	4.375	3.721	0.709	0.026	7.741	2.142	145.3
1975-80	0.847	3.869	15.477	0.384	3.869	18.95	0.584	147.5
	1.735	8.114	10.31	0.469	0.737	7.807	1.734	136.0
	0.921	9.153	27.93	2.116	3.639	24.21	0.406	148.7
	2.168	0.736	22.41	2.967	0.729	5.988	1.848	147.1
	1.070	7.516	29.35	0.966	0.612	5.647	0.766	136.7
	0.299	6.600	5.763	1.003	0.685	3.722	0.040	171.3
	0.354	6.678	20.11	1.593	0.674	20.57	1.397	171.0
	0.437	6.890	28.77	1.399	0.196	18.27	1.974	170.9
	1.399	9.382	21.66	2.676	0.483	12.61	0.829	174.5
Calibration	1.671	1.737	9.418	1.292	0.177	13.89	2.404	170.8
1980-87	1.293	2.691	2.048	2.160	0.176	7.117	1.021	172.3
	0.420	9.257	23.33	1.836	0.478	19.27	0.498	171.3
	0.871	2.546	8.727	1.248	0.047	19.83	0.505	170.9
	0.593	4.174	24.90	1.369	0.240	27.24	1.611	171.4
	0.698	8.986	23.25	1.572	0.184	2.619	0.221	171.1

Table 6.16 STDT4 Model Parameters and Objective Function Values for Nyasara Stream

Data	eval	p1	p2	p3	p4	p5	p6	p7
	25172	38	0.173	108.4	-39.40	0.716	0.652	0.065
	25144	37	0.092	118.8	-16.64	0.876	0.657	0.122
	25060	44	0.057	123.6	-29.57	0.810	0.808	0.197
	25004	38	0.158	134.0	-39.34	0.769	0.615	0.067
Calibration	25172	44	0.209	424.5	-33.99	1.140	0.693	0.423
1978-81	25004	44	0.083	375.4	-27.78	0.851	0.798	0.128
	25032	42	0.033	467.0	-18.50	1.018	0.773	0.153
	25032	38	0.223	27.38	-8.304	0.947	0.693	0.208
	25032	37	0.184	162.6	-47.71	0.744	0.725	0.090
	25032	41	0.003	24.25	-30.63	0.679	0.715	0.054
	25088	37	0.146	292.8	-39.21	0.901	0.901	0.191
	25004	37	0.213	171.8	0.206	0.911	0.916	0.261
	25172	36	0.425	93.06	-0.263	0.996	0.905	0.263
	25060	37	0.544	83.98	0.096	0.904	0.897	0.200
Calibration	25172	36	0.310	249.4	-0.215	1.082	0.856	0.292
1982-87	25004	36	0.138	50.13	1.621	0.806	0.862	0.335
	25004	38	0.374	63.23	0.393	0.575	0.826	0.076
	25060	37	0.405	10.05	0.650	1.125	1.007	0.604
	25172	39	0.087	37.59	0.548	0.933	0.800	0.212
	25032	37	0.247	73.99	0.802	0.685	0.897	0.148

Data	p8	p9	p10	p11	p12	p13	p14	obf
	1.558	2.708	7.490	1.057	1.088	4.298	1.318	97.32
	1.606	2.817	5.654	1.191	1.103	6.024	1.272	94.76
	1.932	3.077	9.256	1.495	0.075	13.405	0.976	101.2
	1.523	2.654	4.454	0.871	1.064	8.231	1.383	94.83
Calibration	1.468	2.832	3.369	1.480	1.032	7.892	1.492	98.08
1978-81	1.487	2.588	4.101	1.027	1.960	3.255	1.073	94.86
	1.211	2.341	6.118	1.244	1.791	6.380	0.909	103.0
	1.441	2.849	4.029	1.315	0.973	6.640	1.516	94.83
	1.394	2.821	4.208	1.014	1.066	10.76	1.272	96.80
	2.019	2.383	5.517	0.889	0.020	8.248	0.438	98.41
	1.256	3.048	1.108	1.130	1.735	5.166	1.235	142.0
	1.352	2.203	2.620	2.167	1.635	14.46	1.224	139.7
	1.062	2.217	2.134	1.904	1.912	8.625	1.202	141.1
	1.023	4.626	3.653	1.584	1.258	5.285	1.234	143.0
Calibration	1.099	2.292	4.974	2.454	1.888	19.63	1.105	143.1
1982-87	2.316	8.834	8.693	1.579	2.013	15.05	1.124	139.2
	1.877	3.125	2.041	1.073	0.440	4.613	1.779	137.6
	1.150	7.116	1.202	1.449	0.683	8.020	0.849	141.2
	1.577	2.873	1.139	1.454	0.601	4.042	1.367	142.1
	1.818	3.231	2.731	1.583	0.020	8.615	1.949	139.6

Table 6.17 STDT4 Model Parameters and Objective Function Values for Chania River

Data	eval	p1	p2	p3	p4	p5	p6	p7
	25088	47	0.003	13.58	-75.94	1.554	1.139	0.690
	25088	35	0.090	229.6	-96.55	1.105	1.114	0.432
	25116	51	0.040	16.72	-71.41	1.026	0.893	0.485
	25172	51	0.061	157.3	-18.82	1.252	1.094	0.685
Calibration	25060	49	0.097	463.9	-33.74	0.701	1.057	0.172
1963-68	25004	51	0.118	12.07	-11.02	1.342	1.035	0.984
	25116	49	0.063	197.6	-53.30	0.833	0.977	0.167
	25088	40	0.165	375.3	0.486	0.768	1.023	0.082
	25144	46	0.425	378.4	0.950	0.675	1.078	0.212
	25088	49	0.035	470.4	-5.622	1.400	1.121	0.264
	25088	42	0.128	117.7	-19.13	1.008	0.900	0.066
	25172	31	0.008	75.00	-29.52	1.089	0.871	0.167
	25144	33	0.067	259.9	-40.53	1.250	0.826	0.081
	25172	40	0.069	267.0	-38.75	1.115	0.950	0.177
Calibration	25144	38	0.096	351.0	-17.67	1.592	0.924	0.137
1968-74	25088	41	0.160	192.9	-50.41	1.263	0.915	0.129
	25144	38	0.102	123.7	-56.35	1.483	0.982	0.188
	25144	36	0.073	263.1	-13.53	1.241	0.872	0.089
	25116	39	0.040	89.90	-71.06	1.315	0.858	0.158
	25172	37	0.009	285.8	-47.39	1.091	0.867	0.101

Data	p8	p9	p10	p11	p12	p13	p14	obf
	1.404	4.488	17.92	3.927	4.250	11.37	4.517	121.2
	1.243	8.684	9.781	1.563	3.322	4.355	0.892	113.1
	2.213	5.084	9.571	0.593	2.413	18.58	1.711	101.6
	1.427	7.020	6.453	0.726	2.369	17.74	1.247	109.3
Calibration	1.534	4.499	8.328	1.632	3.031	24.41	0.599	104.8
1963-68	1.258	8.472	19.47	2.246	3.095	13.79	0.692	101.7
	1.586	3.734	16.69	1.603	1.895	10.10	0.833	100.6
	2.127	9.237	11.35	3.124	1.607	16.83	4.343	117.0
	2.650	6.327	24.24	0.936	2.212	6.161	2.332	109.2
	1.129	2.526	19.80	0.645	1.241	19.67	2.115	116.7
	0.826	1.710	7.955	1.369	1.303	14.28	0.576	109.6
	1.116	3.534	12.87	2.328	2.419	1.367	0.593	116.4
	0.770	1.648	4.527	1.251	1.185	23.43	0.662	108.8
	1.073	4.101	6.768	0.963	2.193	9.929	0.607	115.6
Calibration	0.688	1.762	2.139	1.235	1.205	6.546	0.655	110.0
1968-74	0.908	1.653	1.967	1.068	1.045	12.60	0.761	112.5
	0.711	8.221	8.547	1.068	2.388	15.91	0.500	117.2
	0.839	1.490	1.710	0.899	1.170	3.765	0.760	109.1
	0.988	5.741	9.207	0.897	1.726	10.81	0.741	115.0
	1.113	1.506	2.863	1.196	0.969	9.506	0.780	109.3

Table 6.18 STDT4 Model Performance Coefficients for Babinda Creek

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.941	-0.024	0.203	0.720		0.852	-0.112	0.236	0.622
	0.938	-0.016	0.201	0.748		0.858	-0.103	0.238	0.631
	0.937	-0.007	0.202	0.760		0.860	-0.094	0.237	0.625
	0.932	-0.008	0.202	0.709		0.876	-0.095	0.222	0.613
Calibration	0.930	-0.004	0.204	0.699	Validation	0.872	-0.088	0.228	0.619
1974-80	0.944	-0.030	0.198	0.774	1981-87	0.852	-0.107	0.236	0.597
	0.943	-0.013	0.197	0.727		0.858	-0.092	0.241	0.651
	0.939	-0.004	0.198	0.694		0.864	-0.084	0.239	0.677
	0.943	-0.015	0.197	0.721		0.855	-0.091	0.244	0.648
	0.945	-0.014	0.197	0.761		0.857	-0.091	0.238	0.604
	0.900	-0.047	0.200	0.584		0.677	0.103	0.280	0.680
	0.898	-0.038	0.199	0.495		0.484	0.123	0.310	0.632
	0.904	-0.039	0.193	0.399		0.678	0.118	0.292	0.676
	0.903	-0.035	0.195	0.402		0.688	0.116	0.295	0.621
Calibration	0.902	-0.038	0.199	0.519	Validation	0.663	0.117	0.286	0.688
1981-87	0.897	-0.047	0.202	0.566	1974-80	0.553	0.115	0.300	0.650
	0.905	-0.018	0.193	0.413		0.603	0.152	0.314	0.649
	0.901	-0.069	0.197	0.510		0.684	0.079	0.276	0.650
	0.897	-0.065	0.204	0.527		0.753	0.065	0.268	0.646
	0.892	-0.020	0.201	0.463		0.424	0.145	0.325	0.582

Table 6.19 STDT4 Model Performance Coefficients for Scott Creek

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.809	-0.131	0.300	0.744		0.728	0.330	0.625	0.035
	0.836	-0.124	0.286	0.779		0.708	0.296	0.626	-0.197
	0.831	-0.101	0.297	0.767		0.706	0.345	0.657	-0.203
	0.814	-0.112	0.310	0.805		0.708	0.310	0.621	-0.676
Calibration	0.832	-0.113	0.296	0.751	Validation	0.717	0.361	0.639	0.073
1970-77	0.839	-0.110	0.290	0.777	1978-85	0.715	0.375	0.637	0.052
	0.835	-0.100	0.298	0.783		0.702	0.346	0.641	-0.142
	0.826	-0.092	0.296	0.777		0.701	0.399	0.651	0.036
	0.842	-0.128	0.293	0.830		0.714	0.293	0.629	-0.289
	0.812	-0.120	0.298	0.768		0.706	0.292	0.645	-0.340
	0.795	-0.135	0.411	0.028		0.561	-0.505	0.539	0.530
	0.711	-0.182	0.454	-0.100		0.612	-0.486	0.520	0.580
	0.797	-0.187	0.403	0.257		0.490	-0.550	0.573	0.439
	0.806	-0.188	0.418	0.337		0.573	-0.493	0.567	0.588
Calibration	0.672	-0.216	0.468	0.174	Validation	0.615	-0.492	0.533	0.540
1978-85	0.726	-0.137	0.436	0.023	1970-77	0.680	-0.437	0.509	0.718
	0.791	-0.211	0.411	0.007		0.594	-0.500	0.556	0.595
	0.779	-0.216	0.417	0.193		0.654	-0.468	0.507	0.583
	0.760	-0.245	0.427	0.078		0.601	-0.508	0.551	0.587
	0.825	-0.147	0.400	0.358		0.551	-0.470	0.556	0.647

Table 6.20 STDT4 Model Performance Coefficients for Canning River

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.913	-0.132	0.296	0.752		0.611	-0.187	0.362	0.672
	0.928	-0.100	0.285	0.867		0.583	-0.132	0.410	0.186
	0.931	-0.067	0.285	0.882		0.593	-0.123	0.396	0.461
	0.902	-0.089	0.314	0.844		0.567	-0.111	0.425	0.442
Calibration	0.933	-0.092	0.280	0.909	Validation	0.606	-0.157	0.383	0.281
1977-84	0.924	-0.004	0.292	0.919	1984-87	0.612	-0.091	0.389	0.299
	0.887	-0.146	0.312	0.778		0.635	-0.092	0.385	0.034
	0.943	-0.063	0.267	0.954		0.592	-0.154	0.396	0.196
	0.823	-0.113	0.368	0.895		0.540	-0.211	0.463	0.372
	0.938	-0.073	0.275	0.935		0.618	-0.155	0.379	0.463
	0.941	-0.005	0.216	0.835		-0.552	0.499	0.745	0.216
	0.931	-0.065	0.235	0.802		0.706	0.044	0.421	0.877
	0.913	-0.065	0.232	0.901		0.737	-0.288	0.425	0.476
	0.939	-0.063	0.224	0.756		0.682	0.097	0.430	0.827
Calibration	0.940	-0.043	0.226	0.884	Validation	0.441	0.145	0.531	0.771
1984-87	0.876	-0.090	0.251	0.688	1977-84	0.652	-0.313	0.473	0.409
	0.872	-0.125	0.254	0.780		0.691	-0.287	0.447	0.611
	0.938	-0.043	0.221	0.833		0.841	-0.098	0.359	0.760
	0.943	-0.053	0.218	0.820		0.711	0.093	0.425	0.841
	0.924	-0.026	0.234	0.694		-0.371	0.486	0.706	0.221

Table 6.21 STDT4 Model Performance for Noigameget River

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.322	-0.086	0.336	0.173		-2.331	0.588	0.932	-1.804
	0.239	-0.091	0.367	0.283		-42.819	2.117	2.446	-9.341
	0.350	-0.062	0.336	0.085		-1.354	0.544	0.845	-1.004
	0.230	-0.113	0.361	0.397		-17.806	1.175	1.529	-5.413
Calibration	0.296	-0.074	0.360	0.229	Validation	-2.370	0.656	0.964	-1.814
1975-80	0.245	-0.097	0.364	0.283	1980-87	-2.151	0.589	0.917	-1.766
	0.322	-0.112	0.334	0.250		-1.864	0.521	0.867	-1.599
	0.234	-0.116	0.364	0.219		-5.935	0.757	1.085	-2.842
	0.284	-0.095	0.355	0.103		-1.195	0.431	0.793	-1.180
	0.349	-0.093	0.344	0.307		-2.513	0.631	0.973	-1.882
	0.022	-0.110	0.444	-0.088		-0.312	-0.375	0.466	0.007
	0.027	-0.117	0.443	-0.072		-0.319	-0.372	0.464	-0.006
	0.022	-0.130	0.444	-0.080		-0.348	-0.391	0.473	0.003
	-0.007	-0.141	0.451	-0.063		-0.371	-0.381	0.474	-0.015
Calibration	0.026	-0.118	0.444	-0.080	Validation	-0.327	-0.381	0.468	0.002
1980-87	0.027	-0.112	0.445	-0.069	1875-80	-0.313	-0.367	0.463	-0.010
	0.016	-0.141	0.443	-0.070		-0.362	-0.391	0.473	-0.007
	0.027	-0.115	0.444	-0.081		-0.324	-0.380	0.468	0.002
	0.022	-0.120	0.445	-0.083		-0.326	-0.379	0.467	0.000
	0.028	-0.117	0.443	-0.078		-0.322	-0.376	0.466	-0.003

Table 6.22 STDT4 Model Performance for Nyasara Stream

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.752	-0.035	0.185	0.554		-0.212	0.306	0.401	0.039
	0.764	-0.041	0.183	0.538		-0.461	0.352	0.423	-0.119
	0.758	-0.008	0.193	0.612		-2.334	0.542	0.589	-0.480
	0.743	-0.041	0.184	0.516		-0.158	0.309	0.400	-0.022
Calibration	0.769	-0.033	0.191	0.552	Validation	-1.460	0.520	0.569	-0.672
1978-81	0.786	-0.063	0.181	0.590	1982-87	-0.408	0.331	0.422	0.037
	0.760	-0.028	0.194	0.574		-1.306	0.441	0.530	-0.181
	0.771	-0.045	0.181	0.559		-0.504	0.375	0.442	-0.237
	0.745	-0.057	0.185	0.546		0.040	0.264	0.363	0.168
	0.745	-0.049	0.189	0.501		-0.175	0.328	0.413	0.028
	0.603	-0.034	0.229	0.349		0.467	-0.216	0.283	0.348
	0.607	-0.048	0.226	0.389		0.449	-0.209	0.288	0.314
	0.609	-0.040	0.228	0.345		0.456	-0.220	0.293	0.352
	0.589	-0.038	0.228	0.347		0.430	-0.223	0.295	0.364
Calibration	0.596	-0.034	0.231	0.355	Validation	0.445	-0.226	0.290	0.354
1982-87	0.620	-0.024	0.225	0.400	1978-81	0.414	-0.253	0.303	0.334
	0.617	-0.036	0.223	0.339		0.478	-0.215	0.273	0.383
	0.607	-0.048	0.226	0.394		0.423	-0.234	0.314	0.335
	0.590	-0.064	0.229	0.401		0.369	-0.270	0.304	0.339
	0.604	-0.044	0.226	0.375		0.441	-0.228	0.291	0.358

Table 6.23 STDT4 Model Performance for Chania River

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.697	-0.083	0.279	0.293		0.585	0.269	0.434	0.555
	0.833	-0.045	0.248	0.132		0.526	0.250	0.424	0.402
	0.845	-0.065	0.216	0.512		0.656	0.150	0.391	0.258
	0.844	-0.017	0.239	0.132		0.197	0.311	0.490	0.433
Calibration	0.859	-0.027	0.227	0.586	Validation	0.598	0.249	0.431	-0.164
1963-68	0.787	-0.083	0.232	0.418	1968-74	0.654	0.229	0.387	0.341
	0.825	-0.097	0.232	0.388		0.673	0.147	0.386	0.197
	0.707	-0.097	0.271	0.214		0.640	0.235	0.411	0.358
	0.791	-0.071	0.243	0.228		0.662	0.179	0.378	0.378
	0.819	-0.066	0.260	0.113		0.190	0.271	0.487	0.475
	0.725	-0.024	0.293	0.355		0.652	-0.270	0.324	0.239
	0.730	-0.068	0.292	0.025		0.671	-0.289	0.330	0.334
	0.708	-0.038	0.291	0.314		0.607	-0.291	0.357	0.215
	0.719	-0.060	0.294	0.167		0.638	-0.306	0.342	0.236
Calibration	0.673	-0.057	0.298	0.506	Validation	0.586	-0.294	0.357	0.063
1968-74	0.717	-0.053	0.292	0.423	1963-68	0.635	-0.291	0.332	0.223
	0.668	-0.064	0.308	0.217		0.569	-0.322	0.378	0.116
	0.695	-0.070	0.288	0.370		0.576	-0.324	0.361	0.157
	0.674	-0.085	0.300	0.296		0.588	-0.332	0.366	0.200
	0.722	-0.083	0.284	0.345		0.602	-0.321	0.351	0.276

6.3.2 Parameter Identification, Correlations and Flow Separation Consistency

Parameter identification was assessed by graphical plots showing the extent of grouping of parameters obtained from the multiple calibrations within the specified search range limits. These plots are presented in Figure 6.7 to 6.12 for the six catchments. The scaled values were obtained as $(xb_i^o - XLmin_i)/(XLmax_i - XLmin_i)$ where xb_i^o is the optimized value of parameter i, $XLmin_i$ is the lower search range limit and $XLmax_i$ is the upper search range limit for parameter i. The plots revealed better parameter identification for the Australian than the Kenyan catchments. A reason for this could be the better data quality of the Australian catchments. One Kenyan catchment, Nyasara Stream exhibited a better parameter grouping than the other two. The observed parameter identification trends were also reflected in the consistency of the flow separations given in Tables 6.24 to 6.29 and Figures 6.13 and 6.14. The recorded flows for the same periods in the two Tables and Figures were slightly different for the 10 calibrations of each split data set. This was a result of the slightly different periods over which they were computed. This period depended on parameter *p1* which optimized to different values in different calibrations with the same split sample. It was also observed that some of the annual slow flow averages were greater than the annual total flows in some of the runs, mostly in the modelling of two Kenyan catchments, Chania and Noigameget. Although this observation may not be justified on the basis of catchment processes, the conceptualization of the STDT4 model allows for this possibility especially if the evaporation loss coefficient, parameter *p2* is high. Improvements of the STDT4 model could include a modification that would ensure a total flow greater or equal to the slow flow at all time steps. Most of the flow separations obtained with the Australian catchments however seemed realistic. An exception to this trend was the Canning River 1977-84 run 9 (Table 6.14 and 6.20) which was suspected to have been inadequately calibrated (Section 6.3.1). The three Australian and Nyasara Stream catchment exhibited better consistencies of flow separation than the other two catchments. The exceptions to this trend; the 1977-84 Canning River and the 1982-87 Nyasara Stream validations resulted from inadequate calibration data lengths. With the very poor model performance of Noigameget River (Table 6.21), the poor parameter identification was not unexpected. The model performance for Chania River in calibration and validation (Table 6.23) was much better than the poor parameter identification and flow separation consistency suggested.

The parameter correlation coefficients are given in Tables 6.30 and 6.31 for the six catchments. As the STDT4 model is conceptual-empirical, the occasionally large parameter correlations were not unexpected. Although parameter correlation is often considered an indication of model deficiency, high correlation coefficients are an indication that at least one of the model components relating to the pair of parameters is significantly activated. Parameter identification plots and correlation coefficients together can therefore give an indication of the usefulness of parameters.

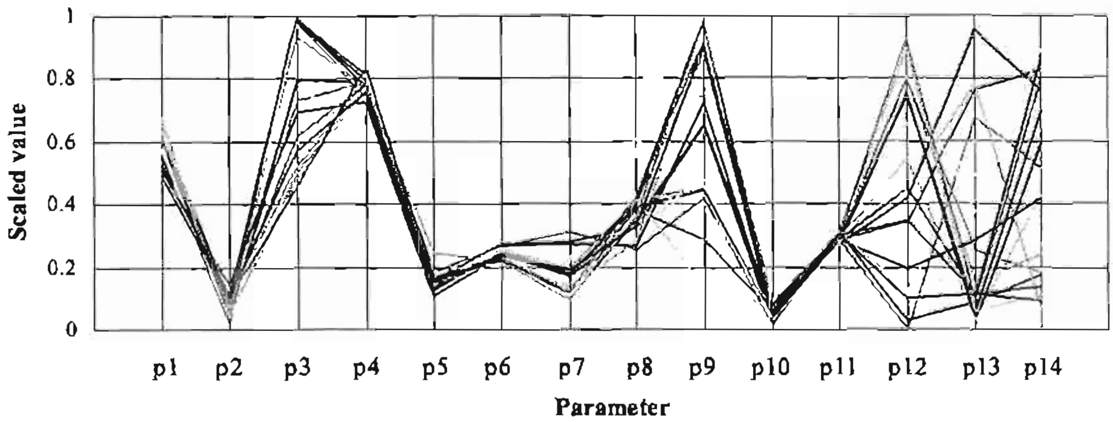


Figure 6.7 STDT4 Model Parameter Identification Plots for Babinda Creek

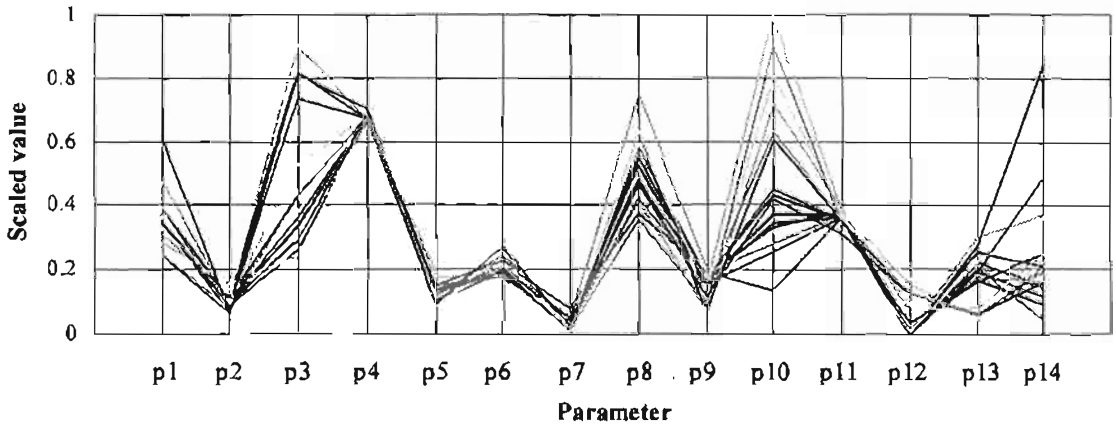


Figure 6.8 STDT4 Model Parameter Identification Plots for Scott Creek

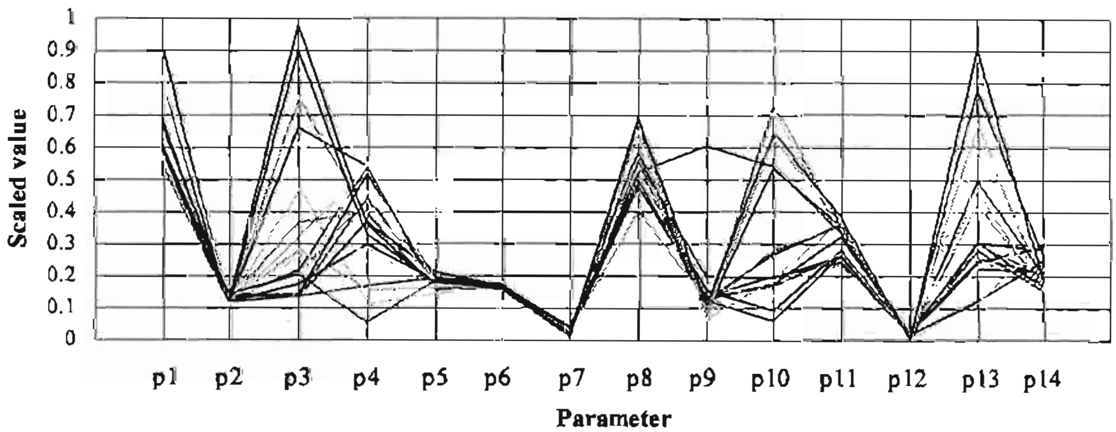


Figure 6.9 STDT4 Model Parameter Identification Plots for Canning River

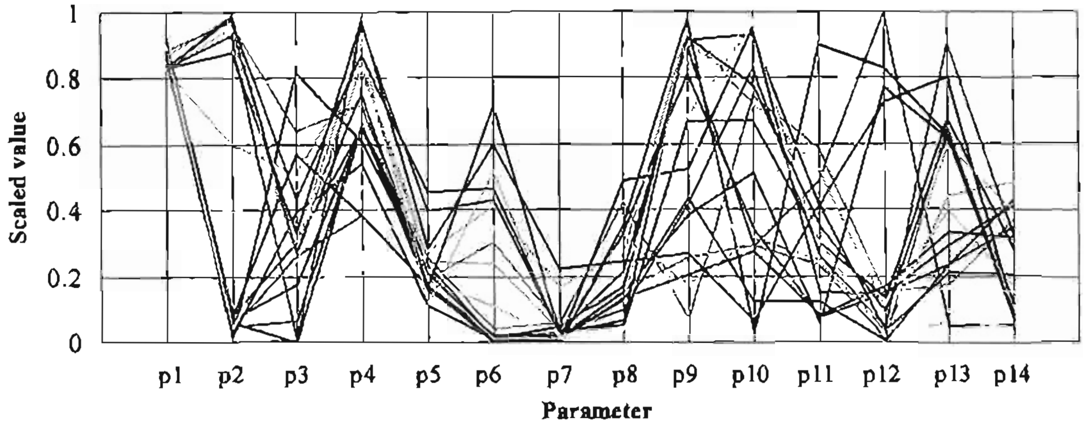


Figure 6.10 STDT4 Model Parameter Identification Plots for Noigameget River

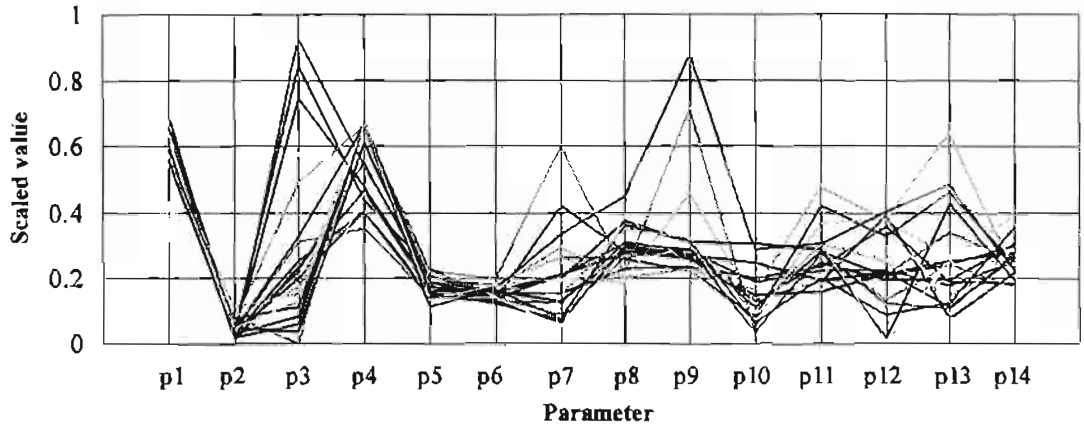


Figure 6.11 STDT4 Model Parameter Identification Plots for Nyasara Stream

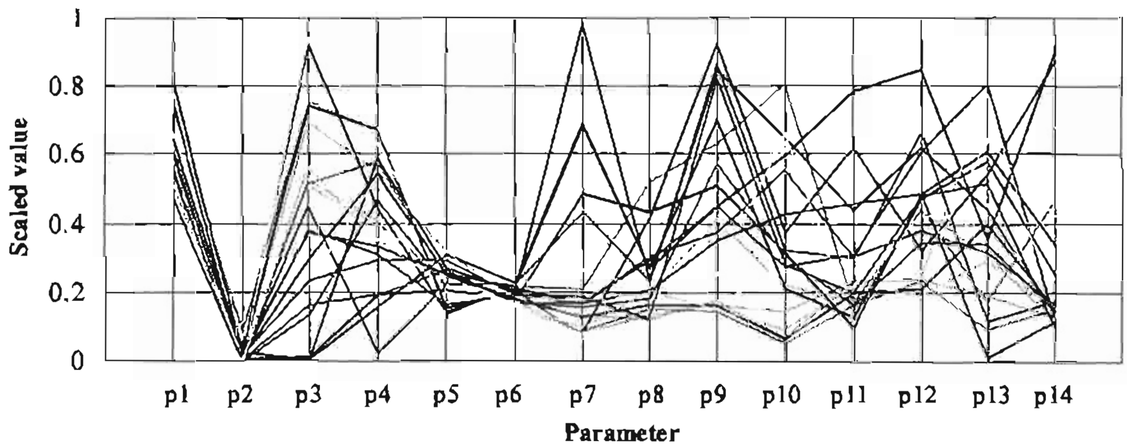


Figure 6.12 STDT4 Model Parameter Identification Plots for Chania River

Table 6.24 Annual Flow averages for 10 STDT4 Model runs of Babinda Creek (mm/year units)

Data	Recorded	Simulated	Slow		Recorded	Simulated	Slow
	4399.0	4293.7	2306.9		4327.1	3841.8	2208.1
	4382.6	4311.9	2374.3		4325.8	3879.2	2314.5
	4371.3	4339.3	2467.5		4311.4	3905.4	2408.7
Calibration	4407.3	4372.1	2418.6	Validation	4316.1	3905.8	2350.1
1974-80	4407.3	4390.1	2418.1	1981-87	4316.1	3938.3	2374.3
	4407.3	4273.3	2344.4		4316.1	3853.1	2279.4
	4375.7	4317.2	2473.1		4318.0	3920.3	2439.8
	4399.0	4379.9	2519.5		4327.1	3962.5	2498.9
	4407.3	4343.3	2531.8		4316.1	3921.3	2499.0
	4382.6	4319.9	2378.6		4325.8	3931.1	2328.3
	4327.1	4122.4	2206.9		4399.0	4854.0	2353.9
	4304.5	4142.1	2303.1		4369.9	4906.1	2433.4
	4316.1	4148.5	2090.7		4407.3	4925.2	2272.1
	4326.3	4174.0	2089.4		4425.1	4937.8	2274.1
Calibration	4320.1	4156.6	2271.9	Validation	4416.1	4933.0	2452.4
1981-87	4327.1	4122.6	2164.7	1974-80	4399.0	4903.6	2310.1
	4298.6	4220.6	2288.0		4363.7	5028.9	2491.7
	4327.1	4029.8	2165.0		4399.0	4744.8	2306.2
	4327.1	4046.5	2144.9		4399.0	4683.4	2248.8
	4311.4	4224.1	2202.0		4371.3	5006.3	2353.0

Table 6.25 Annual Flow averages for 10 STDT4 Model runs of Scott Creek (mm/year units)

Data	Recorded	Simulated	Slow		Recorded	Simulated	Slow
	161.4	140.4	84.9		112.4	149.6	85.1
	161.8	141.7	81.8		112.9	146.2	82.1
	161.8	145.5	86.6		112.9	151.8	87.9
	162.4	144.2	85.9		113.7	149.0	87.2
Calibration	161.8	143.6	86.6	Validation	112.9	153.6	86.6
1970-77	161.8	144.1	83.3	1978-85	112.9	155.1	83.6
	161.4	145.3	78.1		112.4	151.3	78.4
	161.4	146.5	83.4		112.4	157.3	83.6
	161.6	140.9	79.4		112.6	145.7	81.1
	161.6	142.1	83.3		112.6	145.5	83.8
	112.2	97.1	40.4		161.4	79.8	40.8
	111.3	91.1	35.4		160.4	82.4	33.1
	111.8	90.8	40.4		160.9	72.4	39.3
	113.1	91.8	38.4		161.9	82.1	39.9
Calibration	112.0	87.8	32.0	Validation	161.2	82.0	30.5
1978-85	112.0	96.6	32.7	1970-77	161.2	90.7	30.6
	112.9	89.1	31.1		161.8	80.9	31.1
	113.7	89.1	34.6		158.7	84.5	36.0
	111.3	84.1	31.4		160.4	78.9	31.7
	112.9	96.2	33.6		161.8	85.7	33.9

Table 6.26 Annual Flow averages for 10 STDT4 Model runs of Canning River (mm/year units)

Data	Recorded	Simulated	Slow		Recorded	Simulated	Slow
	22.63	19.65	13.01		12.25	9.96	8.50
	22.80	20.53	13.68		11.72	10.17	8.85
	22.81	21.27	14.32		12.42	10.89	9.34
	22.77	20.75	13.80		12.49	11.11	9.69
Calibration	22.80	20.70	14.00	Validation	11.72	9.88	8.33
1977-84	22.65	22.55	15.60	1984-87	11.79	10.71	9.13
	22.65	19.35	14.14		11.79	10.70	8.52
	22.80	21.37	15.28		11.72	9.91	8.54
	22.60	20.05	18.62		11.86	9.36	13.79
	22.63	20.99	14.88		12.25	10.35	8.71
	11.36	11.30	8.44		22.54	33.79	14.63
	11.29	10.56	8.43		22.49	23.47	13.20
	11.36	10.62	7.94		22.54	16.05	11.55
	11.36	10.64	8.14		22.54	24.73	13.69
Calibration	11.29	10.81	8.43	Validation	22.49	25.75	12.37
1984-87	11.29	10.28	8.23	1977-84	22.49	15.45	12.82
	11.50	10.06	7.86		22.65	16.14	13.85
	11.43	10.94	8.65		22.60	20.39	13.73
	11.29	10.69	8.11		22.49	24.57	13.63
	11.43	11.14	8.74		15.86	25.22	11.12

Table 6.27 Annual Flow averages for 10 STDT4 Model runs of Noigameget River (mm/year units)

Data	Recorded	Simulated	Slow		Recorded	Simulated	Slow
	295.5	270.1	146.6		221.5	351.8	252.7
	294.2	267.3	1008.5		221.9	691.9	1329.6
	295.5	277.2	189.8		221.5	342.0	270.7
Calibration	294.5	261.2	729.2	Validation	221.7	482.2	942.3
1975-80	294.2	272.5	268.5	1980-87	221.9	367.6	360.0
	294.2	265.7	455.1		221.9	352.8	604.2
	295.1	262.0	167.4		221.4	336.9	262.4
	294.2	260.2	641.2		221.9	390.0	821.7
	295.5	267.6	161.7		221.5	317.0	234.4
	294.8	267.4	262.5		221.5	361.3	334.6
	222.1	197.6	301.0		293.9	183.6	301.0
	222.3	196.4	252.4		293.8	184.6	252.4
	221.9	193.1	267.7		294.2	179.2	267.7
	222.3	190.9	213.3		293.8	181.7	213.3
Calibration	221.9	195.7	273.2	Validation	294.2	182.2	273.2
1980-87	222.3	197.4	236.3	1975-80	293.8	186.0	236.3
	222.3	191.0	240.7		293.8	179.0	240.7
	221.7	196.3	277.6		294.5	182.7	277.6
	222.3	195.6	267.4		293.8	182.5	267.4
	222.3	196.2	258.6		293.8	183.2	258.6

Table 6.28 Annual Flow averages for 10 STDT4 Model runs of Nyasara Stream (mm/year units)

Data	Recorded	Simulated	Slow		Recorded	Simulated	Slow
	1082.6	1044.2	798.9		1238.8	1618.0	1138.8
	1085.0	1040.4	803.9		1239.9	1676.0	1170.2
	1056.8	1048.7	843.1		1242.2	1915.4	1294.3
	1082.6	1037.9	796.7		1238.8	1621.8	1135.8
Calibration	1056.8	1021.6	845.4	Validation	1242.2	1888.7	1387.5
1978-81	1056.8	989.7	736.2	1982-87	1242.2	1653.1	1049.9
	1068.0	1037.8	783.2		1240.4	1787.9	1068.4
	1082.6	1033.7	849.0		1238.8	1702.7	1289.5
	1085.0	1023.7	839.8		1239.9	1566.7	1170.1
	1073.2	1020.6	762.7		1239.5	1646.7	1080.5
	1239.9	1197.6	1056.8		1085.0	850.2	763.2
	1239.9	1180.6	1123.5		1085.0	858.2	807.6
	1240.0	1189.9	1113.6		1087.9	849.0	782.3
	1239.9	1193.4	1135.4		1085.0	842.8	814.9
Calibration	1240.0	1198.3	1141.3	Validation	1087.9	842.5	803.2
1982-87	1240.0	1210.4	1131.8	1978-81	1087.9	813.1	750.7
	1238.8	1194.1	1100.6		1082.6	849.5	809.1
	1239.9	1179.9	1145.7		1085.0	831.0	810.3
	1238.1	1158.9	1074.0		1079.4	787.9	753.5
	1239.9	1185.3	1115.7		1085.0	837.9	817.0

Table 6.29 Annual Flow averages for 10 STDT4 Model runs of Chania River (mm/year units)

Data	Recorded	Simulated	Slow		Recorded	Simulated	Slow
	605.5	555.3	122.9		368.7	467.9	103.6
	591.9	565.5	554.2		371.1	463.8	484.5
	611.0	571.4	304.4		370.8	426.2	248.3
	611.0	600.8	416.2		370.8	485.9	340.8
Calibration	608.2	592.0	740.3	Validation	369.8	461.7	656.6
1963-68	611.0	560.4	671.6	1968-74	370.8	455.7	580.2
	608.2	549.4	525.8		369.8	424.1	454.8
	596.5	538.6	124.0		367.0	453.4	104.4
	604.1	561.0	231.3		368.4	434.1	186.2
	608.2	568.0	228.7		369.8	470.0	192.3
	367.1	358.4	413.0		598.8	437.1	453.5
	375.5	349.8	495.6		589.5	418.9	555.1
	375.9	361.6	381.5		590.5	418.8	421.2
	367.0	345.0	457.4		596.5	414.0	520.5
Calibration	367.6	346.7	379.4	Validation	594.4	420.0	430.6
1968-74	367.0	347.7	339.3	1963-68	597.6	423.4	388.9
	367.6	344.0	533.7		594.4	403.3	601.1
	369.2	343.4	337.8		592.7	400.7	377.7
	367.2	336.2	366.5		595.4	397.8	422.8
	368.2	337.6	324.4		593.6	402.8	367.0

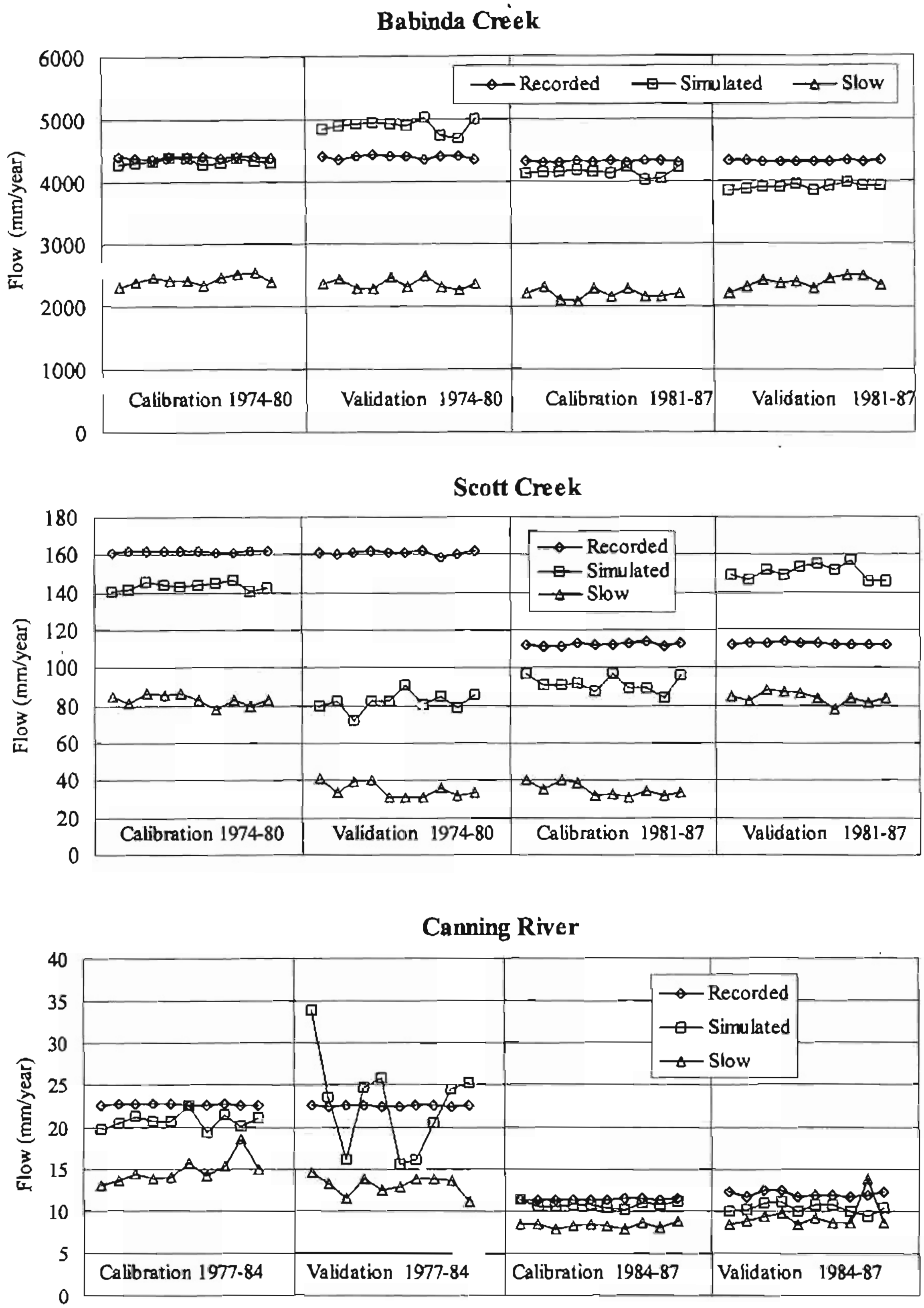


Figure 6.13 Recorded and STDT4 Model Simulated and Slow flows for Australian Catchments

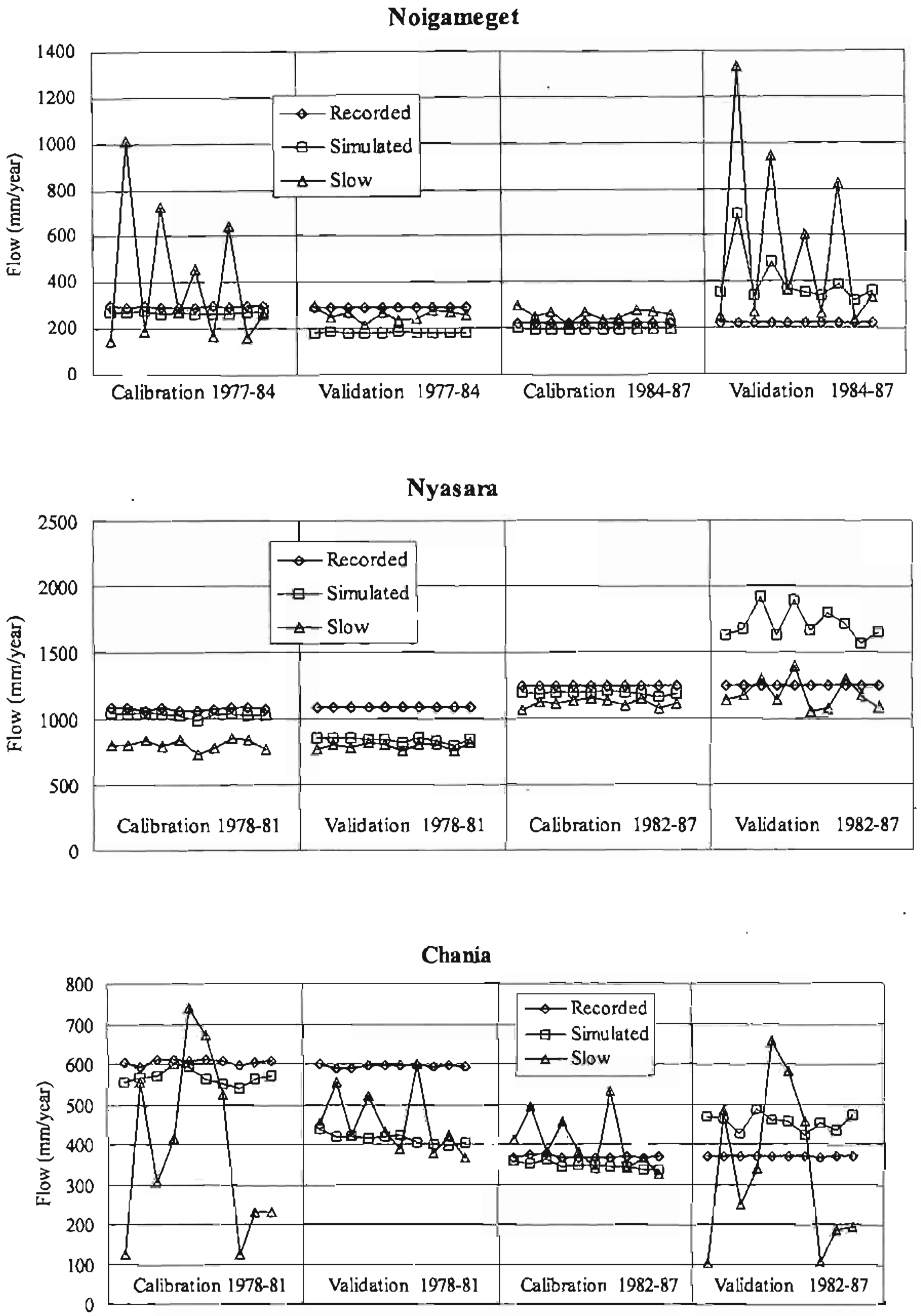


Figure 6.14 Recorded and STDT4 Model Simulated and Slow flows for Kenyan Catchments

Table 6.30 STDT4 Model Parameter Correlation Coefficients for Australian Catchments

Babinda Creek

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	-0.326	1.000												
p3	-0.010	-0.228	1.000											
p4	-0.032	0.088	-0.316	1.000										
p5	0.425	-0.336	-0.221	0.282	1.000									
p6	0.022	0.187	0.702	-0.072	-0.098	1.000								
p7	-0.087	0.270	0.622	-0.187	0.045	0.935	1.000							
p8	-0.177	0.225	-0.424	0.211	-0.660	-0.420	-0.619	1.000						
p9	-0.122	0.295	-0.336	0.207	0.252	-0.305	-0.167	-0.084	1.000					
p10	0.133	-0.240	-0.730	0.283	0.146	-0.931	-0.943	0.494	0.245	1.000				
p11	-0.265	0.531	-0.684	0.067	-0.126	-0.466	-0.336	0.386	0.161	0.413	1.000			
p12	0.501	-0.381	-0.154	0.408	0.229	-0.256	-0.450	0.194	0.315	0.430	-0.281	1.000		
p13	0.130	-0.163	0.395	-0.303	-0.270	0.377	0.284	0.021	-0.684	-0.374	-0.293	-0.298	1.000	
p14	0.138	-0.387	0.448	0.070	-0.136	0.258	0.053	0.042	-0.288	-0.142	-0.349	0.232	0.185	1.000

Scott Creek

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	-0.139	1.000												
p3	0.268	-0.500	1.000											
p4	-0.454	-0.197	0.244	1.000										
p5	-0.436	-0.287	-0.208	0.391	1.000									
p6	0.748	-0.096	0.252	-0.307	-0.558	1.000								
p7	0.351	-0.200	0.013	-0.505	0.127	0.232	1.000							
p8	0.184	-0.109	0.556	0.292	-0.475	0.148	-0.049	1.000						
p9	0.328	0.382	-0.172	-0.778	-0.492	0.141	0.550	0.127	1.000					
p10	-0.447	0.514	-0.292	0.320	-0.086	-0.062	-0.750	-0.258	-0.424	1.000				
p11	-0.409	0.352	-0.215	0.173	0.385	-0.422	0.032	-0.062	-0.045	0.169	1.000			
p12	-0.036	0.420	-0.225	0.091	-0.194	0.359	-0.539	-0.387	-0.330	0.856	-0.104	1.000		
p13	0.026	-0.359	0.271	-0.089	0.119	-0.290	0.447	0.437	0.261	-0.737	0.047	-0.849	1.000	
p14	-0.080	-0.158	-0.081	0.128	-0.017	-0.076	-0.015	0.275	-0.078	-0.193	-0.003	-0.279	0.477	1.000

Canning River

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1													
p2	0.047	1												
p3	-0.38	-0.39	1											
p4	0.465	-0.21	0.068	1										
p5	0.16	0.489	-0.49	-0	1									
p6	0.18	-0.06	-0.37	-0.21	0.361	1								
p7	0.444	0.418	-0.57	0.071	0.894	0.567	1							
p8	-0.66	-0.52	0.61	-0.01	-0.23	-0.21	-0.38	1						
p9	-0.13	0.472	-0.27	-0.36	0.128	-0.17	-0.02	-0.16	1					
p10	-0.65	-0.28	0.548	-0.12	-0.41	-0.59	-0.71	0.605	0.194	1				
p11	-0.74	-0.2	0.666	-0.18	-0.51	-0.27	-0.65	0.733	0.087	0.658	1			
p12	0.808	0.12	-0.59	0.308	0.39	0.35	0.555	-0.79	-0.11	-0.67	-0.9	1		
p13	-0.52	-0.04	0.434	-0.2	-0.08	-0.41	-0.42	0.468	0.289	0.865	0.516	-0.51	1	
p14	0.192	0.38	-0.09	-0.13	-0.05	0.223	0.195	-0.1	0.195	-0.41	0.122	-0.19	-0.35	1

Table 6.31 STDT4 Model Parameter Correlation Coefficients for Kenyan Catchments

Noigameget

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	-0.695	1.000												
p3	0.229	0.019	1.000											
p4	-0.671	0.819	-0.228	1.000										
p5	-0.405	0.373	-0.111	0.506	1.000									
p6	-0.673	0.839	0.007	0.754	0.381	1.000								
p7	-0.363	0.232	0.036	0.405	0.344	0.468	1.000							
p8	0.607	-0.530	0.163	-0.315	-0.143	-0.461	0.135	1.000						
p9	-0.339	-0.052	-0.017	-0.061	-0.083	-0.023	-0.157	-0.162	1.000					
p10	0.007	0.042	-0.040	0.118	0.245	0.082	-0.147	-0.041	0.240	1.000				
p11	-0.165	-0.063	-0.112	-0.017	0.037	0.066	0.315	0.319	0.325	-0.110	1.000			
p12	0.072	-0.549	-0.219	-0.545	-0.335	-0.458	-0.177	0.139	0.369	-0.158	0.399	1.000		
p13	-0.267	0.242	-0.137	0.253	0.248	0.342	-0.052	-0.260	0.021	0.251	0.102	0.112	1.000	
p14	0.384	-0.071	-0.001	0.049	-0.004	0.022	-0.067	0.333	-0.541	0.099	-0.319	-0.478	0.039	1.000

Nyasara

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	-0.522	1.000												
p3	0.532	-0.288	1.000											
p4	-0.431	0.521	-0.393	1.000										
p5	0.071	0.212	0.398	0.216	1.000									
p6	-0.323	0.523	-0.134	0.633	0.269	1.000								
p7	-0.081	0.383	0.014	0.418	0.763	0.562	1.000							
p8	0.201	-0.504	-0.335	-0.063	-0.649	-0.256	-0.274	1.000						
p9	-0.287	0.238	-0.359	0.355	0.083	0.420	0.564	0.290	1.000					
p10	0.280	-0.460	0.042	-0.282	-0.237	-0.418	-0.244	0.496	0.157	1.000				
p11	-0.325	0.422	0.010	0.646	0.518	0.568	0.520	-0.329	0.057	-0.099	1.000			
p12	-0.214	0.103	0.500	0.063	0.439	0.158	0.174	-0.444	0.081	0.020	0.328	1.000		
p13	-0.236	0.031	-0.035	0.212	0.186	0.247	0.313	0.098	0.178	0.352	0.684	0.183	1.000	
p14	-0.258	0.318	-0.078	0.189	-0.238	-0.069	-0.147	0.051	-0.126	-0.330	0.047	-0.140	-0.200	1.000

Chania

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	0.175	1.000												
p3	0.009	0.277	1.000											
p4	0.220	0.393	0.402	1.000										
p5	-0.233	-0.423	-0.260	-0.098	1.000									
p6	0.541	0.356	0.392	0.213	-0.202	1.000								
p7	0.568	-0.036	-0.440	0.002	0.188	0.466	1.000							
p8	0.510	0.545	0.153	0.175	-0.743	0.420	0.209	1.000						
p9	0.243	0.268	-0.199	-0.106	-0.169	0.587	0.545	0.455	1.000					
p10	0.482	0.434	0.048	0.290	-0.349	0.564	0.359	0.587	0.438	1.000				
p11	-0.194	0.060	-0.006	0.236	-0.342	0.080	0.027	0.161	0.378	0.201	1.000			
p12	0.300	0.083	-0.256	-0.272	-0.250	0.532	0.625	0.346	0.725	0.407	0.235	1.000		
p13	0.472	-0.113	0.169	0.076	-0.058	0.165	0.122	0.082	0.067	-0.010	-0.085	0.008	1.000	
p14	0.222	0.398	0.379	0.418	-0.415	0.387	-0.033	0.691	0.405	0.389	0.345	-0.086	0.180	1.000

A parameter with poor identification and low correlation with the others is likely to be redundant with the model component/s represented entirely by such a parameter being either never activated or activated only to a negligible degree. If a parameter is poorly identified but has high correlations with another parameter, then at least one of the model components applying the two parameters is activated sufficiently. It is then probable that one of the parameters could be set to a constant value and the other determined by calibration. However, without initially obtaining the two parameters by calibration, the appropriate value of the one to be set to a constant may not be easily obtainable. On the basis of parameter identification and correlations, none of the 14 parameters of the STDT4 model can be regarded as redundant. It is however noted that parameter *p3*, the upper limit of the past net rainfalls exhibited a low identification throughout and high correlation coefficients only for Babinda Creek, the wettest of the six catchments. Large correlation coefficients were obtained for the three Australian catchments between *p7* and *p10*, the parameters determining the relative contributions of slow and quick flow at each time step. High correlations were also obtained between *p10* and *p13* for Scott Creek and Canning River. This was not unexpected as *p13* is the factor that scales down *p10* to reduce the current net rainfall contribution to quick flow with a change from the very wet to the wet state. *p13* is therefore an important parameter for the Canning River in spite of its poor identification (Figure 6.9 presented earlier in Section 6.3.2). Table 6.14 furthermore shows that *p13* is relatively well identified for the 10 runs of the longer 1978-84 data set and poorly identified for the shorter 1984-87 data set. The identification of parameters *p12*, *p13* and *p14* for Babinda Creek is poorer than for Scott Creek and Canning River reflecting the relatively smaller proportion of time that the 'dry catchment' component of the model is activated for Babinda Creek. The hydrograph plots for the three catchments (Appendix A6) reveal this. After observing the relatively good performance of the modelling of Chania River in spite of the poor identification of parameters and flow separation consistency, it was reasonable to anticipate higher correlation coefficients than with the other catchments. This was found not to be the case. Chania River however gave the highest correlation coefficients between *p5* and *p8* (-0.743) and between *p9* and *p12* (0.725) amongst the six catchments.

Four parameters, *p5*, *p6*, *p8* and *p11* are indices intended to model the nonlinearlities of the rainfall-runoff process. Intuitively, they would be expected to exhibit low variability among catchments. Parameter *p1*, the number of periods of summation of the weighted past net rainfalls and *p2*, the evaporation coefficient are expected to take physically realistic values that are also not highly variable among catchments. The rest of the parameters with the possible exception of *p14*, the dry state slow flow coefficient are expected to be more catchment specific. These trends were largely observed for the five catchments where performance was considered acceptable. The modelling of one of the Kenyan catchments, Noigameget River was considered a failure and possible explanations for this are given in Section 6.3.3. The Australian catchments exhibit smaller summation times (*p1*) and larger evaporation coefficients (*p2*) than the Kenyan catchments. Parameter *p8* also takes notably higher values for the Australian catchments. Table 6.32 gives ranges for *p1*, *p2*, *p5*, *p6*, *p8* and *p11* based on the lowest and highest values of the parameters obtained from the successful optimizations of the five catchments. This excludes the two calibrations assessed as unsatisfactory in Section 6.3.1. Figure 6.15 and 6.16 are plots of the distribution of the six parameters for the three Australian and the two Kenyan catchments respectively. More rigorous statistical analysis was considered unnecessary as not many catchments were involved. Parameter *p6* has taken on values closer to unity than parameters *p5*, *p8* and *p11*. It is probable that *p6* could be discarded without degradation of model performance. To a lesser degree, the same could apply to *p5*. An alternative could be the setting of the two parameters to constant values such as the mode or the mean.

Table 6.32 Reasonable Ranges of some STDT4 Model Parameters

Parameter		p1	p2	p5	p6	p8	p11
Australian Catchments	Lower	15	0.1	0.4	0.8	1.3	1.2
	Upper	48	0.8	1.4	1.4	3.8	2.0
Kenyan Catchments	Lower	31	0	0.5	0.5	0.7	0.6
	Upper	51	0.6	1.6	1.2	3.0	3.2

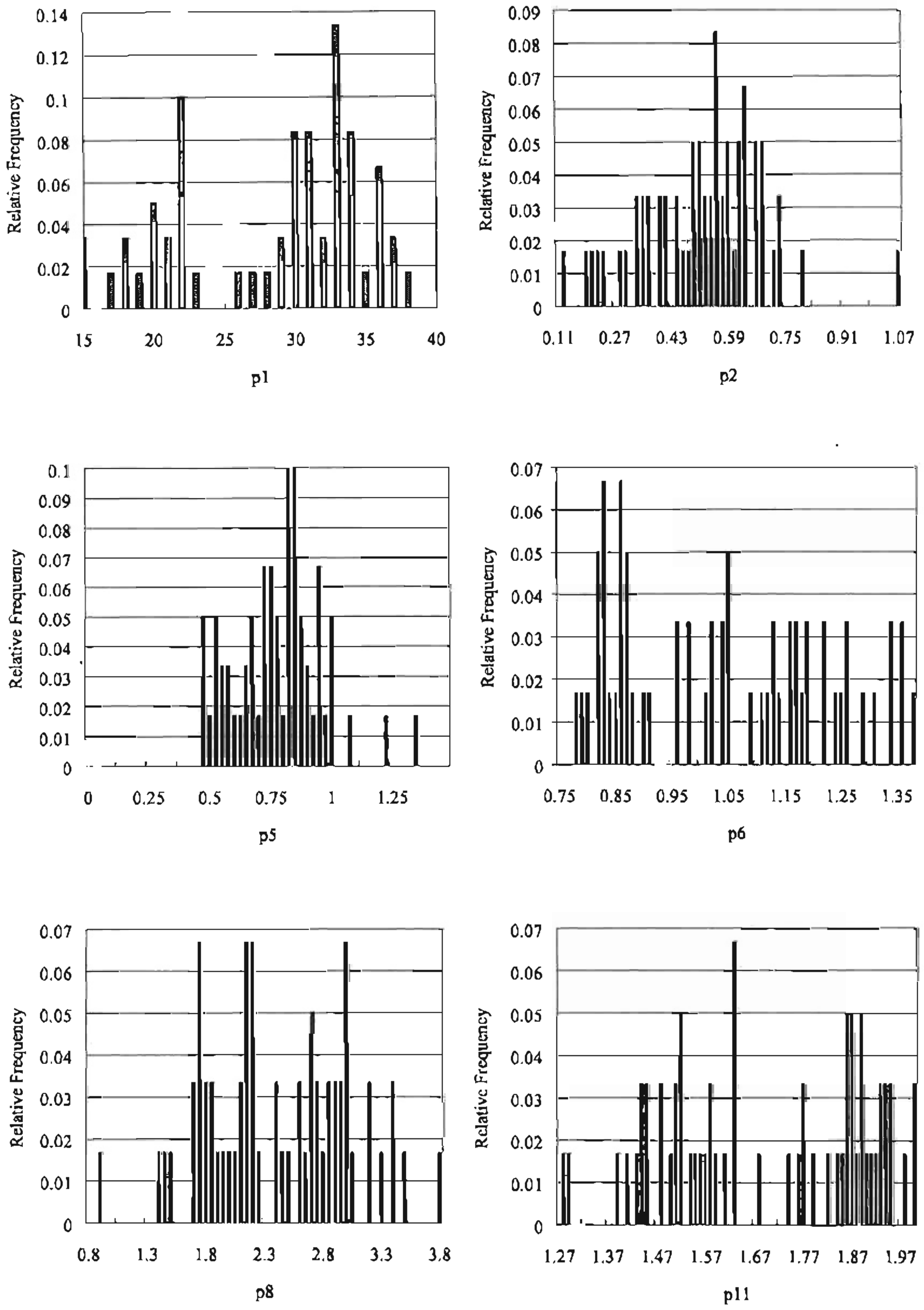


Figure 6.15 Distribution of some STDT4 Model Parameters for three Australian Catchments

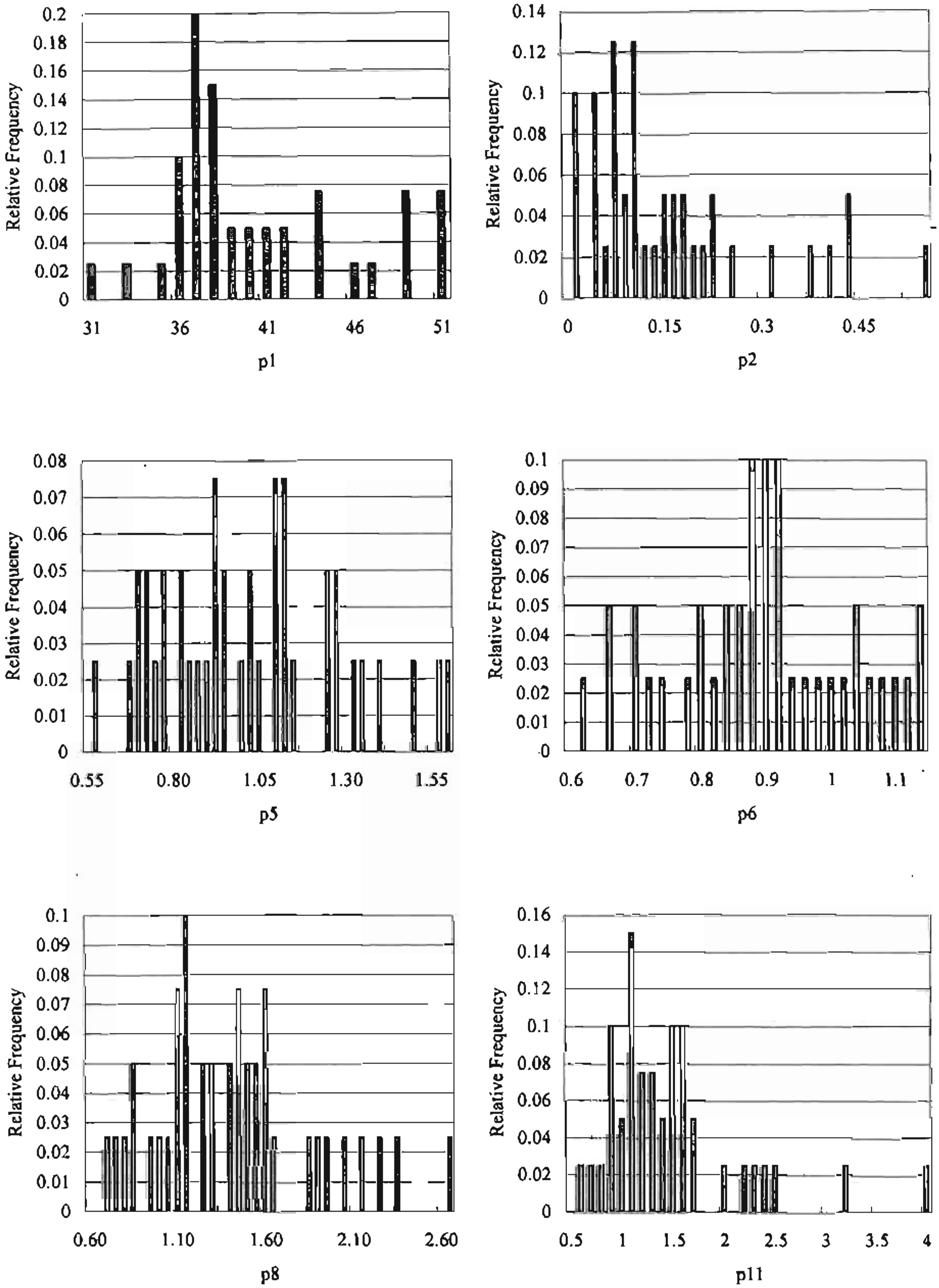


Figure 6.16 Distribution of some STDT4 Model Parameters for two Kenyan Catchments (Nyasara Stream and Chania River)

6.3.3 STDT4 Model performance

This section discusses the model performance on the basis of the four performance coefficients; the coefficient of efficiency (*ce*), the bias, the absolute deviation (*ade*) and the residual mass curve coefficient (*rmcc3*). Hydrograph plots of the simulations that gave the lowest objective function values are given in Appendix A6. The coefficient values are given in Tables 6.18 to 6.23 of Section 6.3.1 for the six catchments. The STDT4 model performed better with the Australian than the Kenyan catchments. As with the parameter identification, this could be attributed to the superior data quality of the Australian catchments. The model seems to have totally failed in the simulation of Noigameget River. A definite reason for this was not found but data quality and/or inadequate model structure were the likely causes. Noigameget catchment has high evaporation losses and contains swampy valleys. The best performance was obtained with the wet Babinda Creek catchment. The calibration performance of driest catchment, Canning River surpassed that of Scott Creek.

The validation performance for Canning River was also better than that of Scott Creek with the exception of the coefficient of efficiency. The 1978-84 validation run 1 and 10 of Canning River were of low performance and gave negative coefficients of efficiency. The short duration of the 1984-87 calibration run and not model inadequacy was considered to be the cause of this. The inadequate length of the 1979-81 calibration period was also regarded as the cause of the poor 1982-87 validation of Nyasara Stream (Table 6.22). The simulation of the Chania River flows gave better coefficients of efficiency than those of Nyasara Stream but the performance of the two was otherwise not notably different ignoring the 1982-87 Nyasara Stream validations. Not unexpectedly, with all the catchments, the calibrations performed better than the validations. Calibrations with the two data sets for each catchment also gave varying performances. These observations were not unexpected and are typical in conceptual rainfall-runoff modelling. Two recent studies, Ye *et al* (1997) and Gan and Biftu (1996) and an earlier one, Hornberger *et al* (1985) provide ample evidence of this.

The adequacy of a model for a given application depends on the application for which the results are intended and there are no strict rules for the acceptability or rejection of a model. The literature search however provided the results obtained by Chiew and McMahon (1993c) as guidelines for evaluating the adequacy of flow estimates for typical hydrology and water resources studies such as reservoir and catchment yield estimates. The guidelines are based on a survey involving one hundred and twelve calibrations of twenty eight unregulated Australian catchments and assessments by sixty three participants from Consulting agencies, Government agencies, Universities and Research institutions. The calibrations optimized monthly flows simulated by the daily rainfall-runoff MODHYDROLOG model. The quantitative component of the guidelines is given in Table 6.33 where *cd* is the coefficient of determination.

As the coefficient of determination was not involved in the current study, the coefficient of efficiency alone was used to assess the STDT4 model performance. By the guidelines, all the calibrations of Babinda Creek and Canning River are classified as either perfect or acceptable. The 1970-77 calibrations of Scott Creek and most of the 1963-68 calibrations runs of Chania River are classified as acceptable. Most of the other calibrations except those of Noigameget River are classified as generally satisfactory. The 1981-87 Babinda Creek validations are in the acceptable category and most of the other validations of the Australian catchments are classified as generally satisfactory. About half of the validations of Chania River would be classified as generally satisfactory.

Table 6.33 Quantitative Guidelines for Assessing the Adequacy of streamflow Estimates (adapted from Chiew and McMahon (1993c))

Level of Adequacy	Range of performance coefficients
Perfect	ce $\geq$ 0.93 or cd $\geq$ 0.97 or cd $\geq$ 0.93 and bias $\leq$ 0.1
Acceptable	ce $\geq$ 0.80 or cd $\geq$ 0.90 or cd $\geq$ 0.77 and bias $\leq$ 0.1
Generally Satisfactory	ce $\geq$ 0.60

The rest of Chania River and all the validations of Nyasara Stream gave coefficients of efficiency lower than 0.60 and therefore fall below the acceptable range of simulations. For the five catchments, 97 percent of the calibrations and 55 percent of the validations were successful to varying levels of adequacy. The guidelines are based on simulation of monthly flows while the STDT4 model optimizations were at the pseudoweekly time step. In the model comparison presented in Chapter 7, the monthly time step was applied and the STDT4 gave better coefficients of efficiency than at the pseudoweekly time step. It is therefore reasonable to expect that the STDT4 model would be assessed more favourably with simulations at the monthly time step.

6.3.4 Discussion

The analysis of various aspects of the STDT4 modelling shows that the model performs acceptably, exhibits a reasonable level of parameter identification and a consistent separation of the total flow into slow and quick flow. The model however failed to simulate flows from one of the six catchments. Though not among the aims of the modelling, the adverse effect of inadequate calibration data length was also observed. The poorer quality of data from Kenya was also considered to be at least partially responsible for the observed poorer performance and parameter identification of the STDT4 in modelling the Kenyan flows. Other reasons could however be responsible for the very poor simulations of the Noigameget River catchment. To check whether model structure inadequacy is a contributing factor, the following two approaches could be taken:

- The STDT4 model could be tested on other catchments of similar characteristics (notably the swampy valleys and high evapotranspirations but whose data is known to be of good quality; and
- The Noigameget River flow simulation could be done with other models and the performance compared to that of the STDT4 model.

Although the analysis of parameter identification and correlations (Section 6.3.2) did not reveal any outrightly redundant parameter, the large number of parameters is a drawback of the STDT4 model. A larger number of parameters means more effort in calibrating and assessing the validity of the calibrations. Parameter *p3*, the upper bound of the past net rainfalls, was however found to be probably significant only for the simulation of the wettest catchment, Babinda Creek. The removal of *p3*, may therefore be appropriate. Parameter *p6*, an index was found to take on values not highly varied from unity. To a lesser extent, the same could be said of parameter *p5*. Considering that there are two more indices available to model the rainfall-runoff process nonlinearlities (*p8* and *p11*), the removal of either *p6* or both *p6* and *p5* could be another reasonable step towards reducing the number of model parameters. Additional steps to ease the calibration effort could be obtained by using smaller parameter ranges based on the results obtained from the current study. Table 6.32 gives guidelines for the ranges of some of the parameters.

The flow separation of the model was found to be satisfactory and consistent for five of the six catchments. Appendix A6 presents an adequate demonstration of typical flow separations for the Kenyan catchments as a linear scale was applied on the flow axes. A logarithmic scale was applied for the hydrographs of the Australian sites as they exhibited higher variabilities. Samples illustrating the flow separation obtained from calibrations of the Australian sites are therefore given within this Section in Figure 6.17. The 'very wet to wet' lines in Figure 6.17 represent parameter *p9*, the slow flow values at which the catchment changes between the very wet and the wet state. The 'wet to dry' lines represent parameter *p12*, the slow flow value at which the catchment changes between the wet and the dry state. The model could be suitable for baseflow separation for the pseudo weekly and longer time steps.

The analysis made in this section is based on the specific objective function applied (equation 4.15 of Section 4.5.1) and could vary if other objective functions were applied. Further studies of the model could include an investigation of the effects of the applied objective function.

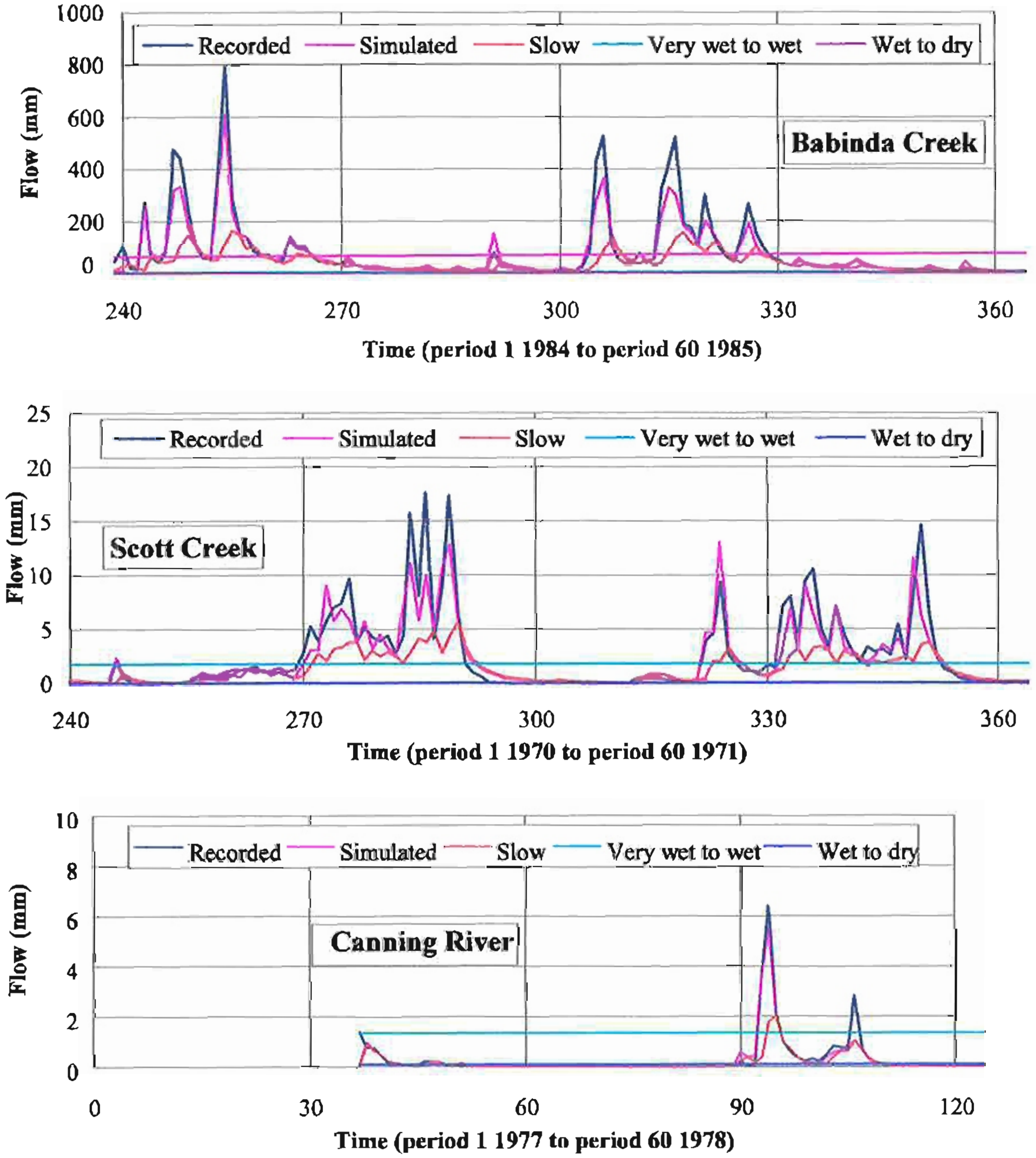


Figure 6.17 An Illustration of STDT4 Model flow Separation for three Australian Catchments

Chapter 7

Comparative Study of Model Performances

7.1 Summary

This Chapter presents a comparative study of the STDT3, the STDT4 and the daily rainfall-runoff MODHYDROLOG model in simulating monthly flows. The STDT3 and STDT4 models are described in Section 4.5.6 and 4.5.7 respectively. The MODHYDROLOG model and its adaptation to the comparative study is presented in Section 4.6. Hydrological data from the three Australian catchments of Babinda Creek, Scott Creek and Canning River was used. Five calibrations were performed for each data set and the split sample calibration-validation approach used in Chapter 6 was applied. The initial parameter search ranges and search limits used in the calibrations are given in Tables 7.1 to 7.3.

Table 7.1 Parameter Search Ranges tor Monthly Simulations with the STDT3 Model

Parameter	Initial parameter ranges		Parameter range limits	
	lower	upper	lower	upper
1	3	25	2	50
2	0.3	0.5	0.00001	10
3	0.05	0.5	0.00001	10
4	0.5	1.5	0.00001	10
5	0.5	1.5	0.00001	10
6	0.01	0.2	0.00001	10
7	3	6	0.1	30

Table 7.2 Parameter Ranges for Monthly Simulations with the STDT4 Model

Parameter	Initial parameter ranges		Parameter range limits	
	lower	upper	lower	upper
1	12	32	3	52
2	0.5	2	0.001	5
3	50	100	10	500
4	-20	0	-100	50
5	0.5	1	0.01	5
6	0.5	1.5	0.01	5
7	0.001	0.2	0.000001	1
8	0.4	1	0.1	5
9	1	5	0.01	10
10	4	10	0.1	30
11	1	2	0.1	5
12	0.2	2	0.0001	5
13	2	10	1	30
14	0.6	1	0.001	5

Table 7.3 Parameter Ranges for Monthly Simulations with the MODHYDROLOG Model

Parameter	Initial parameter ranges		Parameter range limits	
	lower	upper	lower	upper
INSC	1	2	0.5	6
COEFF	90	190	20	400
SQ	1	5	0	10
SUB	0.1	0.3	0	1
CRAK	0.1	0.3	0	2
SMSC	130	230	20	400
EM	7	13	5	20
CO	10	30	1	50
K1	0.02	0.06	0	1
VCOND	0.05	0.15	0	0.5

The parameter ranges for MODHYDROLOG were obtained from Chiew and McMahon (1994). For the STDT3 and STDT4 calibrations, the same optimization parameters of the modified Genetic Algorithm (GA) as used in Chapter 6 were adopted. These are given in Table 6.1 and 6.2. Table 7.4 gives the GA optimization parameters applied in the MODHYDROLOG model calibrations.

Table 7.4 Genetic Algorithm Optimization Parameters used in the MODHYDROLOG Model Calibrations

Optimization Parameter	Symbol	Value
Population size	P	200
Subpopulation size	p_s	20
Number of subpopulations	n_s	10
Bit length of parameter substring	l	20
Maximum number of generations per optimization	g_{max}	1000
Maximum number of function evaluations	Ev_{max}	25000
Probability of crossover	c	1.0
Number of crossover positions	n_{cross}	10
Probability of mutation	m	0.05
Tournament size	t_o	6
Fitness scaling index	f_{scale}	3
Convergence parameter	$cheperf$	0.95
Maximum number of epochs	ep_{max}	50

The model comparison was mainly based on the four performance coefficients given in Section 4.5.1: the coefficient of efficiency (*ce*), the *bias*, the absolute deviation (*ade*) and the residual mass curve coefficient (*rmcc3*). The STDT and the MODHYDROLOG models were calibrated using different objective functions: equations 2.11 and 4.15 respectively. A comparison of the objective functions of the models was therefore not undertaken and this is considered a limitation to what could possibly have been a fairer comparison. However, the two objective functions were biased to the simulation of high flows. The application of the four coefficients to evaluate the performance provides a broad-based comparison. Ye *et al* (1997) used a similar approach in the comparison of three models: the GSFB, the LASCAM and the IHACRES. The GSFB was calibrated using the objective function of equation 2.11 (Section 2.7.2) while the LASCAM calibration applied equations 2.14 and 2.15 (Section 2.7.2). Ye *et al* (1997) indicate that the IHACRES calibration involved several measures including the *bias*. The performance evaluation measures used by Ye *et al* (1997) were the *ce*, the *bias* and the *ade*. Gan and Biftu (1996) used the sum of the daily root mean square of the residuals as the objective function and the *ce* as the main performance evaluation measure. Yapo *et al* (1996) applied the HMLE (Section 2.7.2) and the daily root mean square as objective functions and the *ce* and *bias* as measures of model performance.

Parameter identifications were compared using graphical plots as in Section 6.3 and the parameter correlations compared by examination of the correlation coefficients. Appendix A7 presents the flow hydrographs obtained from the runs giving the least objective function values among the five runs made with each data set. The comparisons for each catchment are presented separately in Sections 7.2 to 7.4, with a summary discussion in Section 7.5.

7.2 Babinda Creek Comparative Model Performance

The optimized parameter and objective function (*obf*) values for the three models are given in Tables 7.5, 7.7 and 7.9. The three tables also include the number of function evaluations (*eval*) used in each case. Figure 7.1 to 7.3 present the parameter identification plots and Table 7.6, 7.8 and 7.10 present the parameter correlation coefficients for the STDT3, STDT4 and the MODHYDROLOG model respectively. The performance coefficients for the three models and their plots are given in Table 7.11 and Figure 7.4.

The parameter identification plot of the MODHYDROLOG model reveals the considerably different values of parameters INSC, SMSC and EM with the two split samples. This is also evident in Table 7.9. Within individual calibrations, the parameter identification of the MODHYDROLOG was high. MODHYDROLOG exhibited higher correlation coefficients than the other two models. A surprising result was the poor performance of the MODHYDROLOG model in the 1974 -80 calibrations and validations. This was caused by the failure of the MODHYDROLOG to model the high peak flows (Figure A7-3 of Appendix A7). The parameter values (Table 7.9) reveal that the model obtained a very high interception storage (INSC) and a very low soil storage (SMSC) for this period. The 1974-80 calibrations also optimized the infiltration parameters COEFF and SQ to their upper and lower limits of 400 mm and 0 respectively. Additional calibrations using 15 subpopulations of 30 individuals each and allowing for up to 50000 function evaluations did not give better performances. Conversely, the 1981-87 MODHYDROLOG calibrations gave better coefficients of efficiency, bias and absolute deviation than the STDT models. The corresponding residual mass curve coefficients were however lower than those obtained with the STDT models. No considerable difference was observed between the STDT3 and STDT4 model calibrations. The STDT4 validations were however better than those of the STDT3 and those of MODHYDROLOG were the worst.

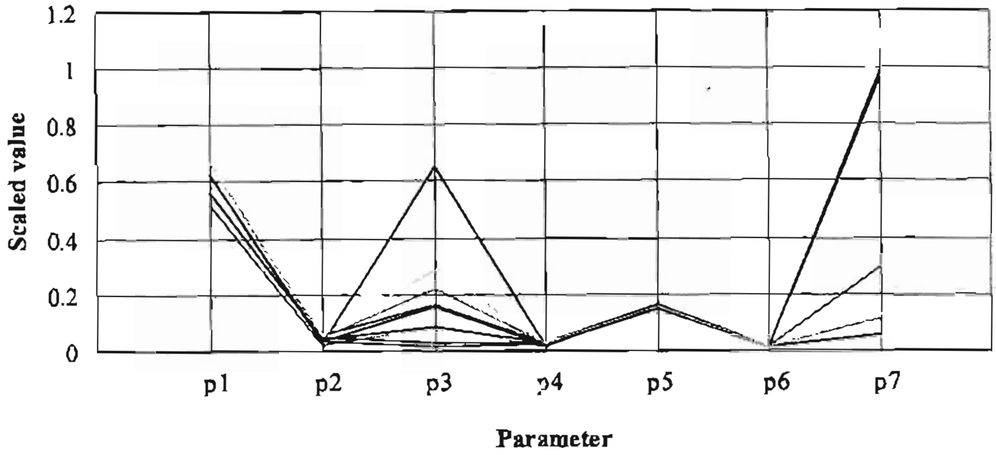


Figure 7.1 STDT3 Model Parameter Identification Plots for Babinda Creek

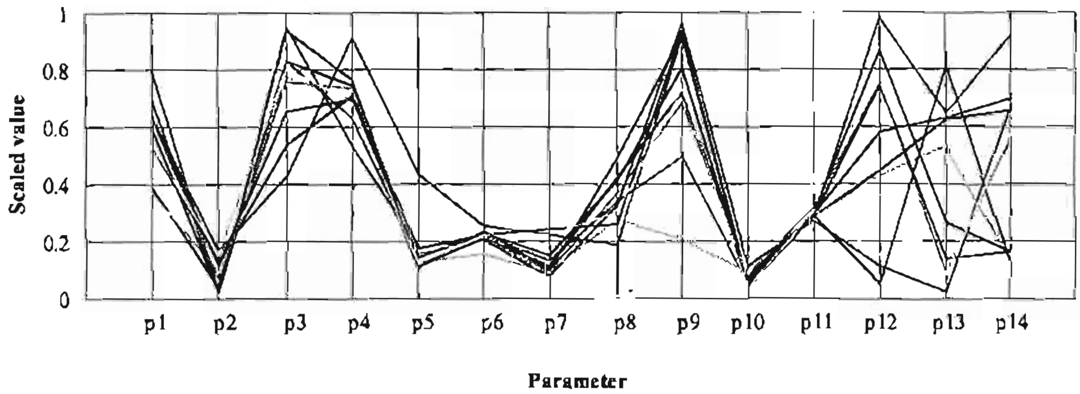


Figure 7.2 STDT4 Model Parameter Identification Plots for Babinda Creek

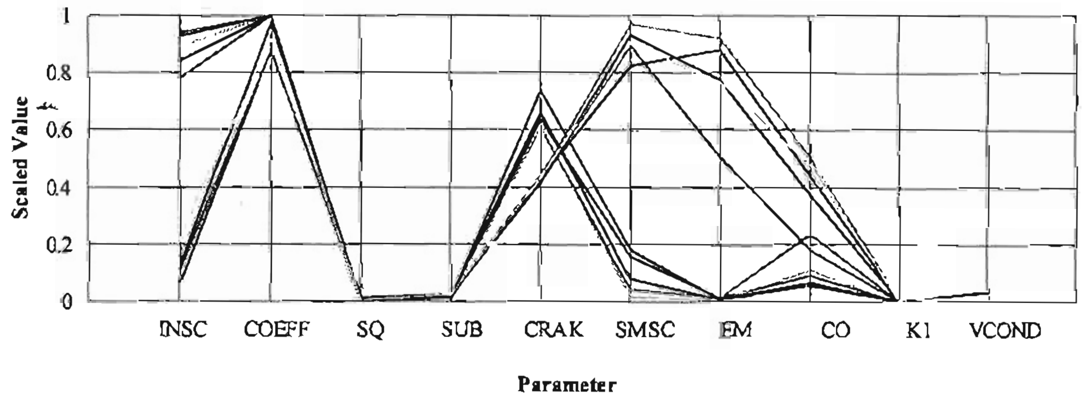


Figure 7.3 MODHYDROLOG Model Parameter Identification Plots for Babinda Creek

Table 7.5 STDT3 Model Parameters for Monthly Flow Simulations of Babinda Creek

Data	eval	P1	P2	P3	P4	P5	P6	P7	obf
	10066	33	0.305	6.564	0.224	1.495	0.123	1.850	426.3
	10010	27	0.245	0.859	0.167	1.601	0.141	9.026	440.9
1974-80	10010	32	0.341	0.750	0.209	1.523	0.133	1.616	434.0
	10066	33	0.340	0.166	0.226	1.494	0.128	1.726	434.4
	10094	33	0.330	1.547	0.221	1.503	0.130	1.693	432.6
	10066	29	0.398	0.829	0.257	1.630	0.133	29.68	472.5
	10052	35	0.535	1.633	0.298	1.551	0.129	3.494	456.4
1981-87	10094	34	0.532	0.276	0.284	1.587	0.130	29.07	463.1
	10038	34	0.523	2.221	0.287	1.579	0.129	3.454	453.7
	10080	35	0.546	2.879	0.296	1.550	0.132	3.973	455.3

Table 7.6 STDT3 Model Parameter Correlation Coefficients for Monthly Flow Simulations of Babinda Creek

	p1	p2	p3	p4	p5	p6	p7
p1	1.000						
p2	0.726	1.000					
p3	0.210	-0.073	1.000				
p4	0.744	0.968	0.058	1.000			
p5	-0.423	0.286	-0.371	0.211	1.000		
p6	-0.680	-0.238	-0.575	-0.410	0.580	1.000	
p7	-0.267	0.223	-0.370	0.222	0.750	0.205	1.000

Table 7.7 STDT4 Model Parameters for Monthly Flow Simulations of Babinda Creek

Data	eval	P1	P2	P3	P4	P5	P6	P7
	25116	22	0.201	416.1	11.73	0.565	1.153	0.149
	25116	37	0.128	417.8	-5.236	0.738	1.120	0.133
1974-80	25144	42	0.107	477.5	-20.31	0.905	1.048	0.081
	25060	21	0.475	390.4	4.618	0.641	0.785	0.091
	25116	32	0.120	470.6	14.39	0.563	1.181	0.100
	25060	29	0.664	274.7	6.159	0.889	1.134	0.240
	25088	34	0.843	219.6	36.96	2.197	1.280	0.222
1981-87	25172	34	0.607	330.7	4.837	0.598	1.067	0.113
	25060	34	0.319	382.7	9.601	0.793	1.069	0.098
	25172	29	0.798	404.8	2.929	0.628	1.122	0.226
	P8	P9	P10	P11	P12	P13	P14	obf
	2.113	8.064	1.487	1.495	2.237	19.12	3.261	449.8
	1.761	4.996	1.793	1.498	4.914	19.88	4.616	413.9
1974-80	1.710	9.632	3.518	1.429	0.574	1.733	3.361	388.4
	1.453	2.144	2.829	1.508	2.144	16.49	0.666	478.7
	2.504	9.204	1.905	1.539	3.732	5.064	0.823	431.7
	1.376	9.318	1.138	1.593	4.330	8.716	0.831	431.0
	1.025	9.149	1.424	1.523	0.266	24.54	0.638	432.5
1981-87	2.191	7.241	2.228	1.554	2.897	19.35	3.486	409.9
	1.916	6.850	2.516	1.675	3.770	3.653	2.781	398.7
	1.583	7.365	1.129	1.607	0.773	3.463	2.875	417.7

Table 7.8 STDT4 Model Parameter Correlation Coefficients for Monthly Flow Simulations of Babinda Creek

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	-0.228	1.000												
p3	0.107	-0.797	1.000											
p4	-0.336	0.503	-0.655	1.000										
p5	0.274	0.477	-0.695	0.602	1.000									
p6	0.344	0.141	-0.305	0.479	0.481	1.000								
p7	-0.191	0.742	-0.664	0.445	0.448	0.538	1.000							
p8	0.030	-0.627	0.640	-0.215	-0.697	0.021	-0.585	1.000						
p9	0.428	0.041	-0.126	0.155	0.320	0.769	0.338	0.099	1.000					
p10	0.348	-0.504	0.476	-0.551	-0.174	-0.618	-0.850	0.165	-0.240	1.000				
p11	-0.149	0.416	-0.311	0.321	-0.093	0.106	0.304	0.024	-0.010	-0.381	1.000			
p12	-0.018	-0.385	0.090	-0.125	-0.457	-0.043	-0.170	0.411	-0.211	-0.151	0.323	1.000		
p13	-0.252	0.234	-0.524	0.478	0.396	0.110	0.164	-0.243	-0.301	-0.270	-0.310	-0.003	1.000	
p14	0.396	-0.405	0.422	-0.586	-0.383	0.030	-0.274	0.343	-0.092	0.163	-0.147	0.146	0.007	1.000

Table 7.9 MODHYDROLOG Model Parameters for Babinda Creek

Data	eval	INSC	COEFF	SQ	SUB	CRAK
	25060	5.153	399.9	0.00195	0.01507	1.324
	25080	5.657	399.9	0.00086	0.01416	1.221
1974-80	25020	4.821	400.0	0.00060	0.01322	1.277
	25120	5.417	400.0	0.00030	0.01447	1.211
	25160	5.604	399.8	0.00012	0.01483	1.480
	25120	0.857	355.3	0.02921	0.02198	0.867
	25020	1.145	353.7	0.01375	0.02092	0.860
1981-87	25180	1.236	391.9	0.12638	0.02194	0.832
	25180	1.112	351.7	0.01492	0.02350	0.874
	25040	1.695	367.8	0.05810	0.02349	0.872
	SMSC	EM	CO	K1	VCOND	obf
	50.84	5.067	4.381	0.000180	0.0123	11.42
	35.42	5.146	12.58	0.000225	0.0141	11.26
1974-80	78.83	5.188	5.496	0.000194	0.0122	11.54
	26.42	5.081	6.379	0.000224	0.0144	10.87
	87.78	5.067	3.650	0.000246	0.0148	11.29
	333.7	18.20	22.53	0.000130	0.0131	2.550
1981-87	361.0	12.60	9.851	0.000195	0.0169	2.674
	373.9	16.61	19.28	0.000148	0.0146	2.539
	387.7	18.82	25.67	0.000111	0.0121	2.529
	362.5	16.57	24.32	0.000125	0.0126	2.527

Table 7.10 MODHYDROLOG Model Parameter Correlation Coefficients for Babinda Creek

	INSC	COEFF	SQ	SUB	CRAK	SMSC	EM	CO	K1	VCOND
INSC	1.000									
COEFF	0.869	1.000								
SQ	-0.595	-0.142	1.000							
SUB	-0.955	-0.846	0.610	1.000						
CRAK	0.949	0.799	-0.627	-0.915	1.000					
SMSC	-0.982	-0.844	0.630	0.973	-0.919	1.000				
EM	-0.961	-0.831	0.619	0.976	-0.918	0.959	1.000			
CO	-0.805	-0.712	0.552	0.881	-0.838	0.814	0.922	1.000		
K1	0.824	0.697	-0.522	-0.851	0.794	-0.801	-0.891	-0.874	1.000	
VCOND	-0.059	-0.045	0.080	-0.011	-0.083	0.081	-0.106	-0.288	0.494	1.000

Table 7.11 SDTD3, STDT4 and MODHYDROLOG Model Performance Coefficients for Babinda Creek

STDT3

Data	ce	bias	ade	rmcc3
	0.972	-0.012	0.126	0.649
Calibration	0.972	-0.006	0.126	0.637
1974-80	0.972	-0.011	0.125	0.64
	0.971	-0.01	0.128	0.662
	0.972	-0.006	0.128	0.634
	0.923	-0.024	0.167	0.384
Calibration	0.925	-0.019	0.165	0.383
1981-87	0.923	-0.022	0.166	0.385
	0.924	-0.02	0.166	0.404
	0.923	-0.021	0.166	0.385
	0.858	-0.129	0.225	0.384
Validation	0.868	-0.121	0.218	0.394
1981-87	0.866	-0.127	0.219	0.397
	0.852	-0.13	0.229	0.376
	0.87	-0.118	0.217	0.4
	0.588	0.174	0.281	0.497
Validation	0.643	0.171	0.27	0.51
1974-80	0.628	0.169	0.273	0.512
	0.627	0.17	0.276	0.495
	0.622	0.171	0.274	0.509

STDT4

Data	ce	bias	ade	rmcc3
	0.952	-0.010	0.149	0.610
Calibration	0.958	-0.007	0.143	0.543
1974-80	0.970	-0.028	0.120	0.640
	0.940	-0.041	0.169	0.698
	0.952	-0.039	0.144	0.648
	0.935	-0.015	0.159	0.401
Calibration	0.948	-0.030	0.147	0.613
1981-87	0.929	-0.051	0.157	0.534
	0.940	-0.012	0.146	0.558
	0.936	-0.029	0.157	0.517
	0.892	-0.104	0.192	0.433
Validation	0.896	-0.118	0.185	0.474
1981-87	0.907	-0.104	0.184	0.592
	0.885	-0.112	0.197	0.411
	0.879	-0.125	0.196	0.478
	0.792	0.147	0.218	0.650
Validation	0.797	0.133	0.246	0.610
1974-80	0.926	0.088	0.169	0.742
	0.628	0.178	0.264	0.507
	0.826	0.123	0.205	0.686

MODHYDROLOG

Data	ce	bias	ade	rmcc3
	0.339	0.061	0.313	0.258
Calibration	0.342	0.082	0.305	0.284
1975-80	0.354	0.067	0.316	0.254
	0.359	0.078	0.298	0.270
	0.336	0.073	0.305	0.261
	0.957	-0.012	0.138	0.280
Calibration	0.955	-0.003	0.145	0.359
1982-87	0.958	-0.014	0.137	0.300
	0.958	-0.008	0.135	0.319
	0.957	-0.011	0.136	0.359
	0.694	-0.230	0.304	0.472
Validation	0.715	-0.212	0.293	0.496
1982-87	0.691	-0.224	0.311	0.480
	0.711	-0.209	0.294	0.484
	0.720	-0.216	0.290	0.475
	-5.728	0.651	0.708	-0.693
Validation	-5.248	0.638	0.697	-0.633
1975-80	-5.490	0.637	0.697	-0.659
	-5.663	0.649	0.708	-0.677
	-5.464	0.635	0.700	-0.649

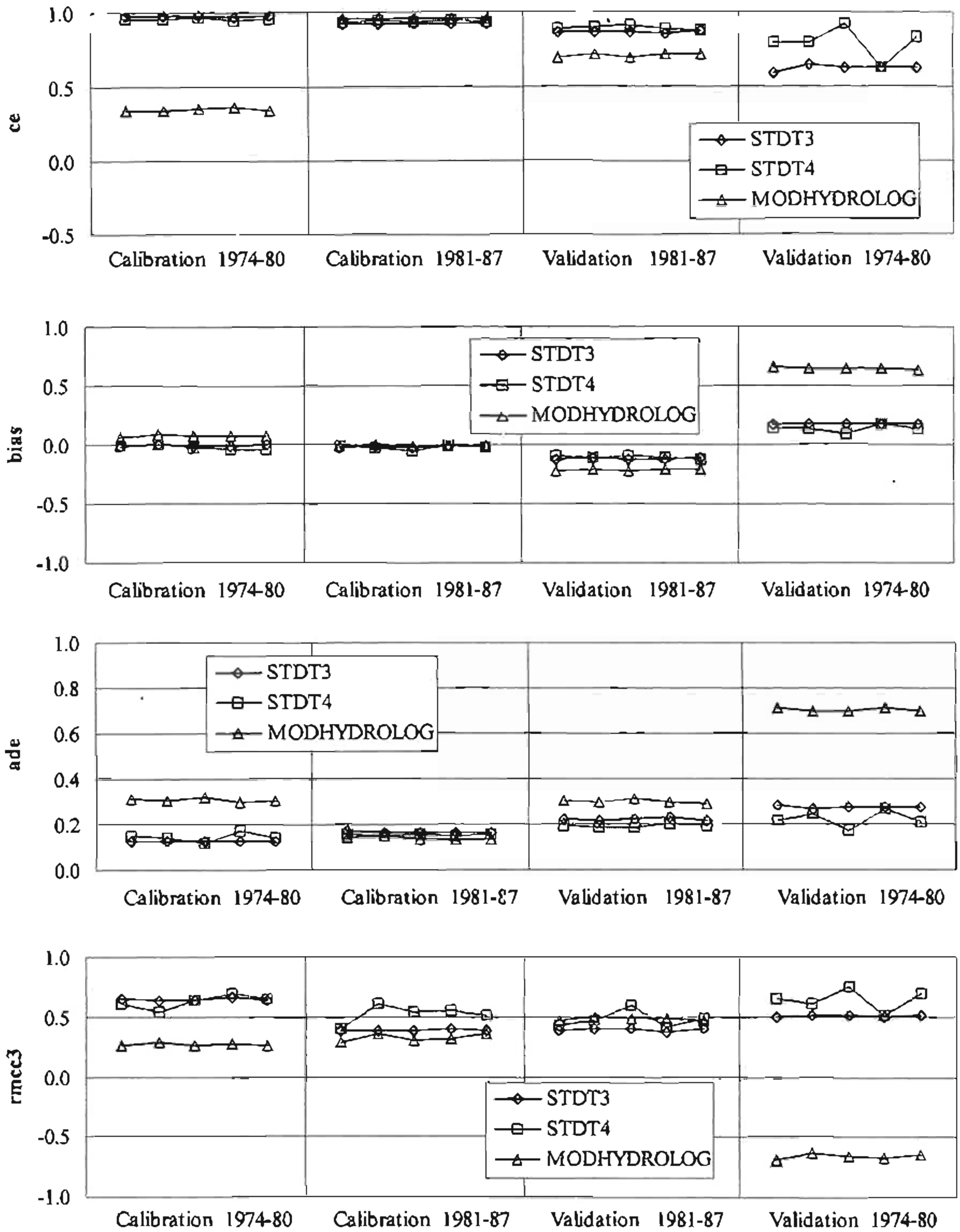


Figure 7.4 SDTD3, STDT4 and MODHYDROLOG Model Performance Coefficients for Babinda Creek

7.3 Scott Creek Comparative Model Performances

The optimized parameter values, objective function values and the number of function evaluations are given in Tables 7.12, 7.14 and 7.16 for the STDT3, the STDT4 and the MODHYDROLOG model respectively. Figure 7.5 to 7.7 are the parameter identification plots while Table 7.13, 7.15 and 7.17 give the parameter correlation coefficients for the three models. The performance coefficient values and their plots are given in Table 7.18 and Figure 7.8.

Table 7.12 STDT3 Model Parameters for Monthly Simulations of Scott Creek

Data	eval	P1	P2	P3	P4	P5	P6	P7	obf
	10080	25	0.443	1.751	0.236	0.700	0.026	16.27	211.4
	10066	25	0.407	1.719	0.212	0.624	0.025	21.22	204.3
1974-80	10066	25	0.463	1.795	0.228	0.661	0.027	17.10	209.5
	10094	25	0.437	1.647	0.187	0.534	0.025	17.34	211.5
	10080	25	0.405	1.557	0.228	0.631	0.023	19.61	208.2
	10024	27	0.167	0.435	0.378	1.363	0.006	29.74	291.9
	10038	27	0.192	0.479	0.382	1.440	0.007	28.89	294.4
1981-87	10024	27	0.181	0.421	0.330	1.270	0.006	28.86	291.6
	10038	27	0.176	0.492	0.366	1.374	0.007	29.78	291.6
	10024	32	0.286	0.607	0.357	1.339	0.009	28.87	300.7

The MODHYDROLOG model consistently gave better coefficient of efficiency and absolute deviations than the STDT models both in calibration and validation. The parameter identification of the MODHYDROLOG model was also notably superior to those of the other two. The STDT4 exhibited a poorer identification than the other two. The bias values obtained with the three models were not considerably different in the calibrations. The STDT4 however gave higher biases in the validations. The residual mass curve coefficients of the STDT4 in the 1978-85 validations were also considerably poorer.

Table 7.13 STDT3 Model Parameter Correlation Coefficients for Monthly Simulations of Scott Creek

	p1	p2	p3	p4	p5	p6	p7
p1	1.000						
p2	-0.525	1.000					
p3	-0.674	0.978	1.000				
p4	0.689	-0.934	-0.957	1.000			
p5	0.707	-0.947	-0.975	0.993	1.000		
p6	-0.667	0.981	1.000	-0.955	-0.972	1.000	
p7	0.691	-0.964	-0.974	0.941	0.957	-0.978	1.000

Table 7.14 STDT4 Model Parameters for Monthly Simulations of Scott Creek

Data	eval	P1	P2	P3	P4	P5	P6	P7
	25116	20	0.510	96.28	-1.101	0.810	1.063	0.060
	25088	20	0.337	96.70	-7.320	0.895	1.033	0.055
1970-77	25088	20	0.544	156.6	-0.162	0.530	1.247	0.085
	25172	25	0.498	142.2	-1.344	0.890	0.984	0.046
	25144	22	0.751	159.2	0.574	0.662	0.844	0.029
	25116	22	0.860	231.7	1.826	0.645	1.512	0.131
	25088	27	0.742	302.7	1.569	0.654	1.171	0.044
1978-85	25088	22	0.701	146.2	0.937	0.817	1.297	0.064
	25088	22	0.542	63.37	0.078	0.557	1.374	0.036
	25004	22	1.230	54.52	0.613	0.658	1.331	0.065
	P8	P9	P10	P11	P12	P13	P14	obf
	1.436	2.020	6.943	1.636	0.071	8.412	2.722	215.6
	1.278	2.667	6.782	1.256	2.157	2.537	0.971	248.2
1970-77	1.914	3.111	4.743	1.352	3.111	24.73	0.960	242.9
	1.524	2.250	8.954	1.189	0.101	9.799	1.016	192.2
	1.934	1.677	15.03	1.793	0.076	9.187	0.764	207.5
	1.612	2.544	2.197	1.283	2.233	3.500	0.276	264.3
	2.175	1.396	10.09	1.644	1.104	10.39	0.537	258.2
1978-85	1.189	2.107	5.162	1.527	1.787	7.363	0.337	256.7
	1.294	2.224	15.23	1.476	1.337	1.514	0.518	235.4
	0.948	2.902	6.281	1.386	2.361	10.63	0.196	247.7

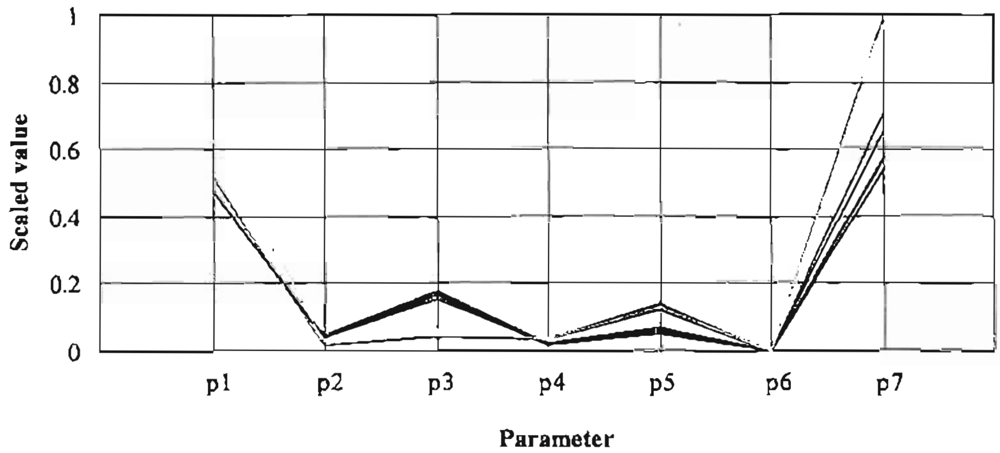


Figure 7.5 STDT3 Model Parameter Identification Plots for Scott Creek

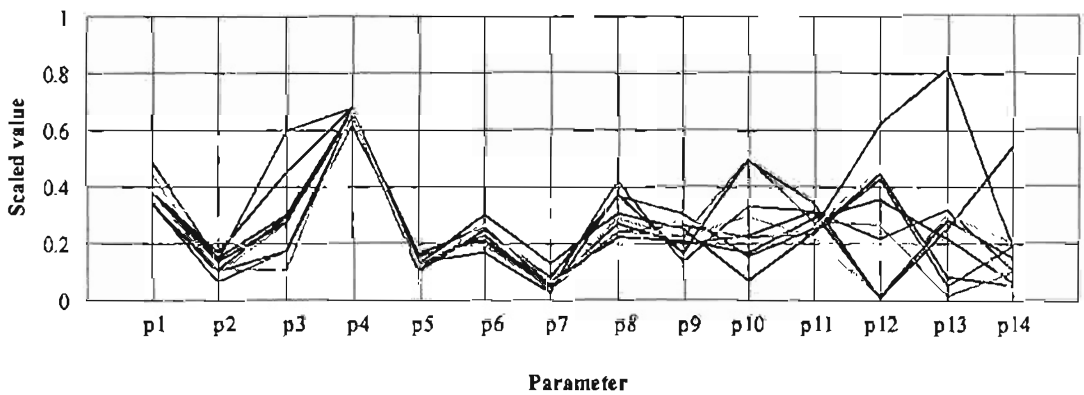


Figure 7.6 STDT4 Model Parameter Identification Plots for Monthly Simulations of Scott Creek

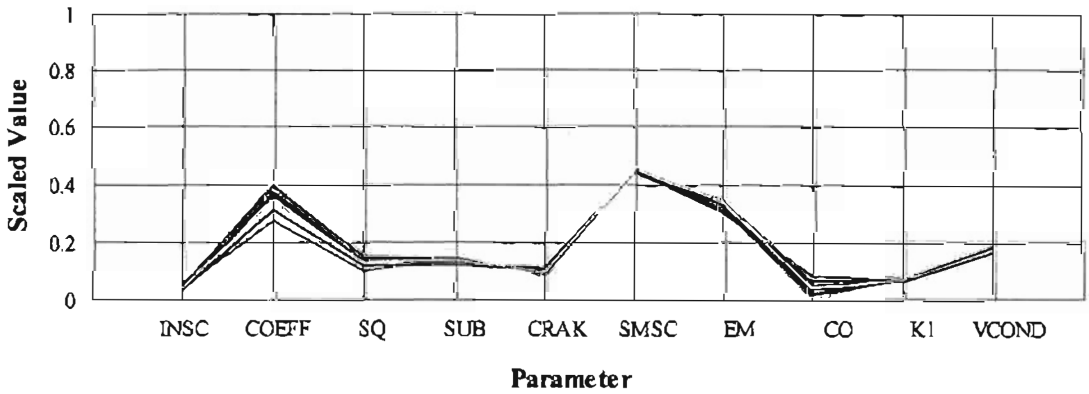


Figure 7.7 MODHYDROLOG Model Parameter Identification Plots for Scott Creek

Table 7.15 STDT4 Model Parameter Correlation Coefficients for Monthly Simulations of Scott Creek

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	0.213	1.000												
p3	0.616	0.069	1.000											
p4	0.410	0.634	0.423	1.000										
p5	0.017	-0.381	-0.158	-0.594	1.000									
p6	-0.061	0.418	0.053	0.434	-0.481	1.000								
p7	-0.279	0.253	0.264	0.214	-0.184	0.667	1.000							
p8	0.404	-0.186	0.790	0.286	-0.346	-0.303	-0.046	1.000						
p9	-0.599	0.085	-0.475	-0.289	-0.144	0.405	0.532	-0.456	1.000					
p10	0.278	-0.161	-0.150	0.035	-0.190	-0.459	-0.844	0.212	-0.565	1.000				
p11	0.099	0.149	0.184	0.397	-0.240	-0.326	-0.468	0.372	-0.721	0.528	1.000			
p12	-0.352	0.229	-0.031	-0.048	-0.396	0.660	0.596	-0.197	0.755	-0.584	-0.476	1.000		
p13	-0.058	0.070	0.163	0.224	-0.359	-0.115	0.106	0.428	0.309	-0.230	0.020	0.283	1.000	
p14	-0.354	-0.524	-0.222	-0.334	0.357	-0.479	-0.155	0.073	-0.136	-0.002	0.211	-0.492	0.115	1.000

Table 7.16 MODHYDROLOG Model Parameters for Monthly Simulations of Scott Creek

Data	eval	INSC	COEFF	SQ	SUB	CRAK
	25040	0.703	159.3	1.404	0.130	0.206
	25040	0.719	125.9	1.039	0.137	0.193
1970-77	25080	0.773	169.0	1.493	0.131	0.215
	25040	0.752	172.3	1.511	0.128	0.220
	25020	0.764	170.1	1.492	0.147	0.181
	25020	0.696	162.0	1.417	0.121	0.229
	25040	0.786	157.5	1.362	0.132	0.213
1978-85	25040	0.684	138.9	1.207	0.121	0.217
	25020	0.720	165.7	1.451	0.139	0.208
	25000	0.730	150.0	1.312	0.141	0.194
	SMSC	EM	CO	K1	VCOND	obf
	190.0	9.827	4.328	0.073	0.092	3.418
	192.8	10.18	1.892	0.072	0.087	3.426
1970-77	188.4	10.19	1.301	0.073	0.086	3.407
	190.1	9.827	1.223	0.073	0.087	3.403
	192.4	9.950	3.577	0.067	0.084	3.418
	190.5	9.808	2.135	0.075	0.093	3.405
	189.1	9.752	2.639	0.075	0.089	3.409
1978-85	192.2	9.576	5.003	0.075	0.091	3.423
	190.4	10.26	4.530	0.072	0.091	3.418
	193.0	10.11	3.060	0.071	0.087	3.410

Table 7.17 MODHYDROLOG Model Parameter Correlation Coefficients for Scott Creek

	INSC	COEFF	SQ	SUB	CRAK	SMSC	EM	CO	K1	VCOND
INSC	1.000									
COEFF	0.469	1.000								
SQ	0.430	0.997	1.000							
SUB	0.441	0.097	0.073	1.000						
CRAK	-0.219	0.213	0.226	-0.888	1.000					
SMSC	-0.425	-0.596	-0.589	0.353	-0.612	1.000				
EM	0.227	0.033	0.009	0.644	-0.423	0.041	1.000			
CO	-0.504	-0.166	-0.121	0.092	-0.203	0.314	-0.245	1.000		
K1	-0.281	-0.179	-0.166	-0.895	0.885	-0.462	-0.522	-0.105	1.000	
VCOND	-0.671	-0.100	-0.075	-0.648	0.660	-0.233	-0.390	0.414	0.707	1.000

Table 7.18 SDTD3, STDT4 and MODHYDROLOG Model Performance Coefficients for Scott Creek

STDT3

Data	ce	bias	ade	rmcc3
	0.919	0.035	0.178	0.889
Calibration	0.916	0.023	0.183	0.887
1970-77	0.920	0.008	0.180	0.882
	0.920	0.043	0.180	0.896
	0.916	0.016	0.182	0.887
	0.916	-0.071	0.296	0.184
Calibration	0.924	-0.078	0.267	0.140
1978-85	0.910	-0.008	0.283	0.118
	0.877	-0.164	0.320	0.215
	0.923	-0.028	0.267	0.145
	0.677	0.444	0.625	0.209
Validation	0.675	0.427	0.612	0.189
1978-85	0.698	0.397	0.616	0.248
	0.673	0.477	0.622	0.151
	0.680	0.404	0.614	0.220
	0.737	-0.330	0.391	0.665
Validation	0.489	-0.246	0.463	0.862
1970-77	0.591	-0.209	0.421	0.857
	0.663	-0.412	0.446	0.631
	0.770	-0.301	0.374	0.725

STDT4

Data	ce	bias	ade	rmcc3
	0.925	0.044	0.195	0.872
Calibration	0.948	0.016	0.157	0.921
1970-77	0.929	0.006	0.186	0.893
	0.947	-0.033	0.164	0.925
	0.912	-0.033	0.190	0.815
	0.912	-0.077	0.303	0.097
Calibration	0.931	-0.066	0.255	0.096
1978-85	0.911	-0.129	0.287	0.105
	0.927	-0.056	0.258	-0.128
	0.939	-0.072	0.243	0.330
	0.663	0.610	0.669	-0.027
Validation	0.778	0.476	0.553	-0.141
1978-85	0.688	0.491	0.611	-0.444
	0.785	0.373	0.527	-0.264
	0.796	0.498	0.573	-0.103
	0.638	-0.435	0.509	0.701
Validation	0.685	-0.400	0.462	0.715
1970-77	0.564	-0.462	0.521	0.623
	0.628	-0.419	0.469	0.585
	0.580	-0.473	0.513	0.635

MODHYDROLOG

Data	ce	bias	ade	rmcc3
	0.979	-0.009	0.121	0.908
Calibration	0.979	-0.009	0.122	0.917
1971-77	0.979	-0.008	0.121	0.921
	0.979	-0.010	0.120	0.914
	0.979	-0.010	0.121	0.913
	0.951	-0.023	0.223	0.522
Calibration	0.952	-0.019	0.222	0.536
1979-85	0.951	-0.023	0.223	0.530
	0.951	-0.022	0.224	0.528
	0.951	-0.020	0.225	0.530
	0.857	0.410	0.449	0.355
Validation	0.852	0.416	0.455	0.348
1979-85	0.853	0.414	0.454	0.320
	0.856	0.410	0.451	0.332
	0.855	0.410	0.451	0.332
	0.856	-0.322	0.329	0.706
Validation	0.858	-0.322	0.327	0.708
1971-77	0.855	-0.324	0.330	0.705
	0.856	-0.322	0.329	0.705
	0.856	-0.323	0.329	0.706

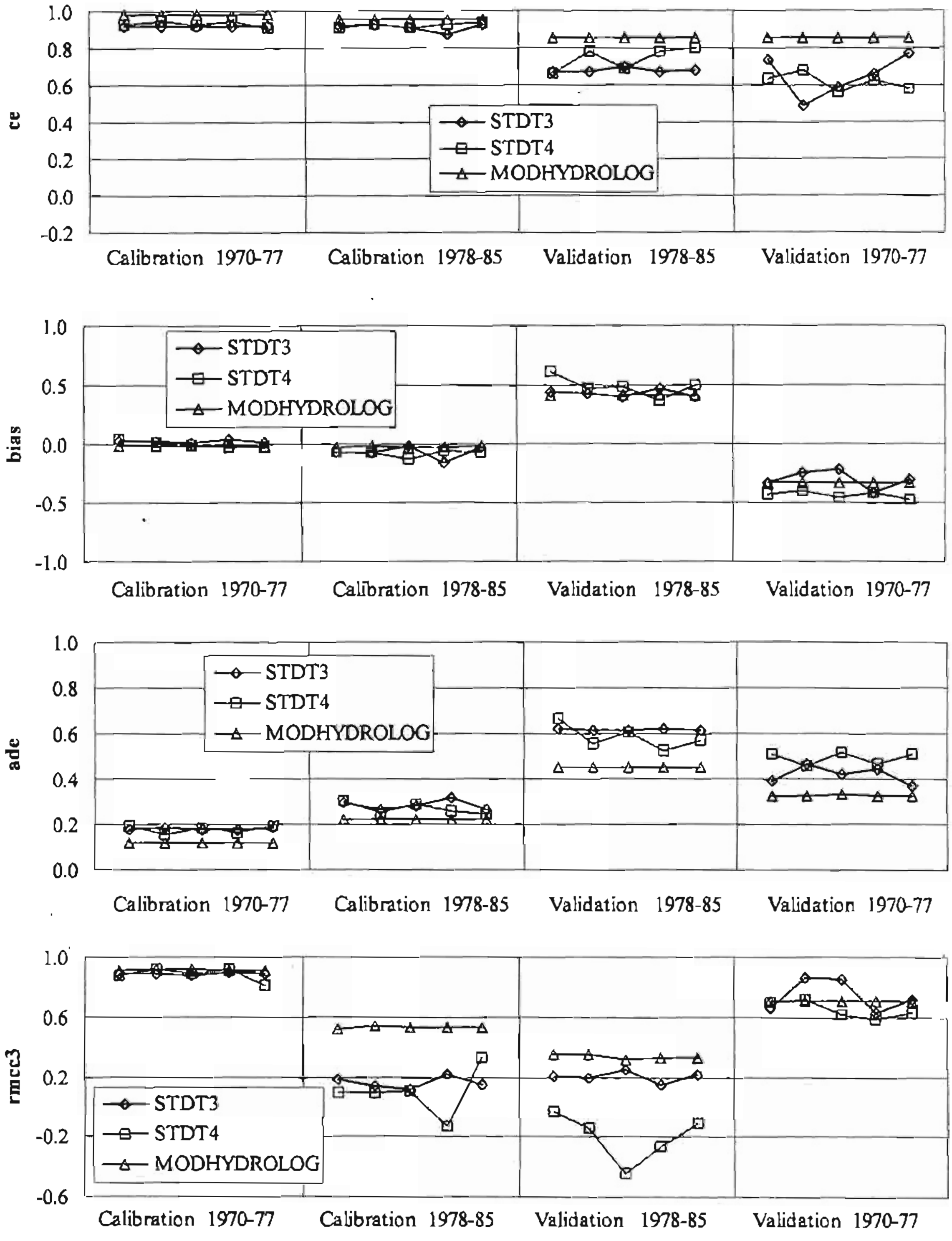


Figure 7.8 SDTD3, STDT4 and MODHYDROLOG Model Performance Coefficients for Scott Creek

7.4 Canning River Comparative Model Performances

Tables 7.19, 7.21 and 7.23 give the parameter values, objective function values and the number of function evaluations obtained in the calibrations of the STDT3, the STDT4 and the MODHYDROLOG model. Figure 7.9 to 7.11 present the parameter identification plots. In Table 7.20, 7.22 and 7.24, the parameter correlation coefficients for the three models are presented. The performance coefficient values and their plots are given in Table 7.25 and Figure 7.12. The missing values in Table 7.25 and Figure 7.12 were beyond the –10 to +10 range.

Table 7.19 STDT3 Model Parameters for Monthly Simulations of Canning River

Data	eval	P1	P2	P3	P4	P5	P6	P7	obf
	10038	34	1.199	2.533	0.00313	6.075	0.0258	25.25	199.6
	10038	34	1.203	1.293	0.00089	6.041	0.0261	7.103	199.6
1977-84	10038	34	1.199	1.681	0.00323	5.969	0.0259	26.66	199.6
	10038	34	1.202	1.394	0.00208	5.937	0.0260	17.12	199.6
	10052	34	1.198	1.061	0.00258	6.039	0.0258	20.59	199.6
	10038	41	0.733	0.571	0.0192	8.199	0.0097	13.62	125.5
	10024	43	0.731	2.147	0.0130	10.00	0.0096	12.00	135.1
1984-87	10024	43	0.730	2.180	0.0106	9.897	0.0096	9.300	135.1
	10080	43	0.730	1.529	0.0147	9.904	0.0096	13.01	135.0
	10010	41	0.733	2.132	0.0054	9.760	0.0096	6.182	125.0

The MODHYDROLOG model version used in this study did not allow simulations starting on a leap year and used the first year to stabilize the storages. Consequently, only twenty four data points (two years of monthly data 1986-87) were effectively used for the MODHYDROLOG simulations of 1984-87 flows. The inadequacy of this data set explains the unrealistic baseflow values obtained in the 1985-87 calibration as Figure A7-9 of Appendix A7 reveals. The unrealistic 1977-84 validations of the MODHYDROLOG (Figure A7-9 of Appendix A7) are also attributed to the inadequate length of the 1985-87 calibration data. The model comparisons are therefore based on the 1978-84 calibrations and the 1984-87 validations only. Model STDT4 gave better coefficients of efficiency, bias, absolute deviation and residual mass curve coefficients than the other two models in the 1977-84 calibrations.

The STDT4 model coefficients of efficiency, bias, and absolute deviations were also better in the 1984-87 validations. The STDT4 however gave lower residual mass curve coefficients than the STDT3 and the MODHYDROLOG in the 1984-87 validations. A notable limitation of the STDT3 model was its inability to simulate the peaks of the 1977-84 flows as Figure A7-7 of Appendix A7 shows. The STDT3 consistently failed to simulate the peaks in all the five runs. This resulted in its considerably poorer calibration results. One of the MODHYDROLOG 1985-87 validations also failed as can be seen in Table 7.25. This could probably be attributed to the relatively lower value of parameter SQ (Table 7.23).

Table 7.20 STDT3 Model Parameter Correlation Coefficients for Canning River

	p1	p2	p3	p4	p5	p6	p7
p1	1.000						
p2	-0.987	1.000					
p3	0.164	-0.107	1.000				
p4	0.833	-0.841	-0.216	1.000			
p5	0.981	-0.965	0.289	0.719	1.000		
p6	-0.986	1.000	-0.110	-0.840	-0.965	1.000	
p7	-0.604	0.622	0.035	-0.308	-0.636	0.620	1.000

Table 7.21 STDT4 Model Parameters for Monthly Simulations of Canning River

Data	eval	P1	P2	P3	P4	P5	P6	P7
	25004	38	0.983	85.75	-19.16	1.099	0.762	0.026
	25004	38	0.846	432.5	-17.48	0.923	0.820	0.022
1977-84	25144	43	0.712	220.4	-61.17	0.907	0.885	0.024
	25004	43	0.840	106.4	-21.24	0.915	0.853	0.030
	25144	43	0.911	103.4	-16.68	0.928	0.755	0.023
	25172	25	0.826	165.7	-20.00	0.863	0.641	0.006
	25032	42	0.818	130.4	-22.60	0.996	0.832	0.062
1984-87	25032	33	1.094	114.3	-12.65	1.048	0.673	0.036
	25004	44	0.769	156.3	-25.94	1.002	0.851	0.047
	25032	32	0.705	128.4	-73.67	1.030	0.866	0.061

Data	P8	P9	P10	P11	P12	P13	P14	obf
	1.361	7.544	23.00	2.484	0.622	2.041	0.636	65.84
	1.729	0.766	10.74	2.286	0.765	16.24	0.842	69.74
1977-84	1.907	8.373	8.477	1.888	0.507	1.071	1.077	66.76
	1.324	1.664	3.830	1.184	1.005	3.097	0.588	70.62
	1.092	1.262	7.540	1.900	1.033	9.744	0.376	72.92
	1.058	7.171	5.137	0.456	0.423	5.501	0.205	23.86
	1.961	4.097	6.692	3.657	1.638	23.48	0.459	21.33
	2.238	6.159	14.55	3.686	1.249	21.07	0.501	18.16
1984-87	2.265	1.095	12.41	1.874	0.166	24.67	1.235	24.73
	3.819	9.006	4.001	0.770	0.201	15.65	2.228	22.33

Table 7.22 STDT4 Model Parameter Correlation Coefficients for Canning River

	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
p1	1.000													
p2	-0.160	1.000												
p3	-0.009	-0.253	1.000											
p4	0.045	0.723	-0.007	1.000										
p5	0.033	0.413	-0.406	-0.022	1.000									
p6	0.679	-0.686	0.194	-0.584	0.027	1.000								
p7	0.249	-0.267	-0.261	-0.387	0.550	0.522	1.000							
p8	-0.145	-0.368	-0.017	-0.713	0.456	0.426	0.766	1.000						
p9	-0.552	-0.087	-0.285	-0.588	0.272	-0.152	0.046	0.373	1.000					
p10	0.082	0.606	-0.061	0.357	0.677	-0.231	-0.143	-0.160	0.102	1.000				
p11	0.322	0.570	-0.012	0.411	0.504	-0.077	0.313	-0.024	-0.141	0.503	1.000			
p12	0.245	0.510	-0.145	0.520	0.055	-0.177	0.147	-0.312	-0.281	-0.028	0.718	1.000		
p13	0.055	0.057	0.105	0.143	0.346	0.046	0.666	0.486	-0.332	-0.010	0.488	0.219	1.000	
p14	0.003	-0.590	0.090	-0.836	0.303	0.627	0.578	0.890	0.307	-0.159	-0.323	-0.606	0.198	1.000

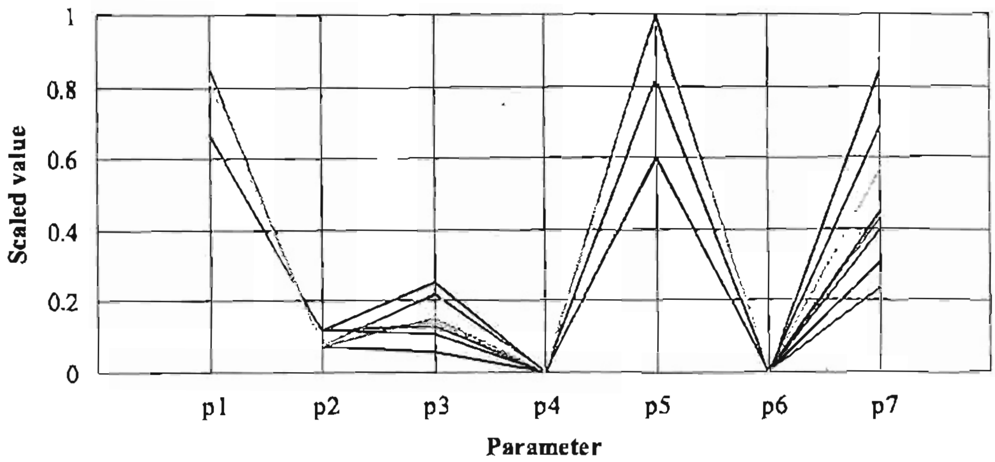


Figure 7.9 STDT3 Model Parameter Identification Plots for Canning River

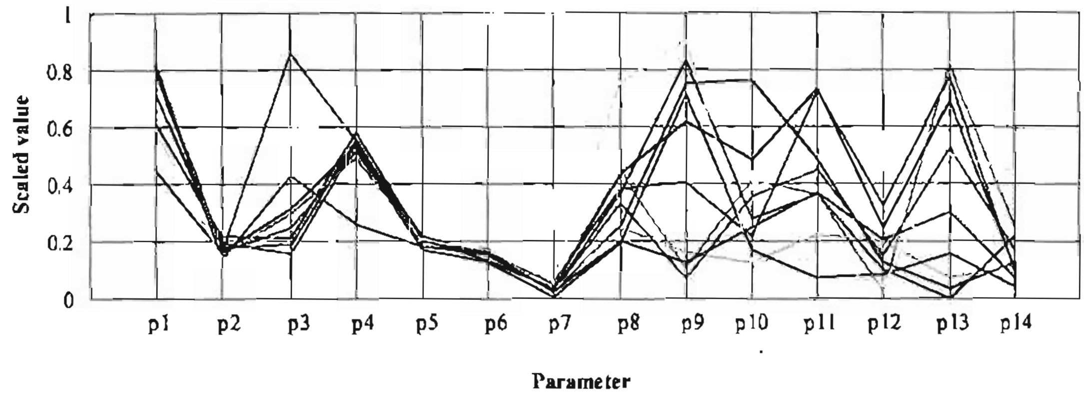


Figure 7.10 STDT4 Model Parameter Identification Plots for monthly Simulations of Canning River

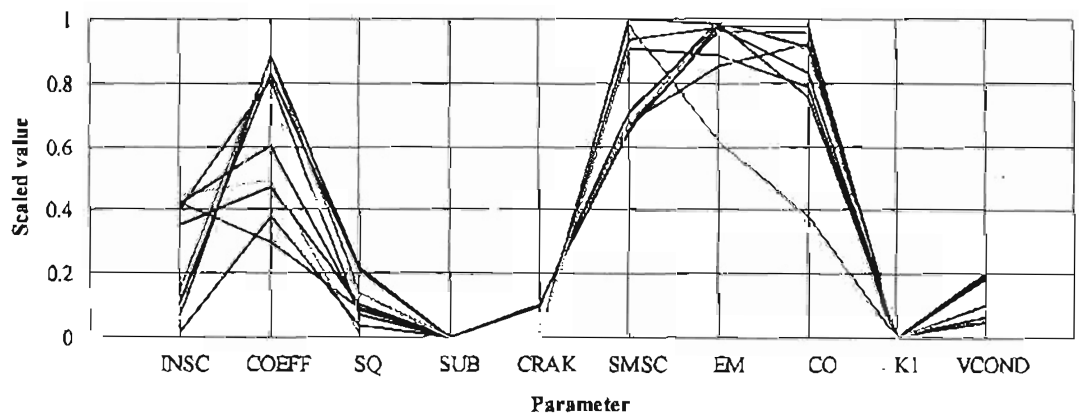


Figure 7.11 MODHYDROLOG Model Parameter Identification Plots for Canning River

Table 7.23 MODHYDROLOG Model Parameters for Monthly Simulations of Canning River

Data	eval	INSC	COEFF	SQ	SUB	CRAK
	25160	2.43	199.5	1.05	0.000001	0.20
	25140	2.84	133.4	0.95	0.000001	0.21
1977-84	25000	2.72	328.0	0.72	0.000000	0.20
	25060	2.94	207.5	0.10	0.000000	0.20
	25100	2.79	248.7	0.88	0.000000	0.21
	25120	0.85	356.3	2.19	0.000058	0.00
	25100	0.58	164.0	0.41	0.000047	0.00
1985-87	25180	1.10	335.2	2.10	0.000064	0.00
	25080	1.35	354.4	1.41	0.000052	0.00
	25040	0.84	302.4	1.32	0.000033	0.00
	SMSC	EM	CO	K1	VCOND	obf
	288.9	19.88	45.83	0.000051	0.102	0.0592
	272.0	19.43	47.90	0.000049	0.093	0.0599
1977-84	276.4	17.76	46.36	0.000050	0.096	0.0605
	274.0	19.81	45.22	0.000052	0.096	0.0601
	266.5	19.68	48.98	0.000047	0.095	0.0604
	375.8	19.60	41.78	0.00292	0.033	0.00140
	399.5	19.72	38.13	0.00212	0.051	0.00229
1985-87	365.6	18.26	39.73	0.00346	0.025	0.00143
	394.1	14.26	19.73	0.00318	0.027	0.00174
	366.8	19.31	17.39	0.00198	0.046	0.00213

Table 7.24 MODHYDROLOG Model Parameter Correlation Coefficients for Canning River

	INSC	COEFF	SQ	SUB	CRAK	SMSC	EM	CO	K1	VCOND
INSC	1.000									
COEFF	-0.397	1.000								
SQ	-0.533	0.672	1.000							
SUB	-0.911	0.544	0.686	1.000						
CRAK	0.972	-0.506	-0.588	-0.960	1.000					
SMSC	-0.964	0.425	0.489	0.935	-0.980	1.000				
EM	0.161	-0.568	-0.244	-0.358	0.331	-0.373	1.000			
CO	0.645	-0.448	-0.279	-0.549	0.718	-0.710	0.551	1.000		
K1	-0.884	0.608	0.709	0.990	-0.957	0.926	-0.454	-0.627	1.000	
VCOND	0.893	-0.610	-0.695	-0.979	0.969	-0.929	0.450	0.676	-0.994	1.000

Table 7.25 SDTD3, STDT4 and MODHYDROLOG Model Performance Coefficients for Canning River

STDT3

Data	ce	bias	ade	rmcc3
	0.546	-0.218	0.535	0.317
Calibration	0.548	-0.215	0.535	0.319
1977-84	0.551	-0.210	0.534	0.322
	0.548	-0.215	0.535	0.319
	0.550	-0.211	0.534	0.321
	0.895	-0.030	0.302	0.792
Calibration	0.847	-0.017	0.330	0.538
1984-87	0.895	-0.025	0.303	0.792
	0.841	-0.017	0.333	0.521
	0.840	-0.019	0.334	0.517
	0.798	0.288	0.402	0.591
Validation	0.796	0.292	0.405	0.588
1984-87	0.790	0.301	0.411	0.580
	0.795	0.293	0.405	0.587
	0.791	0.299	0.410	0.582
	0.503	-0.388	0.557	0.285
Validation	0.281	-0.428	0.657	0.034
1977-84	0.493	-0.389	0.559	0.281
	0.268	-0.430	0.668	0.017
	0.271	-0.432	0.666	0.026

STDT4

Data	ce	bias	ade	rmcc3
	0.990	0.005	0.129	0.959
Calibration	0.991	0.028	0.125	0.888
1977-84	0.992	0.008	0.108	0.928
	0.987	0.033	0.138	0.946
	0.985	-0.008	0.144	0.978
	0.974	0.014	0.135	0.790
Calibration	0.981	-0.062	0.098	0.839
1984-87	0.996	-0.013	0.053	0.860
	0.989	0.065	0.080	0.725
	0.990	0.035	0.069	0.891
	0.751	0.130	0.378	-0.188
Validation	0.938	-0.019	0.200	0.551
1984-87	0.792	0.130	0.342	0.300
	0.868	0.073	0.286	0.246
	0.887	-0.104	0.229	0.468
	0.382	-0.516	0.588	0.194
Validation	0.863	0.179	0.343	0.640
1977-84	0.771	0.181	0.488	0.747
	-0.301	0.762	0.864	0.022
	0.621	0.306	0.448	0.630

MODHYDROLOG

Data	ce	bias	ade	rmcc3
	0.974	-0.043	0.209	0.95
Calibration	0.972	-0.029	0.215	0.939
1978-84	0.972	-0.022	0.218	0.937
	0.971	-0.041	0.213	0.915
	0.97	-0.043	0.226	0.957
	0.986	-0.005	0.121	0.879
Calibration	0.978	-0.017	0.134	0.88
1986-87	0.983	-0.012	0.126	0.876
	0.98	-0.02	0.143	0.912
	0.974	-0.002	0.151	0.866
	0.803	-0.148	0.417	0.747
Validation	-	-	-	-
1986-87	0.8	-0.148	0.419	0.748
	0.784	-0.18	0.428	0.723
	0.785	-0.179	0.427	0.725
	-	-	-	-
Validation	-	-	-	-
1978-84	-	-	-	-
	-	-	-	-
	-	-	-	-

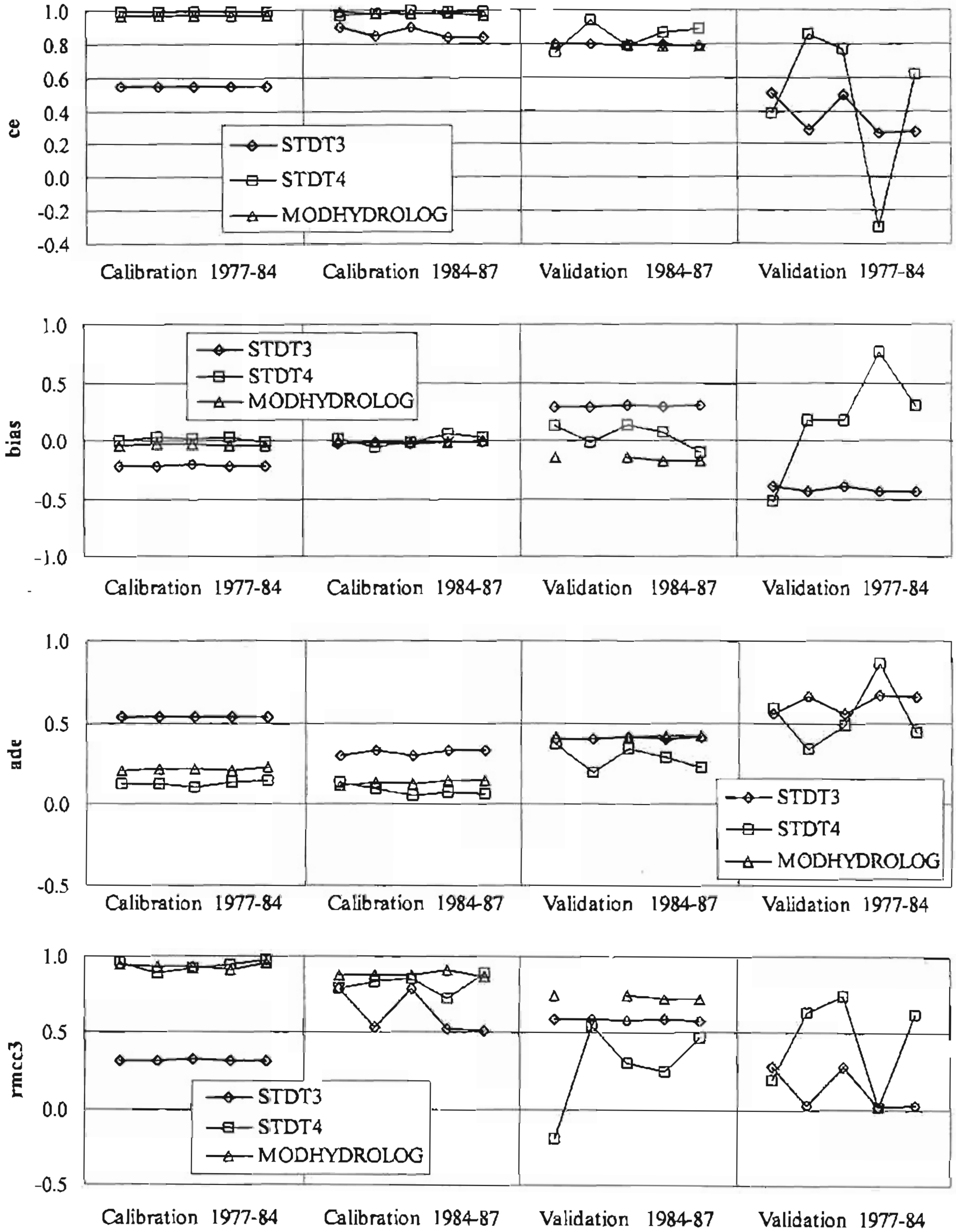


Figure 7.12 SDTD3, STDT4 and MODHYDROLOG Model Performance Coefficients for Canning River

7.5 Discussion

On the basis of the performance coefficients, none of the three models has been determined as superior. MODHYDROLOG failed to simulate some of the peaks of Babinda Creek flows while STDT3 failed to simulate the largest peak of the Canning River flows. No definite failure of the STDT4 was identified but this model had the tendency to give relatively lower residual mass curve coefficients especially in the validations. The MODHYDROLOG performances obtained in this study (Table 7.11, 7.18 and 7.25) compare favourably with those obtained by Chiew and McMahon (1994) with the exception of the 1974-80 Babinda Creek calibrations. The coefficient of efficiency values obtained by Chiew and McMahon (1994) were 0.93, 0.93 and 0.97 for Babinda Creek, Scott Creek and Canning River respectively. The respective bias values for the three catchments were 0.03, 0.02 and 0.03. In Chiew and McMahon's study, a 17 parameter version of MODHYDROLOG was used and the complete data sets were applied in the calibrations. Using the guidelines of Chiew and McMahon (1993c) for assessing streamflow adequacy (Table 6.33), a comparison of the performance of the three models is given in Table 7.26. Table 7.26 is based on 25 calibration-validations: 10 each from Babinda and Scott Creek and five from Canning River. The five split sample tests using the 1984-87 Canning River data for calibration are not used as the data length is considered inadequate especially for MODHYDROLOG. The results of Table 7.26 favour the STDT4 model. It is however recognized that the MODHYDROLOG model version applied in this research used 10 and not all 19 parameters. In addition, the objective function applied in MODHYDROLOG (equation 2.11) was different from that used in the STDT model calibrations (equation 4.15).

The comparative study is in no way exhaustive but shows that at the monthly scale, the STDT models could perform as well and at times even better than the MODHYDROLOG model. The STDT4 model demonstrated versatility by performing satisfactorily in the wet Babinda Creek and the dry Canning River flow simulations. The superior performance of the STDT4 in comparison to the STDT3 is an indicator that some of the additional seven parameters of STDT4 were useful. While the use of all the seven may not be necessary, additional studies would be required to determine which could be set to constant values and which if any could be discarded. As discussed in Section 6.3.4, the removal of parameters *p3*, *p5* and *p6* could be a reasonable step towards reducing the number of the STDT4 model parameters. The basis of selecting the three parameters was:

- the poor identification and correlations of parameter p3; and

- the closeness of parameters p5 and p6, which are indices, to unity.

For the monthly simulations of the STDT4, the same reasons seem to hold good but to a lower degree.

Table 7.26 Comparative Model Performances Using Guidelines from Chiew and McMahon (1993c)

		Calibration		
Model		STDT3	STDT4	MODHYDROLOG
Adequacy	Perfect	5	17	20
	Acceptable	15	8	0
	Generally Satisfactory	0	0	0
	Not Acceptable	5	0	5
		Validation		
Model		STDT3	STDT4	MODHYDROLOG
Adequacy	Perfect	0	1	0
	Acceptable	5	10	12
	Generally Satisfactory	17	12	7
	Not Acceptable	3	2	6

Most of the parameters of the STDT models cannot be correlated directly to the rainfall-runoff process components unlike those of the MODHYDROLOG model. Consequently, manual calibration of the STDT models might be a more difficult task. However comparable level of the validation performances obtained is evidence that at the monthly time step, the STDT models may be capturing these processes just as adequately as the MODHYDROLOG. Although MODHYDROLOG is purported to be physically based (Chiew and McMahon (1994)) it exhibited similar levels of parameter correlations as the STDT models.

A notable difference among the three models was the high disparity in the slow/base flow simulations as the hydrographs (Appendix A7) reveal. In the Scott Creek simulations, the STDT3 model gave much lower slow flows than the STDT4 while MODHYDROLOG gave much higher baseflows than the STDT4 model while MODHYDROLOG gave considerably higher baseflows than the slow flows of the STDT4 model in the Canning River simulations. This observation is a demonstration of the caution that is needed in the application of rainfall-runoff models especially with regards to adequate verification. For instance, in an application requiring baseflow simulations, the verification of the baseflow simulations would be appropriate. As direct baseflow measurements are not practical, the validation could be performed indirectly if other useable data are available. These could be measurements of chemical concentration or groundwater levels within or near the catchment. The use of such data may necessitate modifications of the rainfall-runoff model. This points out to the need for flexibility in practical rainfall-runoff modelling. In addition, all the available data that is considered appropriate to a particular application should be used.

Chapter Eight

Summary, Conclusions and Recommendations

8.1 Summary and Conclusions

8.1.1 Genetic Algorithm Improvements

The traditional genetic algorithm method was improved through an automatic search range variation procedure and the use of independent subpopulation searches coupled with shuffling. The search range variation procedure used two operations: finetuning and hillclimbing. These two procedures gave the genetic algorithm the capability to finetune and to have a more directed search of the promising search space regions. The use of independent subpopulation searches coupled with shuffling gave the genetic algorithm the capability to locate the global optimum in the presence of several regions of attraction in the search space. With all the tests applied, the improved genetic algorithm performed significantly better than the traditional genetic algorithm. The comparative results of the traditional and the improved genetic algorithm can be summarized as follows:

- The improved genetic algorithm achieved up to 98 percent success in the location of the known global optimum of a synthetic data-based calibration problem using the 6-parameter SIXPAR rainfall-runoff model. The traditional genetic algorithm applying the same population size did not achieve even a single success.
- The improved genetic algorithm attained 100 percent success in locating the global optimum of the Hartman function while the traditional genetic algorithm applying the same population size achieved 11 percent success.
- The improved genetic algorithm achieved 97 percent success in the global optimization of the Griewank function while the traditional genetic algorithm of the same population size did not attain even a single success.

- The improved genetic algorithm consistently gave better objective function values in the calibration of the 7-parameter simple time domain tuned rainfall-runoff model 3 (STDT3) than the traditional genetic algorithm. The STDT3 model was developed in this study and applied to two 8-year long historical data sets. Two hundred runs with each of the two data sets gave very close objective function values indicating the improved genetic algorithm had practically located the global optimum.
- Using a 14-parameter rainfall-runoff model, calibrations with the improved genetic algorithm obtained validation runoff series with higher coefficients of efficiency, lower absolute deviations and better consistency than calibrations applying the traditional genetic algorithm. The 14-parameter model, the simple time domain tuned model 4 (STDT4) was developed in this study and applied historical data from three Australian catchments in the genetic algorithm tests. Better parameter identifications were also obtained with the improved genetic algorithm than with the traditional genetic algorithm.

In the STDT4 model calibrations, the variability of the optimized objective function values was evidence that the global optima were not consistently obtained. This part of the study was however aimed at studying the STDT4 model performance and not testing the capability of the genetic algorithm locating the global optima. It is expected that with tuning of the optimization parameters, the improved genetic algorithm can locate precisely the global optima in the STDT4 model calibrations as was achieved with the STDT3 model, the SIXPAR model, the Griewank function and the Hartman function.

The sensitivity analysis of the performance of the improved genetic algorithm to various optimization parameters using the SIXPAR model global optimum location problem and the objective function value based STDT3 model problem found:

- the expected improvement of performance with an increase in the allowed number of function evaluations;
- the expected improvement of performance with an increase in the number of subpopulations applied;
- the performance of the improved genetic algorithm to be highly sensitive to the probability of crossover with crossover probabilities of 0.8 and 1.0 giving better performances than lower ones;
- the improved genetic algorithm performance to be insensitive to the number of crossover positions and the rate of uniform crossover; and

- the improved genetic algorithm performance to be sensitive to the probability of mutation with the SIXPAR problem but not with the STDT3 problem.

With the appropriate values of optimization parameters, the improved genetic algorithm can be depended upon for the global optimum location in rainfall-runoff model calibration while the traditional genetic algorithm cannot. The unsatisfactory results of the traditional genetic algorithm concurred with the findings of Wang *et al* (1995), Tanakamaru and Burges (1996) and Kuczera (1997). The results obtained with the improved genetic algorithm confirmed the suggestion by Kuczera (1997) that the genetic algorithm can be improved for rainfall-runoff model calibration. To obtain the appropriate optimization parameter values for effective global optimum location, trial runs and information from previous studies may be needed.

For practical modelling applications where the calibrated model parameters are applied to generate runoff data, the quality of the generated runoff series is more important than the precise location of the global optimum. The results obtained in the tests using the STDT4 model indicated that the use of the improved genetic algorithm would still be preferred to the traditional genetic algorithm for such applications.

8.1.2 Comparison of the Improved Genetic Algorithm with Other Optimization Methods

Compared with the shuffled complex evolution (SCE-UA) method, the improved genetic algorithm (GA) was as effective in locating the global optima of the SIXPAR calibration, the Hartman function and the Griewank function with success levels exceeding 95 percent being achieved with the three problems. The efficiency, of the improved genetic algorithm, quantified by the average number of function evaluations used in locating the global optima was lower than that of the SCE-UA with the SIXPAR and the Griewank problems and higher with the Hartman problem. With the SIXPAR problem, the Griewank problem and the Hartman problem, the improved genetic algorithm took about 2 times more, 25 times more and 3 times less than the average number of function evaluations used by the SCE-UA method respectively.

The comparative random search (CRS-2) method successfully located the global optima of the SIXPAR problem with about two times less the number of function evaluations taken by the improved GA. The CRS-2 method however only achieved 70 percent success with about four times the number of function evaluations used by the improved GA with the Hartman function. With the Griewank problem, the CRS-2 achieved 90 percent success with nine times less the number of evaluations than with which the improved GA achieved 97 percent success.

The Multi start simplex (MSX) method took about one and a half times more function evaluations than the improved GA with the SIXPAR problem for the same success levels. The MSX failed totally to locate the global optimum of the Griewank function but performed almost as efficiently as the improved GA with the Hartman problem.

On the average, the SCE-UA performed better than the improved GA and the other methods and would be preferred for the optimization of unfamiliar continuous variable optimization problems. The results however showed that the performance of an optimization method is problem dependent as none of the methods turned out superior for all the problems. Where resources allow, the application of more than a single optimization method may therefore be appropriate. Combination of optimization processes will obviously be an area of further research.

8.1.3 Conceptual-Empirical Model Development

The stepwise development of a class of simple conceptual-empirical rainfall-runoff models was undertaken applying the genetic algorithm and two 8-year long split data sets from a typical South Australian catchment. The split-sample calibration-validation approach was used. The models were termed as simple time domain tuned (STDT) models owing to their greater bias towards the time domain than is customary in conceptual rainfall-runoff modelling. The STDT modelling applied a pseudoweekly time step dividing the year into 60 6-day long and a few 7-day long periods. The 7-parameter STDT3 and the 14-parameter STDT4 model were considered to perform acceptably while the other two, the STDT1 and the STDT2 gave unacceptably poor performances for practical applications but were useful in the stepwise model development.

The STDT3 and STDT4 models compute the total flow in a period as the sum of a slow flow and a quick flow. The slow flow is determined from the sum of weighted past net rainfalls to a past period obtained through calibration. A coefficient that takes on different values depending on the state of catchment wetness is then used in the computation of the current quick flow from the current net rainfall. The STDT3 model uses two catchment wetness states; the dry and the wet state while the STDT4 model uses three catchment wetness states; the very wet, the wet and the dry state. The antecedent catchment wetness values at which the wetness state changes are obtained through calibration. In addition, STDT4 uses four indices to model the rainfall-runoff process nonlinearlities. The four indices are parameters obtained through calibration.

An analysis of the STDT4 model using split-sample calibration-validation and data from two other Australian and three Kenyan catchments obtained variable performances. The STDT4 was considered to have successfully modelled flows from five of the six catchments but failed to model one of the Kenyan catchments. The STDT4 modelled both the wet and the dry Australian catchment flows successfully and achieved consistent flow separations in multiple runs.

Using guidelines for assessing the adequacy of streamflow estimates for typical hydrology and water resources studies (Chiew and McMahon (1993c)), 97 percent of the calibrations and 55 percent of the validations were assessed as successful to varying levels of adequacy. This analysis included the five catchments whose modelling was considered successful. The failure to model one of the Kenyan catchments could be attributed to model structure inadequacy, to poor data quality, or both. The STDT4 modelling of the other Kenyan flows was also poorer than that of the Australian flows. This was attributed to the poorer data quality of the Kenyan catchments.

8.1.4 Comparison of the STDT3, the STDT4 and the MODHYDROLOG Model

The STDT3 and the STDT4 model were found to compare favourably with a 10-parameter version of a commonly used daily rainfall-runoff model, MODHYDROLOG in the simulation of monthly flows. The comparative study used data from three Australian catchments and the split-sample calibration-validation approach was applied. On the average, the STDT4 performed better than the STDT3 and the MODHYDROLOG. The STDT3 failed to simulate the peaks of the driest catchment flows while MODHYDROLOG overestimated some of the peaks of the flows from the wettest catchment. Using the guidelines of Chiew and McMahon (1993c), the success levels to varying levels of adequacy in the calibrations were 83, 100 and 83 percent for the STDT3, the STDT4 and the MODHYDROLOG respectively. The success levels in the validations were 88, 92 and 76 percent for the STDT3, the STDT4 and the MODHYDROLOG respectively. Although more tests of the STDT4 model are necessary, the results indicate the model may just be as adequate or superior to the MODHYDROLOG for monthly flow simulations.

Although the 14-parameter STDT4 performed better than the 7-parameter STDT3, the large number of parameters of the STDT4 was considered a drawback. An analysis of the STDT4 model parameter values, their identification and correlations singled out three that could probably be removed without degradation of model performance.

8.2 Recommendations

It is recommended that more tests on the improved genetic algorithm be undertaken for a more comprehensive evaluation of its capability. Additional comparative studies of the improved genetic algorithm and other optimization methods would be appropriate. Modifications of the improved genetic algorithm method should focus on improving the efficiency. As an initial step, the application of other forms of coding such as gray, integer or real number should be considered. Binary coding was used in this research.

With binary or gray coding, the improved genetic algorithm could have good potential for optimization problems having both continuous and discrete decision variables. An investigation of the applicability and performance of the improved genetic algorithm in the optimization of such problems would be appropriate. In such an application, the discrete variables could be subjected to hillclimbing alone and the continuous variables to both finetuning and hillclimbing.

An investigation of the impact on performance of the two range variation operations is recommended. A small number of trials in this study seemed to indicate that the finetuning operation was more important to the overall performance of the genetic algorithm than hillclimbing.

A comprehensive comparison of Duan's shuffling and the overlapping shuffling approach is recommended. Although most of the optimizations in the current study applied Duan's approach, some trials indicated that the overlapping approach could be as effective or at times more effective.

Further studies of the performance of the STDT4 conceptual-empirical model are recommended. This could be undertaken using more data of varying characteristics. Some of the data should be obtained from catchments of similar characteristics to Noigameget, the Kenyan catchment that the STDT4 model failed to simulate. The unique characteristics of Noigameget were swampy valleys and high evapotranspiration losses. An attempt to model the Noigameget catchment flows with another rainfall-runoff model is recommended. This would be a step forward in establishing the cause of the STDT4 failure in modelling the Noigameget flows.

The studies could also include an investigation of the effect of using different objective functions as the research reported here applied only one form of objective function. The studies could also consider further improvements of the STDT4 including a reduction of the number of model parameters as an objective. A study of the effect of the calibration data length on model performance is an appropriate area for further research. Such a study could establish the required minimum data length for an adequate identification of the optimum parameter sets.

The STDT4 model seemed to obtain reasonable slow flows and the potential of STDT4 for baseflow separation at the pseudoweekly and longer time steps could therefore be investigated.

The reasonable performance of the STDT models indicates there could be value in a greater focus of the time domain in catchment modelling. A potential area of application could be the study of pollutant or salt transport at the catchment scale.

References

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E., and Rasmussen, J., An Introduction to the European Hydrological System - Systeme Hydrologique Europeen, "SHE", 1. History and Philosophy of a Physically - Based Distributed Modelling System, *J. Hydrol.*, 87, 45-59, 1986a.

Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E., and Rasmussen, J., An Introduction to the European Hydrological System - Systeme Hydrologique Europeen, "SHE", 2: Structure of a Physically-Based, Distributed System, *J. Hydrol., 87,* 61-77, 1986b.

Aitken, A. P., Assessing Systematic errors in Rainfall-Runoff models, *J. Hydrol.*, 20, 121-136, 1973.

Ambroise, B., Freer, J., and Beven, K., Application of a generalized TOPMODEL to the small Ringelbach catchment, Vosges, France, *Water Resour. Res.*, 32(7), 2147-2159, 1996.

Arnold, J. G., Allen, P. M., and Bernhardt, G., A comprehensive Surface-Groundwater flow Model, *J. Hydrol.*, 142, 47-69, 1993.

Arnold, J. G., and Williams, J. R., Validation of SWRRB-Simulator for Water Resources in Rural Basins, *J. Water Resour. Plann. Manag.*, ASCE, 113(2), 243-256, 1987.

Bäck, T., *Evolutionary Algorithms in Theory and Practice*, Oxford Univ. Press, New York, 314pp., 1996.

Bates, B. C., Calibration of the SFB model using a Simulated Annealing Approach, *Proc. Int. Hydrol. and Water Resour. Symp.*, Adelaide Vol.3, 1-6, 1994.

Bathurst, J. C., Physically Based Distributed Modelling of an Upland Catchment using the Systeme Hydrologique Europeen, *J. Hydrol.*, 87, 79-102, 1986.

Beasley, D. B., Huggins, L. F., and Monke, E. J., ANSWERS: A Model for Watershed Planning, *Trans. Am. Soc. Agric.* 23(4), 938-944, 1980.

Beck, M. B., Kleissen, F. M., and Wheater H. S., Identifying flow paths in models of surface water acidification, *Reviews of Geophysics*, 28(2), 207-230, 1990.

Beven, K. J., and Kirkby, M. J., A physically Based, Variable Contributing Area Model of Basin Hydrology, *Hydrol. Sciences*, 24(1), 43-69, 1979.

Beven, K. J., Claver, A., and Morris, E. M., *The Institute of Hydrology Distributed Model*, Wallingford (UK), Rep. 81, 1987.

Beven, K., Changing Ideas in Hydrology - The case of Physically Based Models, *J. Hydrol.*, 105, 157-172, 1989.

Beveridge, G. S. G., and Schechter, R. S., *Optimization: Theory and Practice*, McGraw-Hill, New York, 1970.

Boughton, W. C., A Hydrograph Based Model for Estimating the Water Yield of Ungauged Catchments, *Int Hyrol. and Water Resour. Symp.*, Newcastle, Vol. 1, 317-324, 1993.

Boughton, W. C., A Mathematical Model for Estimating Runoff, *J. Hydrol.* (NZ), 7(2), 75-100, 1968.

Boughton, W. C., A Mathematical Model for Relating Runoff to Rainfall with Daily Data, *Civil Eng. Trans. IEAust.*, CE8(1), 83-97, 1966.

Boughton, W. C., A Simple Model for Estimating the Water Yield of Ungauged Catchments, *Civil Eng. Trans., IEAust.*, CE26(2), 83-88, 1984.

Burnash, R. J. C., Ferral, R. L., and McGuire, R. A., A generalized streamflow simulation system: conceptual models for digital computers, Joint Federal-State River Forecasting Centre, Sacramento, USA, 1973.

Chiew, F. H. S., and McMahon, T. A., Assessing the quality of catchment streamflow yield estimates, *Aust. J. Soil. Res.*, 1993c.

Chiew, F. H. S., and McMahon, T. A., Australian Data for Rainfall-Runoff Modelling and the Calibration of Models against Streamflow Data Recorded over Different Time Periods, *Civil Eng. Trans., IEAust.*, CE35(3), 261-274, 1993a.

Chiew, F. H. S., and McMahon, T. A., *Complete set of Daily Rainfall, Potential Evapotranspiration and Streamflow Data for Twenty Eight Unregulated Australian Catchments,* Centre for Environ. Appl., Hydrol., Univ. of Melbourne, 1993b.

Chiew, F. H. S., and McMahon, T. A., Estimating Groundwater Recharge using a Surface Watershed Modelling Approach, *J. Hydrol.*, 114, 285-304, 1990.

Chiew, F. H. S., Stewardson, M. J., and McMahon, T. A., Comparison of six Rainfall-Runoff modelling Approaches, *J. Hydrol.,* 147, 1-36, 1993.

Chiew, F. H. S., and McMahon, T. A., Application of the Daily Rainfall-Runoff Model MODHYDROLOG to 28 Australian Catchments, *J. Hydrol.*, 153, 383-416, 1994.

Cohoon, J. P., Hegde, S. U., Martin, W. N., Richards, D. S., Distributed Genetic Algorithm for the Floorplan Design Problem, *IEEE. Trans. on Computer-Aided Design,* 10(4), 483-492, 1991.

Cohoon, J. P., Hegde, S. U., Martin, W. N., Richards, D. S., Punctuated Equilibria: A parallel Genetic Algorithm, in *Proc., Second Int. Conf. on Genetic Algorithms and Their Applications*, Boston, USA, 155-161, 1987.

Crawford, N. H., and Linsley, R. K., *Digital Simulation in Hydrology: Stanford Watershed Model IV,* Technical Report No. 39, Dept. of Civil Eng., Stanford Univ., 1966.

Dandy, G. C., Simpson, A. R., and Murphy, L. J., An Improved Genetic Algorithm for Pipe Network Optimization, *Water Resour. Res.*, 32(2), 449-458, 1996.

Danish Hydraulic Institute (DHI), MIKE11 short description, 1994.

Davis, L. (Ed.), *Handbook of Genetic Algorithms*, Van Nostrand Reinhold, New York, 1991.

Dejong, K, A., Analysis of the Behaviour of a Class of Genetic Adaptive Systems, *PhD Dissertation,* Dept. of Comp. and Comm. Sci., Univ. of Michigan, USA, 1975.

Demetriou, C., and Panthakey, J. F., Integrated Hydrogeological Model Development for the Wakool Irrigation District, *Proc., MODSIM 97, Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Hobart, Vol. 1, 323-328, 1997.

Dietrich, C. R., and Jakeman, A. J., A Model for Stream Sediment Transport with Application to Murray and Murrumbidgee River Reaches, *Proc., MODSIM 97, Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Hobart, Vol. 1, 329-334, 1997.

Diskin, M. H., and Simon, E., A procedure for the selection of objective functions for hydrologic simulation models, *J. Hydrol.*, 34, 129-149, 1977.

Donne, M. S., Tilley, D. G., and Richard's, W., The use of Multi-objective Parallel Genetic Algorithms to aid Fluid Power System Design, *Proc., Inst. Mech. Engrs.* 209, 53-61, 1995.

Duan, Q. Y., Gupta, V. K., and Sorooshian, S., Shuffled Complex Evolution for Effective and Efficient Global Minimization, *J. Optim. Theory and Appl.*, 76(3), 501-521, 1993.

Duan, Q., Sorooshian, S., and Gupta, V., Effective and Efficient Global Optimization for Conceptual Rainfall-Runoff Models, *Water Resour. Res.*, 28(4), 1015-1031, 1992.

Duan, Q., Sorooshian, S., and Gupta, V., Optimal use of the SCE-UA global optimization method for calibrating watershed models, *J. Hydrol.*, 158, 265-284, 1994.

Eshelman, L. J., Caruana, A. R., and Schaffer, D. J., Biases in the Crossover Landscape, In Schaffer, D, J., (Ed.), *Proc., Third Int. Conf. on Genetic Algorithms*, George Mason Univ., USA, 10-19, 1989.

Fletcher, R., and Powell, M. J. D., A rapidly convergent descent method for minimization, *Comput. J.*, 6, 163-168, 1963.

Franchini, M., and Pacciani, M., Comparative Analysis of Several Conceptual Rainfall-Runoff Models, *J. Hydrol.*, 122, 161-219, 1991.

Franchini, M., Wendling, J., Obled, C., and Todini, E., Physical interpretation and sensitivity analysis of the TOPMODEL, *J. Hydrol.*, 175, 293-338, 1996.

GALESIA, *Proc., First Int. Conf. on Genetic Algorithms in Engineering Systems: Innovations and Applications*, Sheffield, UK, 1995.

Gan, T. Y., and Biftu, G. F., Automatic calibration of rainfall-runoff models: Optimization algorithms, catchment conditions, and model structure, *Water Resour. Res.*, 32(12), 3513-3524, 1996.

Gan, T. Y., and Burges, S., An Assessment of a Conceptual Rainfall-Runoff Model's Ability to Represent the Dynamics of Small Hypothetical Catchments 1. Models, Model Properties, and Experimental Design, *Water Resour. Res.* 26(7), 1595-1604, 1990.

Gao, J., and Merrick, N. P., Dissolved Oxygen Stratification Modelling for Shallow Aquaculture Ponds, *Proc., MODSIM 97, Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Hobart, Vol. 1, 341-345, 1997.

Goldberg, D. E., *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison Wesley, 1989.

Grayson, R. B., and Chiew, F. H. S., An Approach to Model Selection, *Proc. Int. Hydrol. and Water Resour. Symp.*, Adelaide, Vol.1, 507-512, 1994.

Grayson, R. B., and Nathan, R. J., On the role of Physically Based Models in Engineering Hydrology, *Inst. Eng. Aust. Nat. Conf. Publ.* 93/2 Melbourne, 45-50, 1993.

Grayson, R. B., Moore, I. D., and McMahon, T. A., Physically Based Hydrologic Modeling 2. Is the Concept Realistic?, *Water Resour. Res.*, 28(10), 2659- 2666, 1992a.

Grayson, R. B., Moore, I. D., and McMahon, T. A., Physically Based Hydrologic Modeling 1. Terrain -Based Model for Investigative Purposes, *Water Resour. Res.*, 28(10), 2639-2658, 1992b.

Grayson, R. B., Terrain Based Hydrologic Modelling for Erosion Studies, *PhD Thesis*, Univ. of Melbourne, 1990.

Gupta, V. K., and Sorooshian, S., The Automatic Calibration of Conceptual Catchment Models Using Derivative-Based Optimization Algorithms, *Water Resour. Res.*, 21(4), 473-485, 1985.

HalHal, D., Walters, G. A., Ouazar, D., and Savic, D. A., Water Network Rehabilitation with Structured Messy Genetic Algorithm, *J. Water Resour. Plann. and Manag.*, ASCE., 123(3), 137-146, 1997.

Hassanli, A. M., and Dandy, G. C., Optimal Layout Model for Pressure Irrigation Systems using Genetic Algorithms, Dept. of Civil and Environ. Eng., *Research Report No.* R 123, Univ. of Adelaide, 1994.

Hendrickson, J. D., Sorooshian, S., and Brazil, L. E., Comparison of Newton - Type and Direct Search Algorithms for Calibration of Conceptual Rainfall-Runoff Models, *Water Resour. Res.*, 24(5), 691-700, 1988.

Hirayama, K., Kawai, H., and Tatano, H., A hybrid Genetic Algorithm for a Single Reservoir Operation Optimization Model with Multiple Reliability Constraints, *Proc. Int. Conf. on Water Resour. and Environ. Res.*, Kyoto, Japan, Vol. 2, 47-54, 1996.

Holland, J. H., *Adaptation in Natural and Artificial Systems*, Univ. of Michigan Press, Arbor, 183pp., 1975.

Hooke, R., and Jeeves, T. A., Direct search solutions of numerical and statistical problems, *J. Assoc. Comput. Mach.*, 8(2), 212-229, 1961.

Hornberger, G. M., Beven, B. J., Cosby, B. J., and Sappington, D. E., Shenandoah Watershed Study: Calibration of a Topography-Based, Variable Contributing Area Hydrological Model to a Small Forested Catchment, *Water Resour. Res.*, 21(12),1841-1850, 1985.

Hughes, D. A., and Sami, K., A Semi-distributed, Variable Time Interval Model of Catchment Hydrology - Structure and Parameter Estimation Procedures, *J. Hydrol.*, 155, 265-291, 1994.

Hughes, D. A., Soil Moisture and Runoff Simulations using four Catchment Rainfall-Runoff Models, *J. Hydrol.*, 158, 381-404, 1994.

Jakeman, A. J., and Hornberger, G. M., How much Complexity is Warranted in a Rainfall-Runoff Model?, *Water Resour. Res.*, 29(8), 2637-2649, 1993.

Jakeman, A. J., Green, T. R., Dietrich, C. R., Zhang, L., Beavis, S. G., and Crapper, P. F., A Modelling Framework for Erosion, Sediment and Nutrient Transport from Catchment to Basin Scale, *Proc., MODSIM 97, Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Hobart, Vol. 1, 354-361, 1997.

Jakeman, A. J., Littlewood, I. G., and Whitehead, P. G., Computation of the Instantaneous Hydrograph and identifiable Component flows with application to two small upland Catchments, *J. Hydrol.*, 117, 275-300, 1990.

Johnston, P. R., and Pilgrim, D. H., Parameter Optimization for Watershed Models, *Water Resour. Res.*, 12(3), 477-486, 1976.

Kachroo, R. K., River flow forecasting, 5, Applications of a conceptual model, *J. Hydrol.*, 133, 141-178, 1992.

Kirkpatrick, S., Gellat, C. D., and Vecchi, M. P., Optimization by Simulated Annealing, *Science*, 220, 671-680, 1983.

Kleissen, F. M., Beck, M. B., and Wheater H. S., Identifiability of conceptual hydrochemical models, *Water Resour. Res.*, 26(2), 2979-2992, 1990.

Knudsen, J., Thomsen, A., and Refsgaard, J. C., WATBAL: A semi-distributed, physically based hydrological modelling system, *Nordic Hydrol.*, 17, 347-362, 1986.

Kuczera, G., Efficient subspace probabilistic parameter optimization for catchment models, *Water Resour. Res.*, 33(1), 177-185, 1997.

Kuczera, G., *Fitting and testing Mathematical Hydrologic Models: A User Manual for Program NLFIT*, Dept. of Civil Engineering and Surveying, Univ. of Newcastle, 1987.

Kuczera, G., Improved Parameter Inference in Catchment Models 1. Evaluating Parameter Uncertainty, *Water Resour. Res.*, 19(5), 1151-1162, 1983.

Kuczera, G., The Soil Dryness Index Streamflow Yield Model: An Overview of Its Development and Capabilities, *Hydrol. and Water Resour. Symp.*, A.N.U., Canberra, 103-107, 1988.

Kwong, S., Ng, A. C., and Man, K. F., Improving Local Search in Genetic Algorithms for Numerical Global Optimization Using Modified GRID-point Search Technique, *Proc. First IEE/IEEE Conf. on Genetic Algorithms in Engineering Systems: Innovations and Applications*, Sheffield, UK, 419-423, 1995.

Laurenson, E. M., and Mein, R. G., RORB-Version 4 Runoff Routing Program User Manual, Dept. of Civil Eng., Monash Univ., Australia, 186 pp., 1990.

Liong, S. Y., Chan, W. T., and Khu, S. T., Application of Genetic Algorithm and Neural Network in Catchment Model Calibration, *Proc. Int. Conf. on Water Resour. and Environ. Res.*, Kyoto, Japan, Vol. 2, 67-83, 1996.

Liong, S. Y., Chan, W. T., and ShreeRam, J., Peak-Flow Forecasting with Genetic Algorithm and SWMM, *J. Hydr. Eng.*, ASCE., 121(8), 613-617, 1995.

Mahfoud, S. W., Nitching methods for Genetic Algorithms, *IliGAL Report No.* 95001, Univ. of Illinios, 1995.

Marquardt, D. W., An algorithm for the least squares estimation of nonlinear parameters, *SIAM J. Appl. Math.*, 11, 431-441, 1963.

McDonald, A. D., and McAleer, M., (Eds.), *MODSIM* 97., *Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Hobart, 1901 pp., 1997.

Michaud, J., and Sorooshian, S., Comparison of simple versus complex distributed runoff models on a midsized semiarid watershed, *Water Resour. Res.*, 30(3), 593-605, 1994.

Miller, B. L., and Shaw, M. L., Genetic Algorithms with Dynamic Niche Sharing for Multimodal Function Optimization, *illiGAL Report No.* 95010, Dept. of General Eng., Univ. of Illinois, USA, 1995.

Mohan, S., Parameter Estimation of Nonlinear Muskingham Models using Genetic Algorithm, *J. Hydra.*, ASCE., 123(2), 137-142, 1997.

Monteith, J. L., Evaporation and Environment, in *The State and Movement of Water in Living Organisms, Proc. Fifteenth Symp.*, Soc. for Exp. Biol., Swansea, Cambridge Univ. Press, 205-234, 1965.

Morton, F. I., Operational Estimates of Areal Evapotranspiration and their Significance to the Science and Practice of Hydrology, *J. Hydrol.*, 66, 1-76, 1983.

Mudgway, L. B., Nathan, R. J., McMahon, T. A., and Malano, H. M., Application of the SHE Model to an Irrigated area Subject to Saline Groundwater Discharge. *Int. Hydrol. and Water Resour. Symp.*, Adelaide, Vol. 1, 591-594, 1994.

Mühlenbein, H., Schomisch, M., and Born, J., The Parallel Genetic Algorithm as Function Optimizer, *Parallel Computing*, 17, 619-632, 1991.

Murphy, L. J., Simpson, A. R., and Dandy, G. C., Pipe Network Optimization Using an Improved Genetic Algorithm, Dept. of Civil and Environ. Eng., *Research Report No.* R 109, Univ. of Adelaide, 1993.

Nandarkumar, N., and Mein, R. G., Calibration of a Rainfall-Runoff Model in Forested and Pasture Catchments, *Int. Hydrol. and Water Resour. Symp.*, Adelaide, Vol. 3, 481-484, 1994.

Nash, J. E., and Sutcliffe, J. V., River Flow Forecasting Through Conceptual Models Part I - A discussion of Principles, *J Hydrol., 10,* 282-290, 1970.

Nathan, R. J., and McMahon, T. A., The SFB model. part I. Validation of fixed model parameters, *Aust. Civ. Eng. Trans.*, 32(3), 157-161, 1990.

Nelder, J. A., and Mead, R., A simplex method for function minimisation, *Comput. J.*,7(4), 308-313, 1965.

Ndiritu, J. G., and Daniell, T. M., A Simple Time Domain Tuned Rainfall-Runoff Model Optimized Using Genetic Algorithms, *Proc., Twenty third Hydrol. and Water Resour. Symp.*, Hobart, Australia, 711-713, 1996.

Ndiritu, J. G., and Daniell, T. M., An Improved Genetic Algorithm for Rainfall-Runoff Model Calibration and Function Optimization, *Proc., MODSIM 97, Int. Congress on Modell. and Simul.,* Modell. and Simul. Soc. of Aust., Hobart, Vol. 4, 1689-1694, 1997.

Ndiritu, J. G., and Daniell, T. M., Time domain tuned rainfall-runoff models optimized using genetic algorithms, in Zannetti, P., and Brebbia, C. A., (Eds.), *Proc., Int. Conf. on Dev. and appl. of Comp. Techniques to Env. studies,* Comp. Mech. Publ., Southampton, Boston, 268-275, 1996.

O'Connell, P. E., and Todini, E., Modelling of rainfall, flow and mass transport in hydrological systems: an overview, *J. Hydrol.*, 175, 3-16, 1996.

O'Loughlin, E. M., Prediction of Surface Saturation Zones in Natural Catchments by Topographic Analysis, *Water Resour. Res.*, 22(5), 7794-804, 1986.

Obled, C., Wendling, J., and Beven, K., The sensitivity of hydrological models to spatial rainfall patterns: an evaluation using observed data, *J. Hydrol.*, 159, 305-333, 1994.

Pettey, C. B., Leuze, M. R., and Grefenstette, J. J., A Parallel Genetic Algorithm, in *Proc., Second Int. Conf. on Genetic Algorithms and Their Applications*, Boston, USA, 155-161, 1987.

Pinter, J. D., *Global Optimization in Action, Continuous and Lipschitz Optimization: Algorithms, Implementations and Applications,* Kluwer Acad., Netherlands, 1996.

Powell, M. J. D., An Efficient Method for Finding the Minimum of a Function of Several Variables Without Calculating Derivatives, *Comput. J.*, 7, 155-162, 1964.

Price, W. L., Global Optimization by Controlled Random Search, *J. Optim. Theory and Appl.*, 40(3), 333-348, 1983.

Raper, G. P., and Kuczera, G., Groundwater recharge estimation using a lumped-parameter catchment process model, *First Int. Hydrol. and Water Resour. Symp.*, Perth, Inst. Eng. Aust., Canberra, Nat. Conf. Publ., 91/22: 563-568, 1991.

Refsgaard, J. C., and Knudsen, J., Operational validation and intercomparison of different types of hydrological models, *Water Resour. Res.*, 32(7), 2189-2202, 1996.

Refsgaard, J. C., Parametirisation, calibration and validation of distributed hydrological models, *J. Hydrol.*, 198, 69-97, 1997.

Rogers, C. C. M., Beven, K. J., Morris, E. M., and Anderson, M. G., Sensitivity Analysis, Calibration and Predictive Uncertainty of the Institute of Hydrology Distributed Model, *J. Hydrol.*, 81, 179-191, 1985.

Rosenbrock, H. H., An automatic method for finding the greatest or least value of a function, *Comput. J.*,3, 175-184, 1960.

Rutter, A. J., Kershaw, K. A., Robins, P. C., and Morton, A. J., A Model of Rainfall Interception in Forests, 1. Derivation of the Model from Observations in a Plantation of Corsican Pine, *Agric. Meteorol.*, 9, 367-384, 1971/72.

Savic, D. A., and Walters, G. A., Genetic Algorithms for Least-Cost Design of Water Distribution Networks, *J. Water Resour. Plann. and Manag.*, ASCE., 123(2), 1997.

Schaffer, D, J., (Ed.), *Proc., Third Int. Conf. on Genetic Algorithms*, George Mason Univ., USA, 51-60, 1989.

Schaffer, D. J., Caruana, R. A., Eshelman, L. J., and Rajarshi, D., A Study of Control Parameters Affecting Online Performance of Genetic Algorithms, In Schaffer, D, J., (Ed.), *Proc., Third Int. Conf. on Genetic Algorithms*, George Mason Univ., USA, 51-60, 1989.

Sellers, P. J., Mintz, Y., Sud, Y. C., and Dalcher, A., A Simple Biosphere Model (SiB) for use within general circulation Models, *J. Atmos. Sci.*, 43: 503-531, 1991.

Simpson, A. R., Dandy, G. C., and Murphy, L. J., Genetic Algorithms compared to other Techniques for Pipe Optimization, *J. Water Resour. Plann. and Manag.*, ASCE., 120(4), 423-443, 1994.

Simpson, A. R., and Goldberg, D. E., Pipe optimisation via genetic algorithms: from theory to practice, *Second Int. Conf. on Pipeline Systems*, Edinburgh, Scotland, 1994.

Singh, V. P. (Ed.), *Computer Models for Watershed Hydrology*, Water Resour. Publications, U.S.A., 1130 p, 1995.

Sivapalan, M., and Viney, M. R., Large scale catchment modelling to predict the effects of landuse changes, *Water J.*, 21(1), 33-37, 1994.

Smith, R. E., and Hebbert, R. H. B., Mathematical Simulation of Interdependent Surface and Subsurface Hydrologic Processes, *Water Resour. Res.*, 19(4), 987-1001, 1983.

Sorooshian, S., and Dracup, J. A., Stochastic Parameter Estimation Procedures for Hydrologic Rainfall-Runoff Models: Correlated and Heteroscedastic Error Cases, *Water Resour. Res.*, 16(2),430-442, 1980.

Sorooshian, S., and Gupta, V. K., Automatic Calibration of Conceptual Rainfall-Runoff Models: The Question of Parameter Observability and Uniqueness, *Water Resour. Res.*, 19(1), 260-268, 1983.

Sorooshian, S., Duan, Q., and Gupta, V. K., Calibration of Rainfall-Runoff Models: Application of Global Optimization to the Sacramento Soil Moisture Accounting Model, *Water Resour. Res.*, 29(4), 1185-1194, 1993.

Sorooshian, S., Gupta, V. K., and Fulton, J. L., Evaluation of Maximum Likelihood Parameter Estimation Techniques for Conceptual Rainfall-Runoff Models: Inference of Calibration Data Variability and Length on Model Credibility, *Water Resour. Res.*, 19(1), 251-259, 1983.

Sorooshian, S., Parameter Estimation of Rainfall-Runoff Models with Heteroscedastic Streamflow errors - The Noninformative Data Case, *J. Hydrol.*, 52, 127-138, 1981.

Stephenson, D., and Paling, W. A. J., A Hydraulically Based Model for Simulating Monthly Runoff and Erosion, *Water SA*, 18(1), 1992.

Sugawara, M., Watanabe, I., Ozaki, E., and Katsuyame, Y., *Reference Manual for the TANK Model,* Nat. Res. Center for Disaster Prevention, Tokyo, 1983.

Sukvanachaikul, Y., and Laurenson, E. M., An Improved Rainfall-Runoff Model for Semi-arid Regions, *Hydrol. and Water Resour. Symp.*, Hobart, 108-112, 1983.

Syswerda, G., Uniform Crossover in Genetic Algorithms, In Schaffer, D, J., (Ed.), *Proc., Third Int. Conf. on Genetic Algorithms*, George Mason Univ., USA, 2-9, 1989.

Törn, A., and Zilinskas, A., *Global Optimization,* Lecture Notes in Computer Science 350, Springer-Verlag, Germany, 255pp., 1989.

Tanakamaru, H., and Burges, S. J., Application of Global Optimization to Parameter Estimation of the TANK Model, *Proc. Int. Conf. on Water Resour. and Environ. Res.*, Kyoto, Japan, Vol. 2, 39-46, 1996.

Tanesse, R., Parallel Genetic Algorithm for a Hypercube, in *Proc., Second Int. Conf. on Genetic Algorithms and Their Applications,* Boston, USA, 177-183, 1987.

Todini, E., Rainfall-Runoff Modelling - Past, Present and Future, *J. Hydrol.,* 100, 341-352, 1988.

Tomassini, M., The Parallel Genetic Cellular Automata: Application to Global Function Optimization, in Albrecht, R. F., Reeves, C. R., and Steele, N. C., (Eds.), *Artificial Neural Nets and Genetic Algorithms*, Springer-Verlag, New York, 385-391, 1993.

Tyskin, E. N., Multiple Nonlinear Statistical Models for Runoff Simulation and Prediction, *J. Hydrol.*, 77, 209-226, 1985.

Vertessy, R. A., Hatton, T. J., O'Shaughnessy, P. J., and Jayasuriya, M. D. A., Predicting Water Yield from a Mountain Ash Catchment using a Terrain Analysis based Catchment Model, *J. Hydrol.*, 150, 665-700, 1993.

Wang, Q. J, Chiew, F. H. S., and McMahon, T. A., Calibration of Environmental models by genetic algorithms, *Proc., MODSIM 95, Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Newcastle, Vol. 3, 185-190, 1995.

Wang, Q. J., The Genetic Algorithm and Its Application to Calibrating Conceptual Rainfall-Runoff Models, *Water Resour. Res.*, 27(9), 2467-2471, 1991.

Western, A. W., Green, T. M., and Grayson, R. B., Hydrological Modelling of the Tarrawarra Catchment: Use of Soil Moisture Patterns, *Proc., MODSIM 97, Int. Congress on Modell. and Simul.*, Modell. and Simul. Soc. of Aust., Hobart, Vol. 1, 409-416, 1997

Wheater, H. S., Jakeman, A. J., and Beven, K. J., Progress and Directions in Rainfall-Runoff Modelling, in Jakeman, A. J., Beck, M. B., and McAleer, M. J., (Eds.), *Modelling Change in Environmental Systems,* John Wiley & Sons, England, 1993.

Williams, J. R., Nicks, A. D., and Arnold, J. G., Simulator for Water Resources in Rural Basins, *J. Hydr. Eng.*, ASCE., 111(6), 970-986, 1985.

Wong, K. P., and Wong, Y. W., Development of Parallel Hybrid Optimization Techniques Based on Genetic Algorithms and Simulated Annealing, in Xin Yao (Ed.), *Progress in Evolutionary Computation*, 155-165, Lecture Notes in Artificial Intelligence 956, Springer, 1995.

Woolhiser, D. A., Search for Physically Based Runoff Model - A Hydrologic El Dorado?, *J. Hydr. Eng.,* ASCE., 122(3), 122-129, 1996.

Wu, S., and Chow, P., Genetic Algorithms for Nonlinear Mixed Discrete-Integer Optimization Problems via Meta-Genetic Parameter Optimization, *Eng. Opt.*, 24, 137-159, 1995.

Wu, Z. Y., and Simpson, A. R., Messy Genetic Algorithms for Optimization of Water Distribution Systems, Dept. of Civil and Environ. Eng., *Research Report No.* R 140, Univ. of Adelaide, 1996.

Xin Yao (Ed.), *Progress in Evolutionary Ccmputation*, Lecture Notes in Artificial Intelligence 956, Springer, 314pp., 1995.

Yapo, P. O., Gupta, H, V., and Sorooshian, S., Automatic calibration of rainfall-runoff models: sensitivity to calibration data, *J. Hydrol.* 181, 23-48, 1996.

Ye, W., Bates, B. C., Viney, N. R., Sivapalan, M., and Jakeman, A. J., Performance of conceptual rainfall-runoff models in low-yielding ephemeral catchments, *Water Resour. Res.*, 33(1), 153-166, 1997.

Zhao, R. J., *Flood Forecasting Method for Humid Regions of China,* East China College of Hydraulic Engineering, Nanking, 1977.

Appendix A4

Data Acquisition and Preparation

A4-1 AUSTRALIAN DATA

Figure A4-1 to A4-3 present the pseudoweekly time interval data for Babinda Creek, Scott Creek and Canning River. The split samples are presented in separate plots as used in the split sample calibration-validation tests.

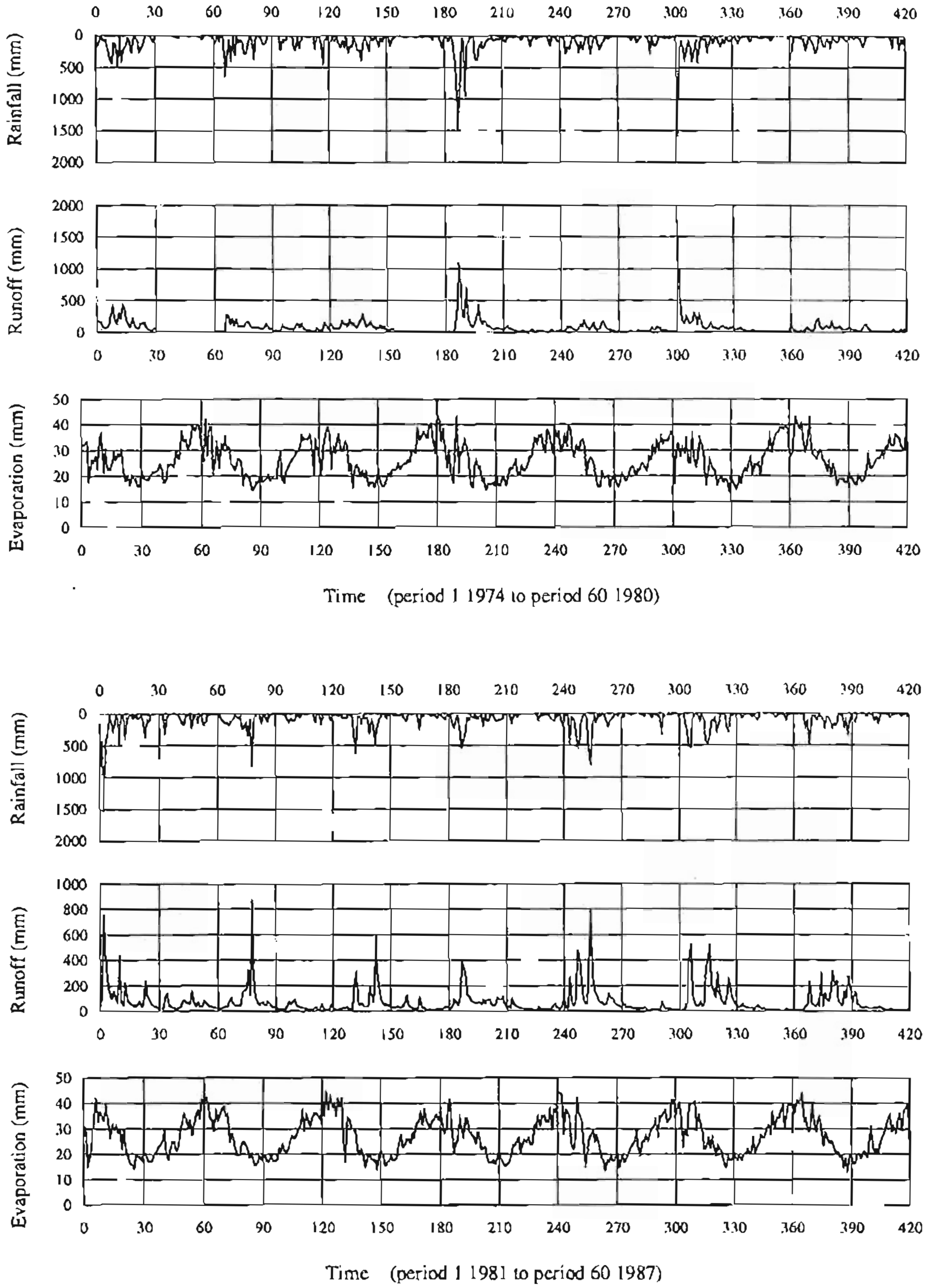


Figure A4-1 Rainfall, Runoff and Potential Evapotranspiration for Babinda Creek (111105)

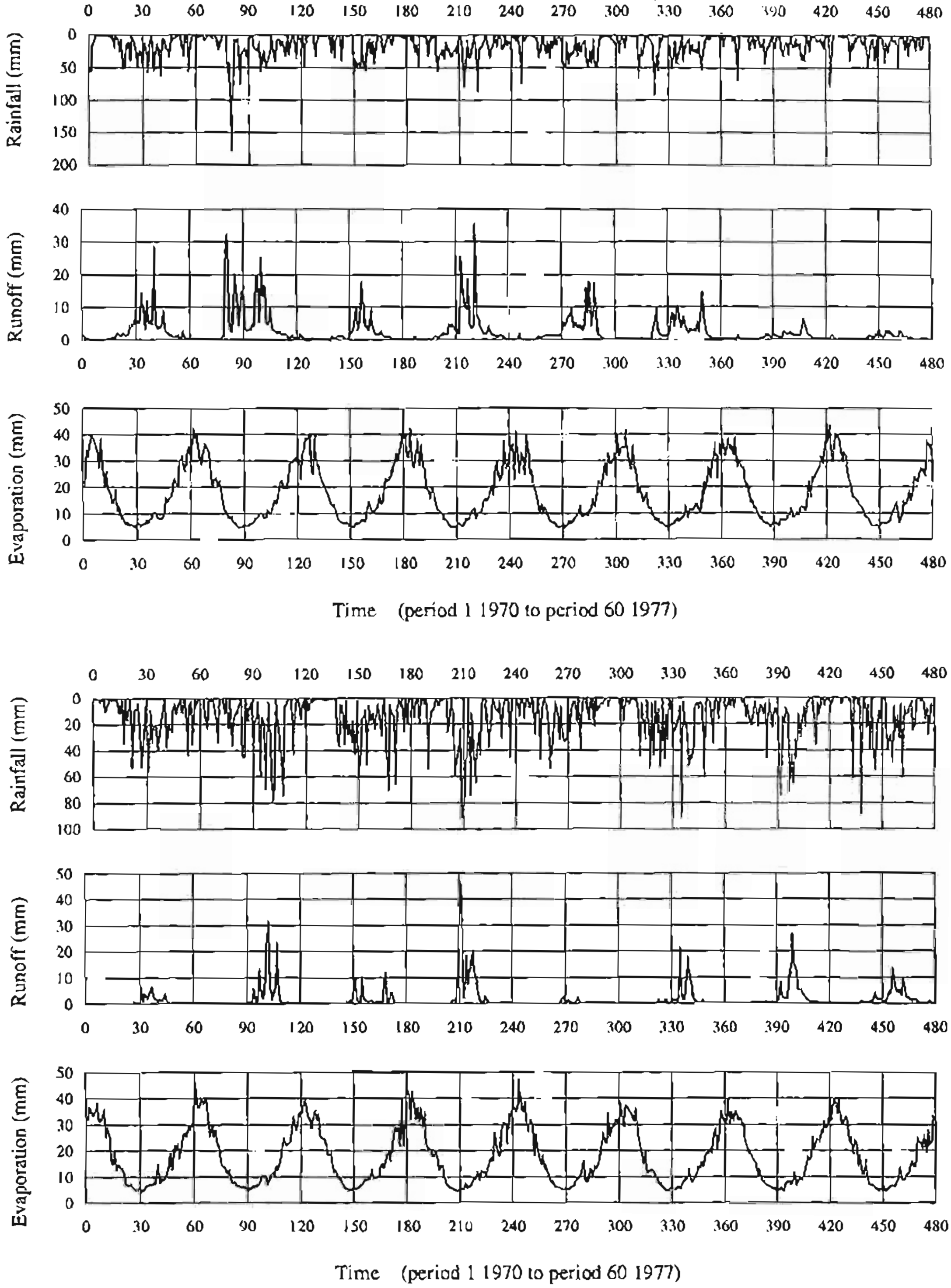


Figure A4-2 Rainfall, Runoff and Potential Evapotranspiration for Scott Creek (503502)

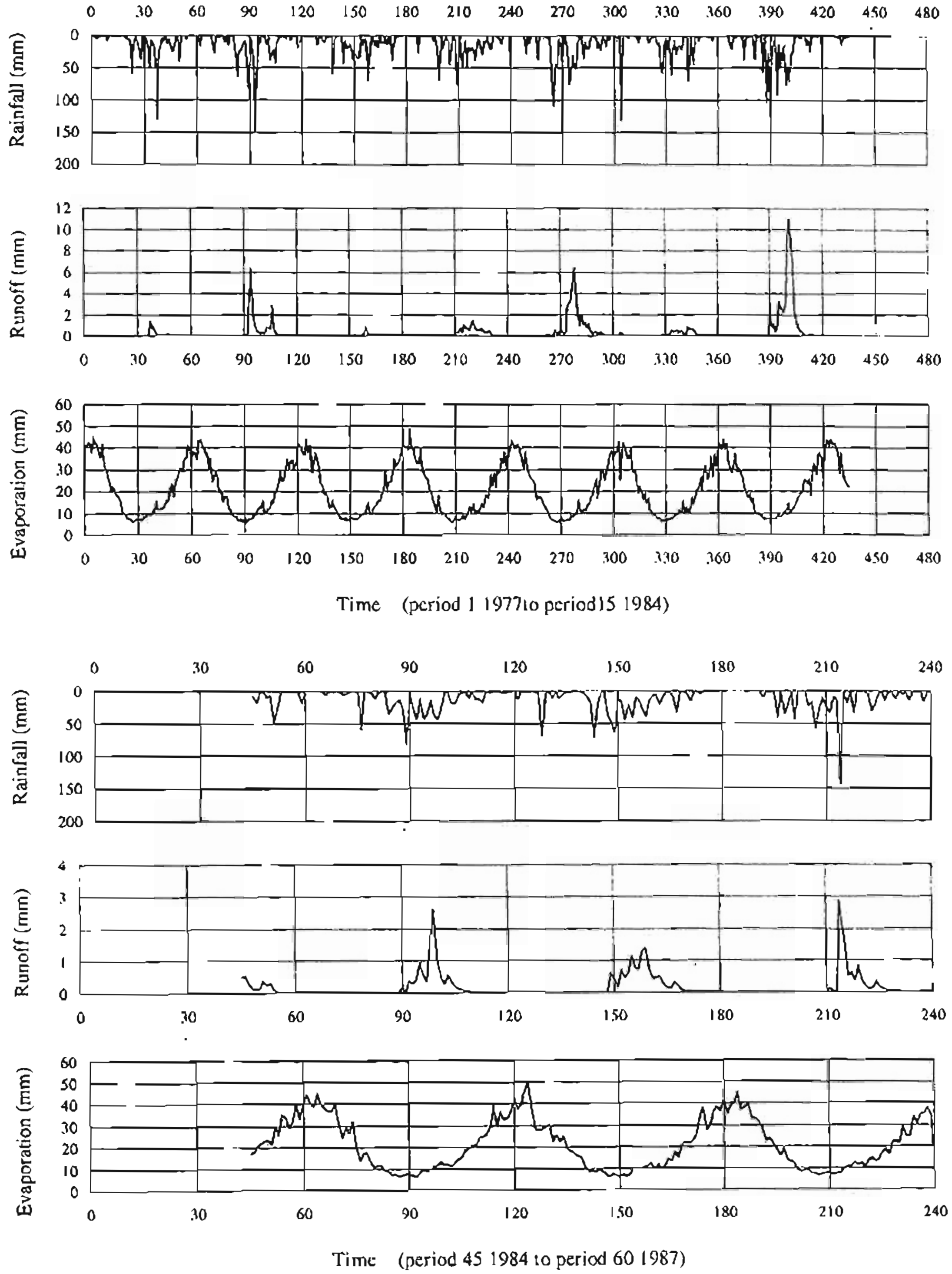


Figure A4-3 Rainfall, Runoff and Potential Evapotranspiration for Canning River (616065)

A4-2 Collection And Preparation Of Modelling Data From Kenya

A4-2.1 Runoff Data

Table A4-1 gives details of the runoff gauge height records obtained from the Kenyan Ministry of Land Reclamation, Regional and Water Development. The data was obtained as spreadsheets in centimetres. The corresponding rating equation coefficients are given in Table A4-2. The rating curve equations take the form $Q = A(h - DH)^B$ where Q is the discharge in m^3/s and h is the measured stage in metres. SEG, LWL and HWL denote the segment of the rating curve, the low and the high water level for each segment.

A4-2.2 Rainfall Data

Information on the rainfall stations whose data was obtained from the Kenyan Drought Monitoring Centre is given in Table A4-3. The station names are given in Table A4-4.

A4-2.3 Pan Evaporation Data

Details pertaining to the eight meteorological stations whose pan evaporation records were obtained from the Kenyan Meteorological Department are given in Table A4-5.

Table A4-1 Catchment Runoff Records obtained from the Kenyan Ministry of Land Reclamation, Regional and Water Development

Name	RGS Number	RGS Type	RGS Location	Nearby Town	Catchment Area (Km^2)	Period of record
Noigameget	1BC01	S	00° 55' 40" N 35° 08' 00" E	Kitale	718	1948-1992
Nyasara	1KA05	SW	00° 01' 25" S 35° 47' 00" E	Kisii	4.1	1935-1993
Mzima	3G03	S	00° 20' 50" S 38° 01' 40" E	Mtito Andei	306	1951-1990
Sagana	4AA01	S	00° 18' 00" S 37° 04' 00" E	Nyeri	96	1948-1976 1981-1987
Chania	4CA02	SWA	00° 38' 08" S 37° 03' 47" E	Thika	529	1921-1995
Uaso Narok	5AC03	SW	00° 16' 00" S 36° 32' 48" E	Rumuruti	878	1945-1994
Teleswar	5BE05	SW	00° 04' 57" N 37° 13' 49" E	Nanyuki	36	1944-1994

S: Staff Gauge W: Broad Crested Weir A: Automatic Recorder

Table A4-2 Rating Curve Coefficients for the River Gauging Stations of Table A4-1

RGS Station	Start Date	End Date	SEG.	LWL (m)	HWL (m)	*A*	*B*	*DH*
1BC01	02 02 48	01 05 63	1	0	0.37	2.6986	0.8583	0
			2	0.37	2.32	4.2016	1.3099	0
			3	2.32	5	2.3596	1.9884	0
	02 05 63	02 05 68	1	0	5	3.8381	1.5898	0
	03 05 68	27 04 70	1	0	1.16	3.3222	2.5501	0
			2	1.16	5	3.8351	1.5905	0
	28 04 70	31 12 94	1	0	5	3.4851	1.59	0
1KA05	11 10 70	02 01 86	1	0	3	3.9	2.65	-0.05
	03 01 86	31 12 95	1	0	3	4.57	2.8	-0.04
3G03	01 05 50	04 11 67	1	0	99	12.89	1.12	0
	01 06 67	31 10 68	1	0	99	14.097	1.46	0
	01 11 68	22 02 70	1	0	99	12.617	1.18	0
	23 02 70	23 09 71	1	0	99	13.925	1.16	0
	24 09 71	31 12 90	1	0	99	12.229	1.16	0
4AA01	03 09 47	31 12 90	1	0	0.3	5.7788	1.5084	0
			2	0.3	0.43	5.607	1.483	0
			3	0.43	0.61	8.8395	2.0175	0
			4	0.61	2	10.865	2.4343	0
4CA02	01 01 56	31 12 93	1	0	99	55.966	1.6098	0
5AC03	07 01 45	31 12 95	1	0	5	2.333	1.497	0
5BE05	01 06 44	31 01 91	1	0	0.3	3.1992	1.4869	0
			2	0.3	3.5	7.738	2.2303	0

Table A4-3 Information for Kenyan Rainfall Stations

Catchment	Station Number	Location		Start year	End year
		Latitude	Longitude		
1BC01	9134011	01 00 N	34 53 E	1957	1987
	9135008	01 00 N	35 14 E	1960	1986
	9135013	01 35 N	35 14 E	1965	1987
1KA05	9034001	00 41 S	34 46 E	1957	1987
	9034080	00 41 S	34 47 E	1959	1987
3G03	9237040	02 57 S	37 35 E	1973	1985
	9338003	03 24 S	38 24 E	1957	1985
	9338004	03 00 E	38 28 E	1957	1985
	9338007	03 24 S	38 08 E	1957	1985
4AA01	9037064	00 11 S	37 07 E	1957	1987
	9037069	00 21 S	37 07 E	1957	1987
	9037115	00 23 S	37 19 E	1958	1987
	9037120	00 17 S	37 09 E	1957	1987
4CA02	9036025	00 35 S	36 38 E	1957	1987
	9036128	00 33 S	36 56 E	1957	1987
	9036164	00 43 S	36 41 E	1957	1987
	9036212	00 45 S	36 51 E	1958	1987
	9036250	00 51 S	36 38 E	1959	1987
	9037005	00 58 S	37 02 E	1957	1987
	9037028	00 54 S	37 14 E	1957	1987
	9037109	00 44 S	37 09 E	1957	1987
	9136035	01 06 S	36 40 E	1957	1987
	9136063	01 01 S	36 55 E	1957	1987

Table A4-4 Names of Rainfall Gauging Stations of Table A4-3

Station Number	Station Name
9134011	Sotik Division Agricultural Office
9135008	Sotik Kaboson Gospel Mission
9135013	Narok Keekorok Game Lodge
9034001	Kisii District Commissioner's Office
9034080	Kisii Coffee Sub-Station
9237040	Illassit Water Development Camp
9338003	Wundanyi District Commissioner's Office
9338004	Tsavo Railway Station
9338007	Maktau Railway Station
9037064	Naromoru Forest Guard Post
9037069	Karatina Hombe Forest Station
9037115	Kerugoya Castle Forest Station
9037120	Kabaru Forest Station
9036025	North Kinangop Forest Station
9036128	Nyeri Othaya Agricultural Office
9036164	South Kinangop Forest Station
9036212	Muran'ga Gituamba Farm
9036250	Kamae Forest Station
9037005	Thika Githumbuini Estate
9037028	Muĩtumberia Estate
9037109	Muran'ga Water Supply
9136035	Limuru Mabroukie Factory
9136063	Ruiru Gatundu

Table A4-5 Kenyan Pan Evaporation Data Station Information

Catchment	Station Name	Station Number	Location		Start year	End year
			Latitude	Longitude		
1BC01	Kitale	8835024	1 00 N	34 59 E	1975	1992
1KA05	Kisii	9034088	0 41 S	34 48 E	1975	1991
3G03	Voi	9338001	03 24 S	38 34 E	1974	1990
4AA01	Nyeri	9036288	0 30 S	36 58 E	1975	1988
4CA02	Kimakia	9036233	0 48 S	36 45 E	1964	1995
	Thika	9037130	01 01 S	37 06 E	1963	1986
5AC03	Rumuruti	8936064	0 23 N	36 39 E	1966	1989
	Nyahururu	9036135	0 02 N	36 17 E	1966	1994

A4-2.4 Data processing for Noigameget Catchment (1BC01)

Figure A4-4 shows the location of the catchment and the climatic stations in which 'R' denotes a rainfall and 'E' a pan evaporation data source. After obtaining the pseudoweekly data, the period 1975 to 1987 was selected for the modelling. The average rainfalls at each period were computed with the available records using the Theissen polygon method. Rainfall records for the three stations were available for about 85 percent of the period while about 10 percent were available at two stations only. The rest of the data except for the five periods with no rainfall data at all was filled in from a single station. The period with no rainfall records formed a reasonable location to split the data and was used as such. About 10 percent of the pan evaporation records were missing as Table A4-6 shows. A plot of the yearly variation of pan evaporation shown in Figure A4-5 shows the expected strong seasonal trend. The corresponding pseudoweekly evaporations of 1981 and 1982 gave a better correlation than concurrent rainfalls and evaporations (Figure A4-6 and A4-7). The missing records were filled in by values for the corresponding periods from the years in which the data was available. This was done in a manner that avoided bias towards any year. After a filling in value was obtained from a year, all other years were given the chance to provide more filling in data before that year could provide the next value.

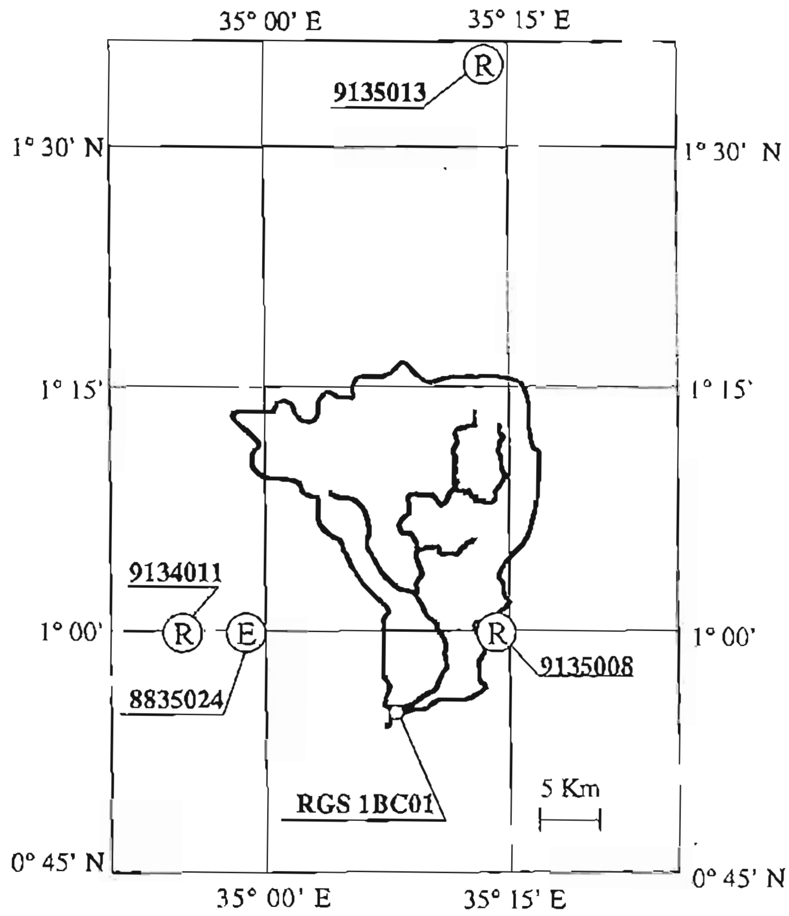


Figure A4-4 Noigameget Catchment (1BC01)

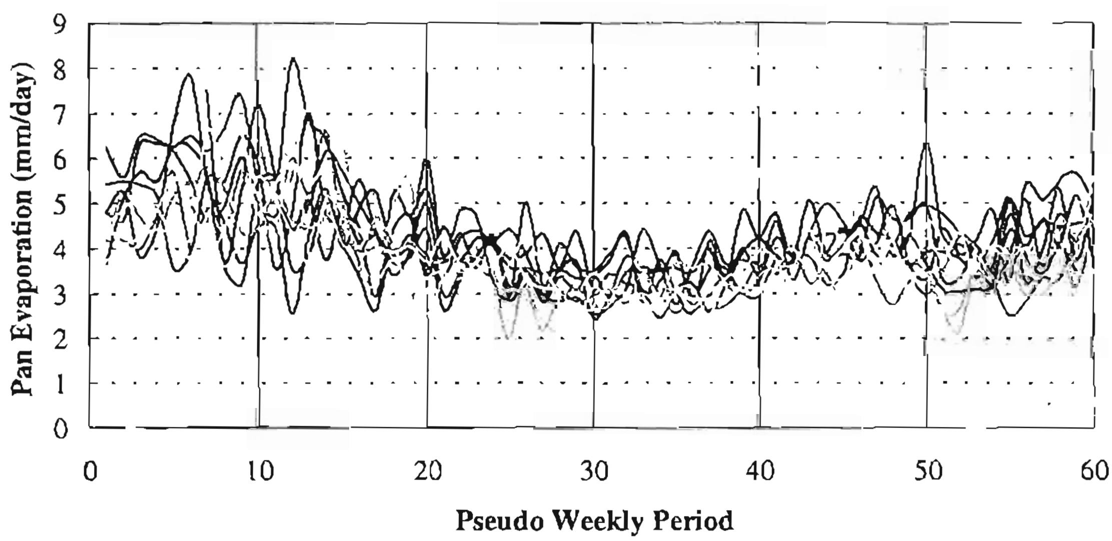


Figure A4-5 Seasonal variation of Historical Pan Evaporation for Kitale (885024)

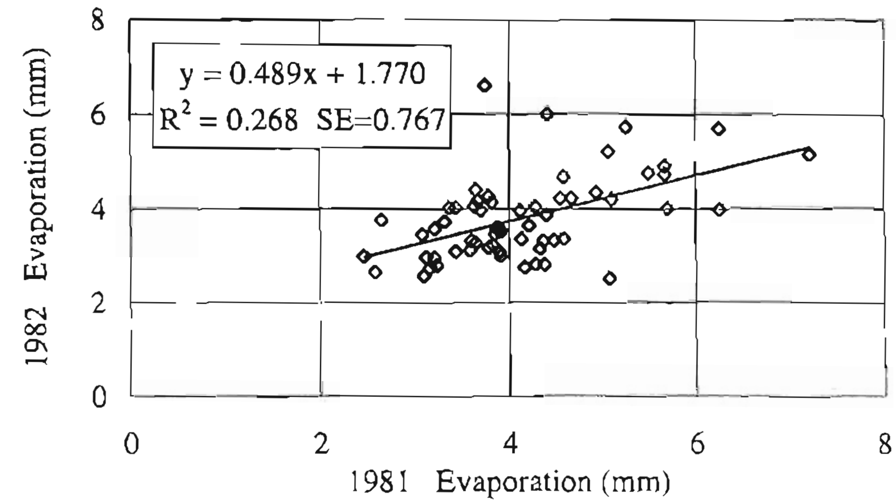


Figure A4-6 Relationship between Pseudoweekly Evaporation Rates for Consecutive Years

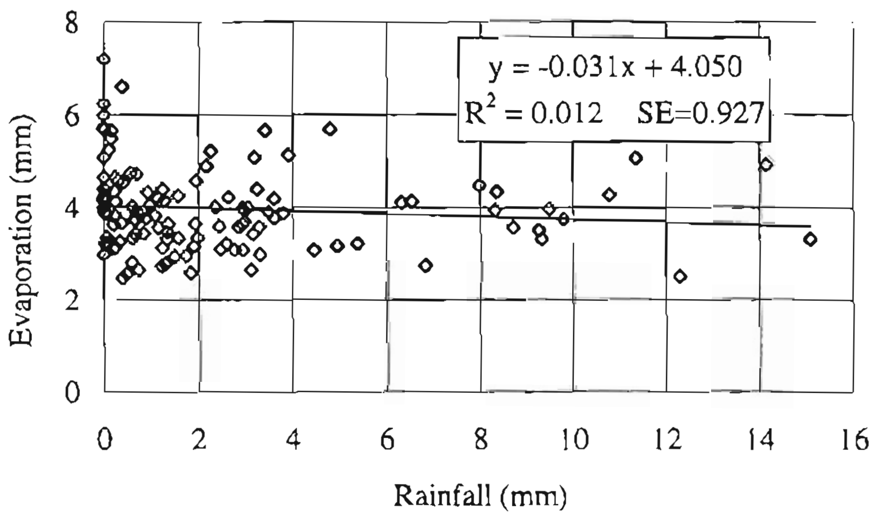


Figure A4-7 Relationship between the 1981 and 1982 Pseudoweekly Rainfall and Evaporation Rates for Noigameget Catchment.

Table A4-6 Recorded and filled in pan evaporation values for Kitale (8835024)

All values in mm/day units

3.67 obtained from other years

5.68 obtained from other years and adjusted to annual trend

Period	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987
1	6.25	4.80	4.17	4.83	3.67	5.42	3.67	4.17	3.73	4.67	5.68	4.25	4.83
2	5.58	4.63	5.25	5.25	4.2	5.5	5.1	4.2	4.07	4.02	4.21	4.92	5.5
3	6.50	6.33	4.7	3.82	4.25	5.42	5.7	4	4.25	4.13	4.27	5	5.7
4	6.42	6.33	4.33	4.52	4.83	5.18	5.5	4.75	4.43	4.83	4.1	4.93	4.75
5	6.25	6.17	5.17	6.75	5.58	3.55	6.25	5.7	4.25	4.18	3.23	5.58	4.25
6	6.50	5.50	5.5	7.83	5.1	3.97	6.25	3.98	3.82	4.25	5.68	5.03	5.1
7	6.17	4.60	6.17	5.5	7.5	5.58	5.67	4.9	4.68	6.63	4.45	3.92	5.92
8	6.65	4.93	4.93	4.62	3.63	5.48	3.65	4.4	3.62	5.83	3.29	4.43	5.33
9	7.42	6.02	3.67	3.67	3.2	6.5	5.26	5.73	4.3	6.58	5.98	5.5	4.37
10	5.56	5.13	6.5	4.5	5.41	5.93	7.21	5.14	5.57	4.76	4.74	5.21	4.47
11	5.50	5.08	5.15	4.5	5.58	3.57	5.67	4.73	5.08	5.42	4.73	4.18	5.2
12	4.58	8.17	5.62	2.55	3.55	4.8	4.42	6	4.35	5.88	4.17	6.67	4.6
13	4.98	6.85	7.32	4.35	3.93	7	5.07	5.22	3.72	5.45	6.23	3.9	4.47
14	6.17	6.43	8.9	5.33	5.17	4.75	3.75	6.62	4.97	5.75	8.09	5.13	4.68
15	5.70	5.22	6.68	4.05	4.13	4.58	4.93	4.35	4.08	4.8	3.68	4.73	5.03
16	4.98	4.42	3.6	4.93	3.38	5.53	4.12	3.95	4.03	4.4	3.07	3.77	3.72
17	4.33	2.95	3.12	5.27	2.65	4.38	4.28	4.03	4.52	4.07	3.98	3.3	4.7
18	3.42	5.22	4.92	3.87	4.43	3.9	3.7	3.97	4.23	3.92	3.36	3.75	4.02
19	4.02	4.72	5.52	4.3	4.75	4.08	3.82	4.13	2.73	4.07	3.76	3.02	4.17
20	6.00	5.30	2.98	3.63	3.41	4.97	4.4	3.87	3.34	3.74	3.04	2.54	3.79
21	3.83	3.88	4.48	3.33	4.48	2.97	2.65	3.77	3.48	4.27	3.88	3.33	3.67
22	4.85	4.33	3.48	4.23	3.78	3.48	3.32	3.72	3.33	3.62	3.17	3.48	3.8
23	4.73	3.58	3.87	4.38	4.23	3.8	3.87	3.58	3.67	3.5	3.47	3.38	3.82
24	3.28	4.23	3.35	4.18	4.05	4.28	4.13	3.35	3.05	3.65	2.98	2.95	3.5
25	2.95	2.85	3.63	4.42	3.6	3.1	3.78	3.17	3.63	4.02	2.59	3.08	2
26	5.02	3.50	3.35	3.88	3.55	3.56	3.9	3.57	4.25	3.35	3.53	2.98	3.2
27	3.18	2.97	2.48	3	3.47	2.82	4.33	3.15	3.53	3.12	3.15	2.48	2.2
28	4.10	3.50	2.83	2.82	3.55	3.37	3.58	3.12	3.02	3.1	3.06	2.08	2.83
29	3.62	3.35	3.62	2.9	3.72	3.08	4.38	2.82	2.7	3.02	3.98	2.18	3.12
30	3.50	3.40	3.4	2.53	2.46	3.43	3.13	2.96	2.66	3.46	2.69	3.14	2.73
31	3.88	3.73	2.72	2.72	2.95	2.93	3.43	3.08	3.17	3.13	2.88	2.82	2.73
32	4.25	4.35	3.82	3.12	3.82	3.48	3.23	2.78	3	2.97	2.7	2.87	3.75
33	3.07	2.82	3.6	4.42	3.45	3.6	3.08	3.45	2.43	2.88	2.71	2.98	3.48
34	3.27	3.75	2.47	3.65	3.57	3.5	2.47	2.98	3.05	2.57	2.71	2.87	2.98
35	3.93	3.05	2.57	2.77	3.55	3.84	3.1	2.57	3.07	3.02	3.57	3.12	3.65
36	2.73	2.58	2.85	3.65	3.48	2.93	3.22	2.95	2.85	2.68	2.35	3.12	3.58
37	2.97	4.17	3.05	4.38	4	3.53	2.58	2.65	2.88	3.05	3.98	2.52	3.63
38	3.42	3.32	3.33	3.67	3.27	3.55	3.17	2.73	2.88	3.18	2.97	3.33	3.25
39	3.03	4.00	2.88	3.75	4.83	3.02	3.9	3.08	3.18	3.07	2.74	3.47	2.88
40	3.27	3.43	3.27	3.66	4.26	2.94	4.21	3.64	3.09	3.01	3.83	3.96	3.39
41	4.62	4.23	4.23	3.45	4.78	3.75	3.85	3.47	3.2	3.5	3.15	3.75	3.58
42	3.30	3.90	3.75	3.75	3.83	3.65	3.63	4.05	3.43	3.25	3.12	2.83	3.62
43	4.33	4.22	5.07	4.22	5.07	4.25	3.83	3.22	4.38	3.12	2.83	2.4	3.83
44	4.98	4.32	3.73	3.92	3.9	3.73	3.22	3.57	3.3	3.55	4.03	4.43	3.45
45	4.60	4.37	6	4.45	3.88	4.08	3.43	4.02	3.32	4.02	2.73	4.13	3
46	4.08	4.52	4.3	3.75	3.83	4.58	4.67	4.22	3.12	4.35	3.71	3.62	4.15
47	3.62	5.37	4.5	4.1	5.13	3.87	4.37	3.32	3.62	3.67	4.88	3.52	4.05
48	4.05	3.87	3.93	4.95	4.67	3.78	4.17	2.75	3.77	4.18	3.57	4.78	3.65
49	4.77	4.30	3.58	3.63	4.66	4.28	3.65	3.27	3.47	3	3.3	4.38	3.78
50	4.94	6.37	3.27	3.33	4.94	3.66	3.91	2.99	3.44	4.51	4.49	4.21	3.43
51	4.75	4.25	2.72	4.43	3.3	3.08	3.92	3.52	3.65	4.18	2.8	3.77	2.65
52	4.33	4.08	2.17	3.87	3.35	3.05	3.78	4.27	4.37	3.3	3.44	3.4	2.63
53	3.73	4.18	3.35	4.02	4.08	3.1	3.37	4.02	3.22	3.8	3.65	3.72	3.48
54	4.15	4.87	3.1	3.18	3.45	3.13	3.6	3.32	3.93	3.35	3.57	4.07	3.28
55	5.12	3.22	3.93	4.75	4.4	3.83	5.08	2.52	3.78	3.2	2.91	3.85	3.58
56	3.27	5.42	4.08	3.85	4.05	5.08	4.28	2.82	4.03	3.97	2.77	3.05	3.42
57	3.98	5.07	4.65	3.45	4.63	3.62	4.58	3.35	3.72	2.9	3.07	3	3.38
58	5.50	5.33	4.4	4.03	4.12	4.75	4.48	3.33	3.93	3.75	5	3.4	4.67
59	5.67	3.77	3.18	3.5	5.17	4.17	4.55	4.22	2.78	5	3.42	3.92	4.25
60	5.08	5.09	4.58	4.57	3.8	4.93	4.58	4.67	3.5	4.57	4.17	5.58	4.67
Total	275	270	248	245	247	246	249	228	219	237	223	226	231

The filled in values for 1977 which had about half of the records missing and 1985 which had all the records missing were then adjusted to a linear trend of annual totals derived from the eight years that had complete data. This trend is presented in Figure A4-8 and in reality could be an indication of a longer term climatic cycle. Another possibility is the gradual reduction of the evaporation measurements resulting from nearby vegetation growth which could reduce the wind speed on the pan. This possibility was not investigated as visits to the recording sites were not made. Table A4-6 presents the complete evaporation data with a differentiation of the recorded, the 'filled in' only and the 'adjusted and filled in' values. Three missing runoff values in the period required filling in. Figure A4-9 shows the rainfall, evaporation and runoff series as used in the modelling in mm/day units.

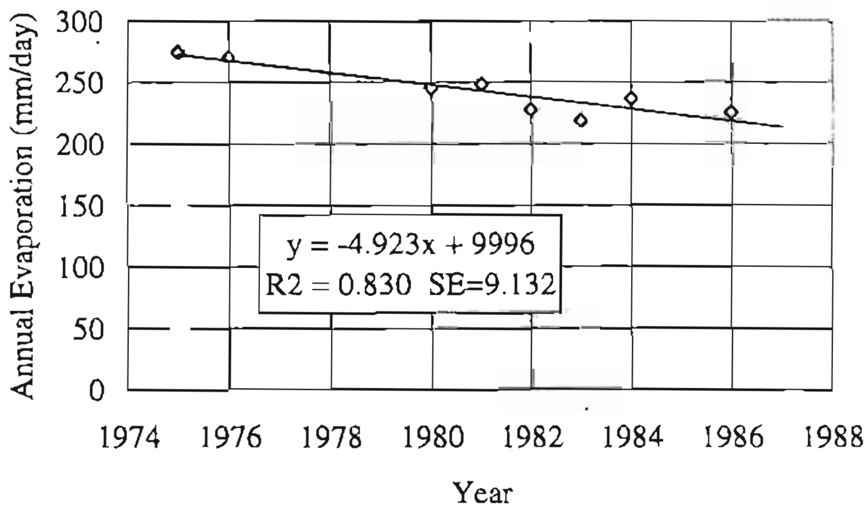


Figure A4-8 Linear Fitting of Annual Evaporation Totals for Kitale (8835024)

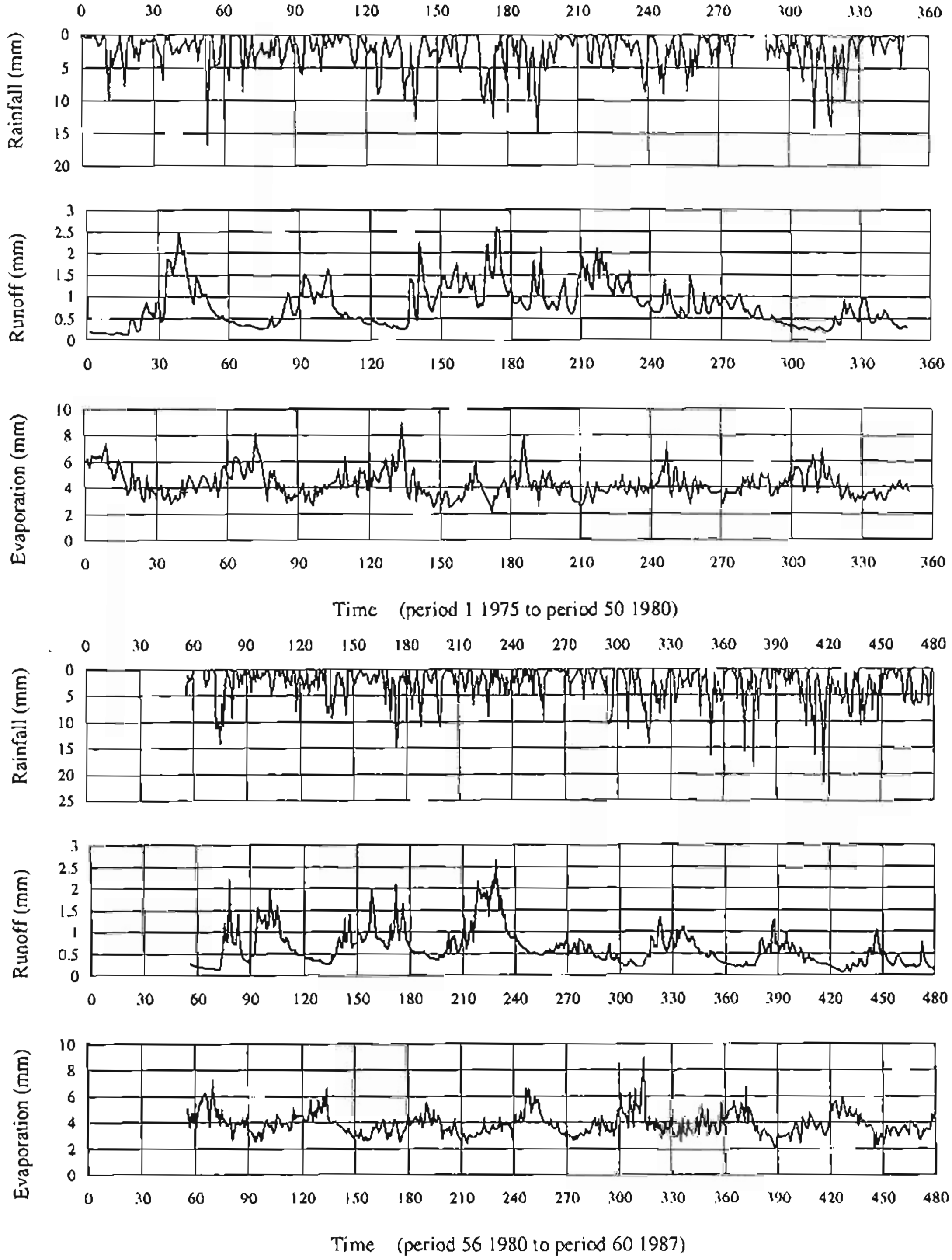


Figure A4-9 Rainfall, Runoff and Pan Evaporation Series for Noigameget (1BC01)

A4-2.5 Data processing for Nyasara Catchment (1KA05)

Nyasara catchment and the meteorological station locations are presented in Figure A4-10. The split samples selected with the aim of keeping the filling in of missing data to a minimum were period 35, 1975 to period 55, 1981 and period 1, 1982 to period 60, 1987. The rainfall data was obtained from station 9034080 which is much closer to the catchment than station 9034001. The missing rainfall records in station 9034080 were then derived from station 9034001 applying a multiple of 1.0551. This was the gradient of a linear relationship between concurrent rainfalls from the two stations (Figure A4-11). Runoffs for eight periods, four from each sample were missing and filled in. No evaporation data was missing for the selected periods. Figure A4-12 is a plot of the modelling data for the two split samples in mm/day units.

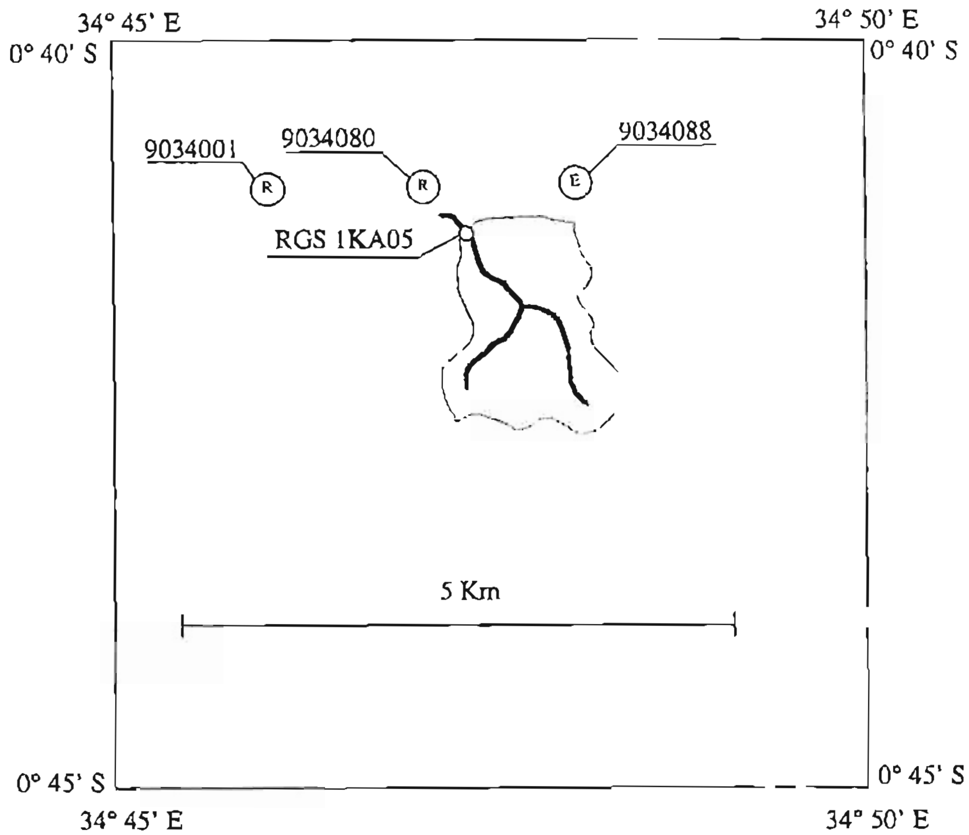


Figure A4-10 Nyasara Catchment (1KC05)

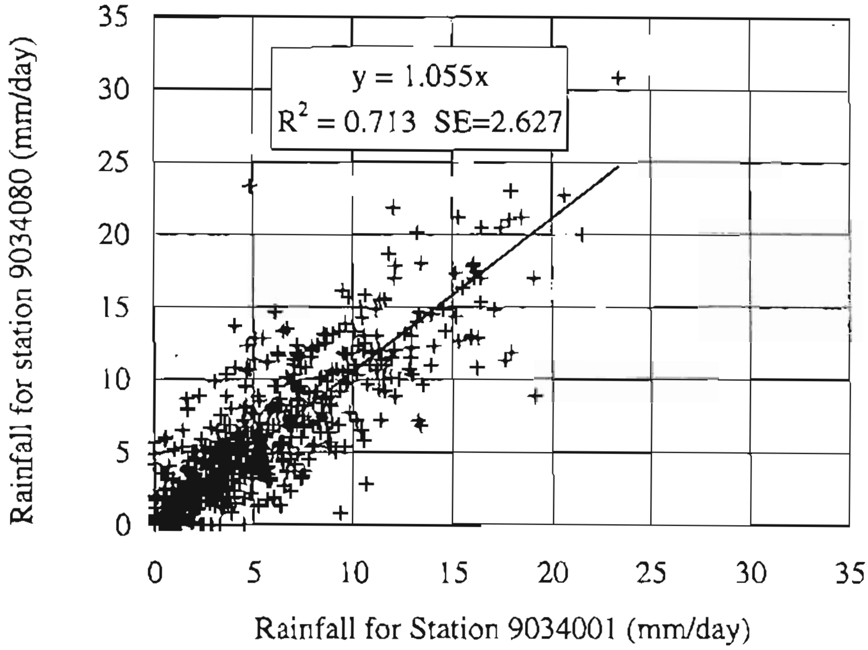


Figure A4-11 Correlation of Pseudoweekly Rainfalls of Stations 9034001 and 9034080.

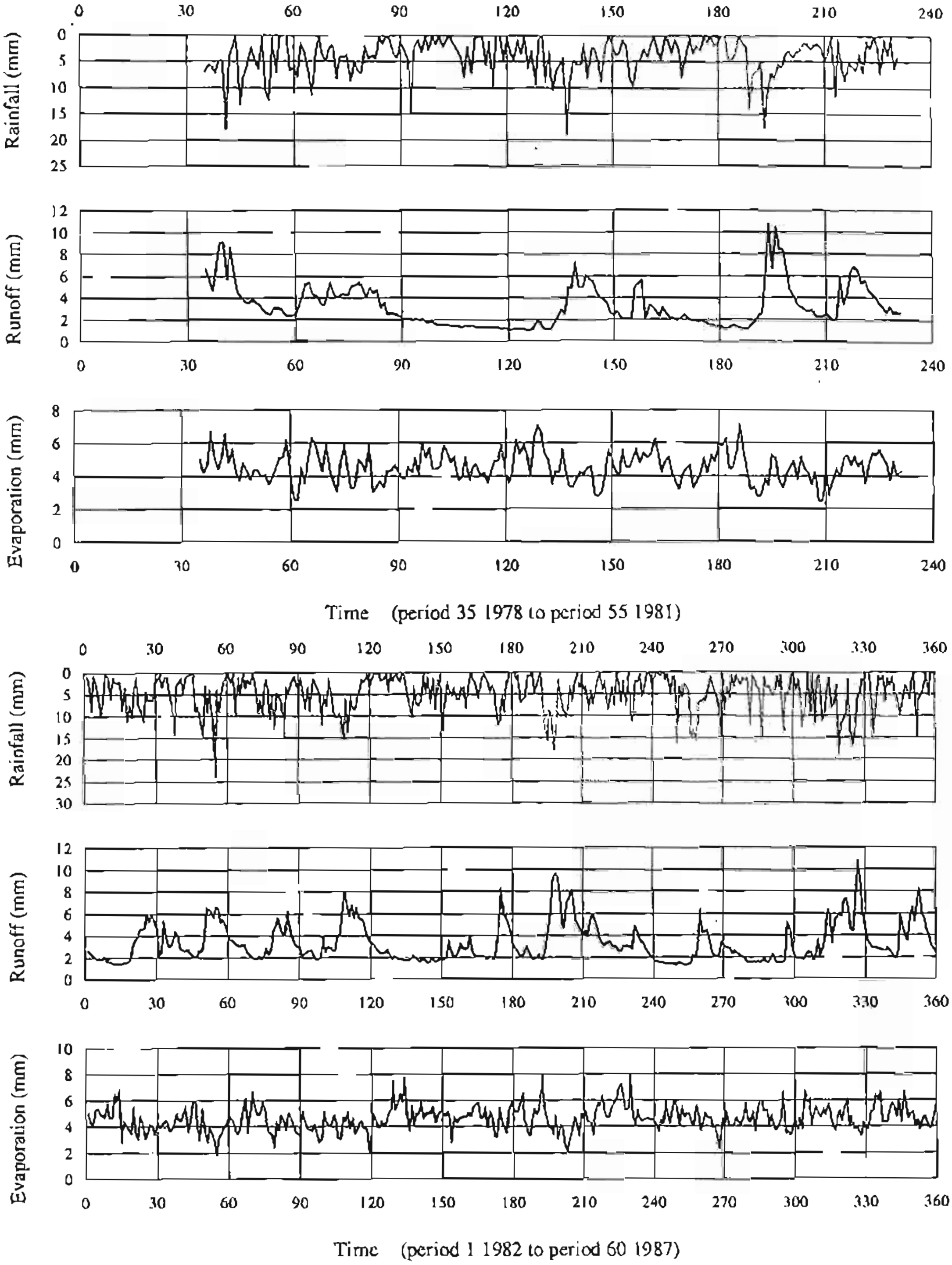


Figure A4-12 Rainfall, Runoff and Pan Evaporation Series for Nyasara (1KA05)

A4-2.6 Data processing for Chania Catchment 4CA02

Out of the 10 rainfall stations in and around the catchment whose records were available, four were selected on the basis of closeness to the catchment and the extent of missing data. The locations of the four rainfall and the two evaporation station are shown in Figure A4-14. Period 1, 1963 to period 35, 1974 was selected for the modelling. Within this period, all the rainfall records for the four stations were available. Four periods of station 9036233 had no evaporation records. A hand plot based on a correlation with the evaporation records from station 9037130 was used to fill them in. Runoff records for 5 periods also required filling in. A 2 months (10 pseudoweekly period) displacement of the runoff data for the rainy period in 1971 (period 180-210 of the 1968-74 series) was found. This was corrected with a 10 period shift of 38 pseudoweekly periods to the past. The runoff, evaporation and rainfalls used in the modelling are plotted in Figure A4-15 in mm/day units.

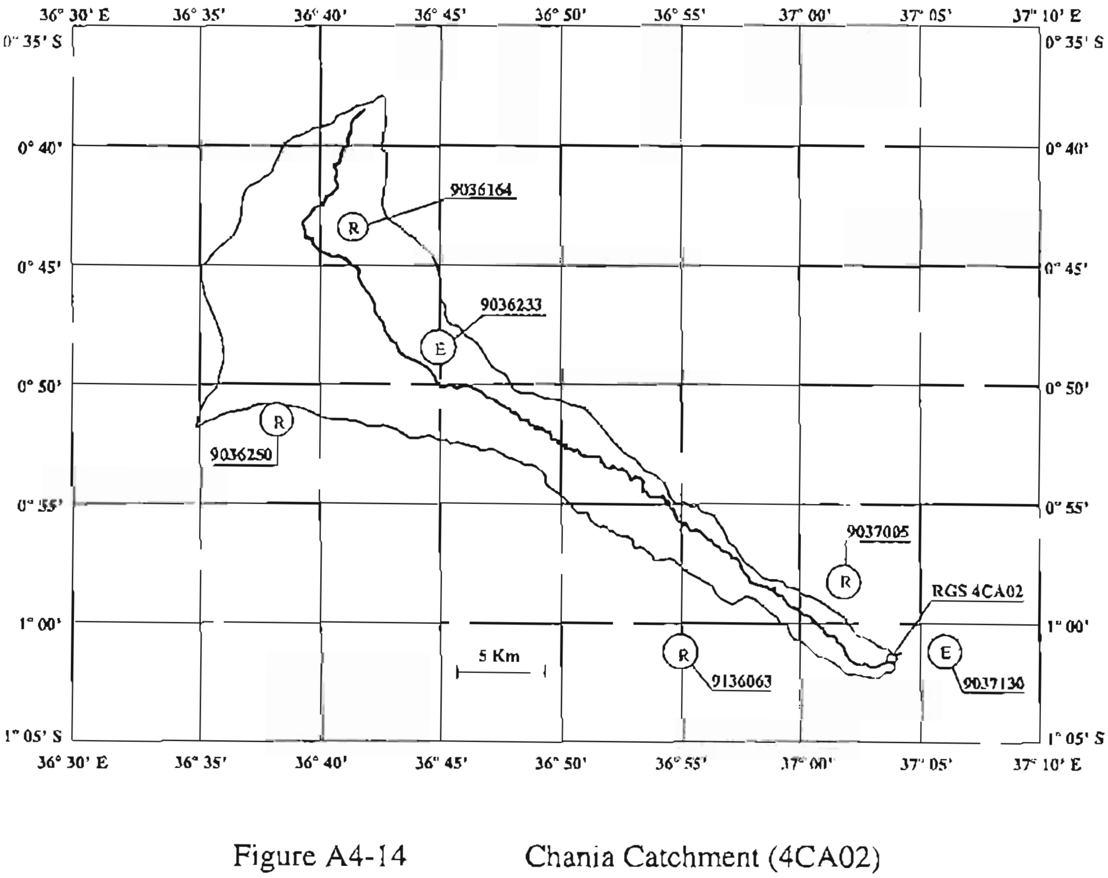


Figure A4-14 Chania Catchment (4CA02)

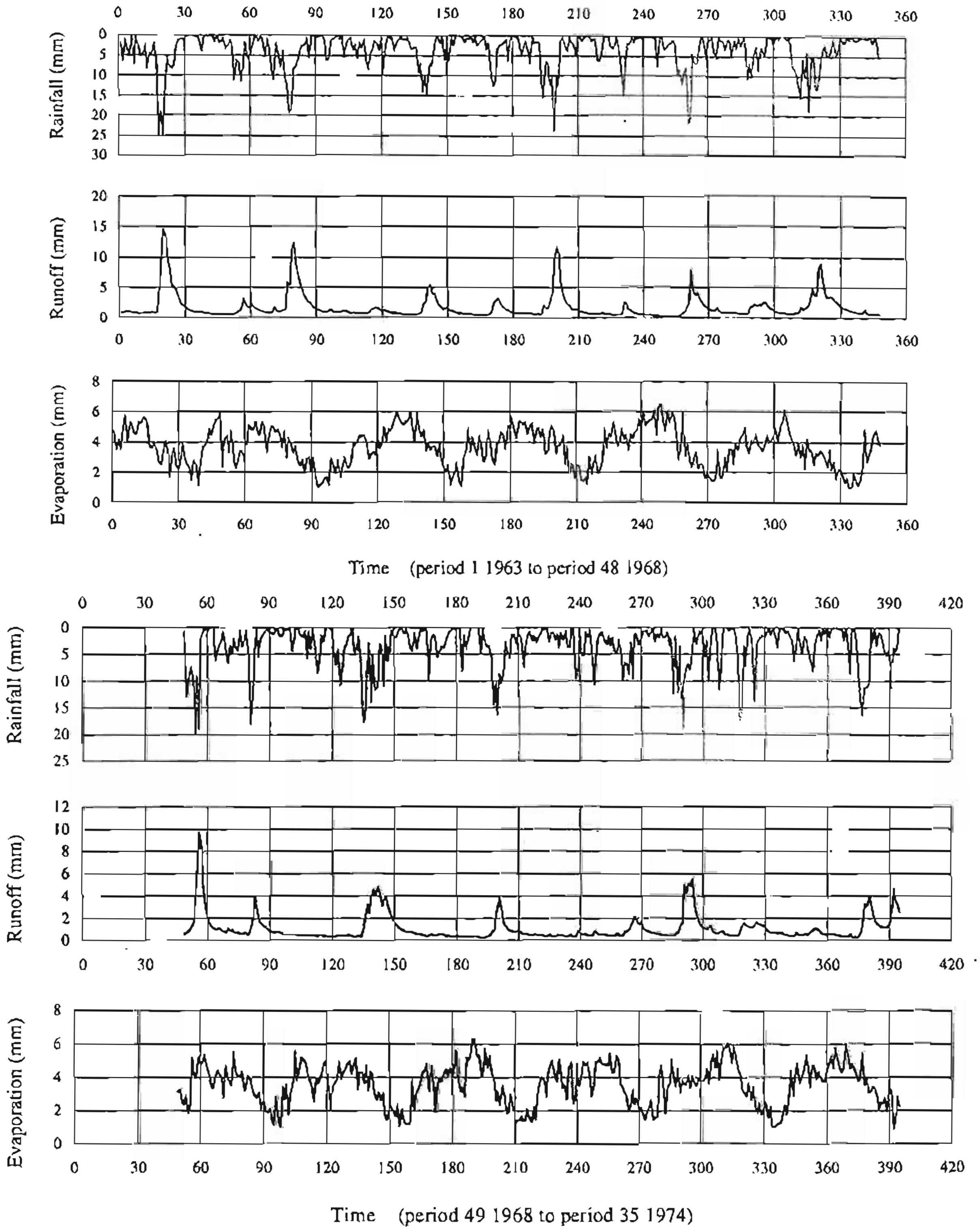


Figure A4-15 Rainfall, Runoff and Pan Evaporation Series for Chania (4CA02)

Appendix A5

Genetic Algorithm Results

This Appendix presents results of the sensitivity analysis of the genetic algorithm using the STDT3 model in Appendix A5-1 and the results of the application of the traditional genetic algorithm to the three Australian catchments, Babinda Creek, Scott Creek and Canning River in Appendix A5-2.

Appendix A5-1 Tabular Results of Genetic Algorithm Sensitivity Analysis using the STDT3 model

Table A5-1 Sensitivity of Genetic Algorithm Performance to the Number of Function Evaluations using the STDT3 Model (test 1)

Data	eval	obf	eval	obf	eval	obf	eval	obf	eval	obf
	2058	257.8	4004	242.9	6020	239.9	8036	239.2	10052	238.1
	2086	243.4	4018	240.4	6034	238.5	8050	237.6	10066	237.5
	2002	244.3	4046	240.5	6062	239.0	8078	237.8	10094	237.8
	2086	243.0	4004	239.5	6020	238.8	8036	237.9	10052	237.7
1970-77	2072	239.9	4004	239.6	6020	239.5	8036	238.5	10052	237.8
	2072	241.7	4088	239.7	6006	239.0	8022	237.8	10038	237.8
	2072	281.2	4004	239.8	6034	239.0	8050	238.1	10066	238.1
	2002	248.0	4018	241.2	6034	239.1	8050	238.1	10066	237.8
	2002	241.4	4018	240.1	6034	239.0	8050	238.0	10066	237.7
	2072	246.6	4004	240.9	6020	238.9	8036	237.9	10052	237.7
	2002	269.1	4018	254.4	6034	253.4	8050	253.0	10066	251.9
	2016	263.9	4060	257.3	6076	255.2	8092	252.0	10010	252.0
	2002	276.0	4046	261.2	6062	255.2	8078	253.8	10094	252.2
	2002	273.7	4046	252.4	6062	251.8	8078	251.8	10094	251.8
1978-85	2002	272.2	4032	256.7	6048	254.4	8064	253.3	10080	251.8
	2002	273.6	4032	256.2	6048	253.0	8064	252.4	10080	252.0
	2086	270.8	4018	257.5	6034	254.2	8050	253.6	10066	252.5
	2086	280.8	4032	256.2	6048	252.8	8064	252.5	10080	252.0
	2002	267.2	4032	265.2	6048	258.4	8064	254.5	10080	252.1
	2086	269.7	4018	254.1	6034	253.3	8050	252.6	10066	252.1

Table A5-2 Sensitivity of Genetic Algorithm Performance to the Probability of Crossover using the STDT3 Model (test 2)

Data	c Values					
	0	0.2	0.4	0.6	0.8	1
1970-77	241.1	239.0	239.1	238.3	237.8	238.0
	239.7	239.3	238.3	237.7	237.9	237.8
	241.9	240.4	238.4	237.7	237.8	237.4
	238.7	240.1	238.3	238.0	237.8	237.9
	239.4	240.5	238.0	238.2	237.7	237.6
	239.1	240.1	238.4	237.8	237.9	237.8
	238.7	239.2	238.3	238.0	237.8	237.1
	239.9	241.2	238.5	238.2	238.0	237.7
	257.6	240.3	239.0	237.8	237.8	237.9
	239.9	240.3	238.5	238.8	238.1	237.8
1978-85	260.5	257.4	252.6	252.1	251.4	252.0
	260.8	254.8	252.7	253.2	251.7	251.0
	260.6	262.1	254.0	252.4	251.1	252.7
	260.8	254.9	256.0	253.6	252.5	252.3
	254.9	252.1	254.7	252.9	251.3	251.7
	270.5	254.4	254.7	253.3	251.6	252.0
	257.2	257.5	253.6	253.1	251.5	252.6
	264.7	266.8	253.5	251.6	251.5	251.5
	261.2	255.5	254.8	254.1	252.0	251.6
	262.6	256.9	253.8	253.3	253.0	251.7

Table A5-3 Sensitivity of Genetic Algorithm Performance to the Number of Crossover Positions using the STDT3 Model (test 3)

Data	ncross Values				
	2	6	10	14	18
1970-77	238.2	238.0	237.8	237.7	237.9
	237.7	237.8	237.8	237.8	238.0
	238.0	237.4	238.3	237.9	237.9
	237.8	237.9	238.1	237.8	238.0
	238.0	237.6	238.0	237.7	237.8
	238.0	237.8	237.8	237.4	237.9
	237.8	237.1	237.9	237.8	237.9
	237.4	237.7	237.9	237.8	237.9
	238.0	237.9	237.9	238.1	237.9
	237.5	237.8	237.8	238.0	238.3
1978-85	252.8	252.0	251.7	252.2	252.0
	252.7	251.0	251.7	251.7	251.4
	253.0	252.7	253.1	251.2	252.0
	252.8	252.3	252.5	252.3	251.8
	253.0	251.7	252.4	253.1	251.6
	251.3	252.0	251.9	252.7	251.1
	252.2	252.6	251.6	251.4	251.9
	251.9	251.5	251.8	252.0	252.2
	253.0	251.6	251.8	251.7	251.8
	253.2	251.7	252.6	251.3	252.9

Table A5-4 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 4)

Data	ucross Values						
	0	0.1	0.2	0.3	0.4	0.5	0.6
	237.8	237.9	237.8	238.2	238.1	238.2	238.8
	237.9	238.1	237.9	238.0	238.3	238.4	238.7
	237.8	237.9	238.0	238.7	238.0	238.5	238.3
	237.8	237.8	237.9	237.9	238.0	237.9	238.2
1970-77	237.6	237.6	238.1	238.1	237.8	238.1	238.4
	237.8	237.9	237.8	237.9	238.2	238.7	238.6
	237.3	237.8	238.0	237.6	238.2	238.7	239.1
	237.8	237.9	238.2	238.2	238.3	237.9	238.0
	237.5	238.1	237.8	238.0	238.8	238.0	238.5
	237.8	237.5	237.9	237.6	238.1	238.5	237.8
	251.5	253.0	252.0	251.4	253.0	253.2	252.2
	252.9	252.0	252.9	251.9	252.4	251.8	253.2
	251.1	251.9	251.8	252.4	252.1	254.2	252.1
	251.7	251.9	252.4	252.1	252.4	252.6	252.4
1978-85	251.5	253.1	251.5	253.1	252.8	252.2	252.1
	251.2	252.3	253.2	251.9	253.9	251.9	251.9
	251.8	251.9	251.6	252.7	251.6	253.2	252.3
	251.5	251.7	253.3	251.9	251.8	252.2	253.4
	252.0	252.2	252.3	253.3	253.0	252.8	253.2
	251.4	251.3	252.1	252.7	253.0	253.2	253.2

Table A5-5 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 5)

Data	ucross Values						
	0	0.1	0.2	0.3	0.4	0.5	0.6
	255.6	278.1	280.2	255.6	320.5	284.8	273.8
	303.9	275.8	261.0	290.8	257.7	264.2	283.7
	264.3	288.8	288.0	287.4	304.5	304.5	290.4
	284.7	318.5	283.9	288.1	262.7	276.3	300.8
1970-77	343.1	334.9	253.4	305.3	275.7	264.8	272.9
	311.1	347.6	297.0	271.2	272.3	249.9	332.5
	260.0	306.2	300.5	260.8	275.5	254.5	269.9
	305.1	315.7	304.6	297.4	297.2	268.4	246.7
	583.4	287.0	264.1	253.8	272.7	265.8	511.6
	302.3	262.1	273.3	251.1	304.6	281.4	273.4
	348.8	349.1	361.9	300.1	306.9	322.5	304.5
	419.9	399.7	339.1	338.8	311.2	337.4	340.8
	324.2	361.8	340.9	327.7	336.1	376.0	300.6
	337.5	348.2	314.3	335.7	384.7	333.9	365.5
1978-85	419.0	371.1	405.7	333.9	279.8	414.4	440.1
	412.5	363.1	351.6	336.5	274.7	335.6	391.0
	370.8	335.8	314.3	307.9	354.7	317.2	319.5
	351.6	411.2	404.5	381.8	354.6	341.3	497.8
	343.5	396.2	390.9	343.7	349.4	338.8	361.9
	441.7	337.7	316.0	347.1	341.7	359.2	298.5

Table A5-6 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 6)

Data			ucross		Values		
	0	0.1	0.2	0.3	0.4	0.5	0.6
	238.5	239.9	241.6	241.5	238.5	239.5	239.5
	241.2	248.1	245.1	241.6	241.1	238.9	240.0
	242.5	238.7	241.9	239.2	239.8	246.7	239.2
	238.7	240.6	237.8	239.2	239.3	238.1	241.6
1970-77	239.6	239.0	240.9	240.7	240.4	241.1	242.9
	237.8	238.8	238.3	243.0	239.1	238.4	239.9
	239.7	241.6	237.8	238.2	238.7	238.4	237.9
	237.8	238.9	245.6	239.5	238.2	240.1	245.6
	239.6	242.3	243.4	240.1	239.8	238.2	240.2
	243.4	239.7	242.2	239.0	241.1	239.7	249.6
	253.4	254.7	253.5	255.6	252.0	253.4	313.1
	253.3	253.8	253.2	253.8	256.6	255.2	256.4
	251.6	253.1	253.9	255.0	252.8	254.2	256.0
	253.5	252.4	255.5	253.2	254.5	255.1	253.5
1978-85	255.3	252.7	252.3	253.3	256.1	253.4	253.5
	254.0	253.2	252.2	257.6	257.2	252.9	252.2
	253.1	252.4	253.7	256.3	255.7	255.2	253.3
	254.9	255.4	252.1	252.3	254.2	256.9	255.9
	251.8	253.4	254.3	255.8	253.2	252.7	255.1
	253.8	253.9	256.7	251.6	255.8	255.2	253.2

Table A5-7 Sensitivity of Genetic Algorithm Performance to the rate of Uniform Crossover using the STDT3 Model (test 7)

Data			ucross		Values		
	0	0.1	0.2	0.3	0.4	0.5	0.6
	272.3	272.0	254.0	304.8	255.8	318.5	316.5
	290.5	284.9	284.8	285.7	246.5	259.4	315.5
	309.1	308.0	311.8	341.3	275.3	298.1	255.5
	273.3	252.6	253.6	305.2	260.3	301.3	252.0
1970-77	309.5	318.2	367.0	248.8	254.7	249.4	316.8
	311.5	256.3	263.7	238.2	263.3	256.5	255.9
	252.9	361.2	243.4	253.7	259.3	592.1	264.7
	285.6	363.0	307.6	308.3	284.2	337.1	246.6
	252.1	246.4	272.5	252.0	371.1	347.8	267.6
	313.6	282.6	278.7	285.9	305.1	275.3	266.0
	264.8	325.2	331.9	306.7	356.1	316.0	334.3
	338.5	271.4	318.3	365.8	323.9	319.7	465.6
	537.6	336.2	334.6	336.5	265.3	326.4	319.9
	321.6	295.8	334.6	337.6	271.5	279.0	324.4
1978-85	310.5	291.6	469.1	389.9	333.2	270.6	662.2
	282.0	325.3	269.8	325.1	273.3	301.8	335.6
	375.0	394.0	295.3	701.2	416.3	268.1	270.9
	314.8	304.5	274.1	279.1	319.1	337.3	261.0
	386.4	297.4	307.3	267.4	268.8	380.7	390.5
	361.7	335.6	308.9	327.7	270.4	311.9	335.7

Table A5-8 Sensitivity of Genetic Algorithm Performance to the Probability of Mutation using the STDT3 Model (test 8).

Data	m Values					
	0	0.2	0.4	0.6	0.8	1
1970-77	237.6	237.8	237.8	238.1	237.4	238.4
	237.8	237.3	237.8	238.4	237.8	238.5
	237.7	237.7	237.8	238.2	238.0	238.1
	237.8	237.8	237.8	237.7	238.8	238.5
	237.2	237.8	238.3	238.2	238.5	238.2
	237.8	237.7	237.3	237.8	237.9	238.5
	237.8	237.7	237.9	237.8	238.0	239.2
	238.0	237.7	238.0	237.2	237.3	238.1
	237.8	237.7	237.8	237.8	237.6	238.6
	237.3	237.3	237.4	238.0	238.2	238.2
1978-85	251.3	251.9	252.2	252.2	253.9	254.4
	252.0	252.5	251.9	252.7	252.4	254.8
	254.0	251.9	251.8	252.0	252.9	254.0
	251.5	251.0	252.4	251.9	253.0	253.8
	251.4	251.1	252.6	252.3	252.5	253.8
	251.7	252.5	251.2	253.1	253.1	252.5
	252.1	251.1	251.8	252.0	252.7	252.4
	252.2	251.8	253.1	252.3	252.1	253.0
	253.2	252.6	253.0	252.6	252.3	252.8
	253.8	252.0	252.8	251.9	252.5	253.4

Table A5-9 Sensitivity of Genetic Algorithm Performance to the Probability of Mutation using the STDT3 Model (test 9).

Data	m Values					
	0	0.2	0.4	0.6	0.8	1
1970-77	647.1	315.9	287.5	285.1	257.2	346.3
	478.2	356.6	284.8	305.1	275.9	263.0
	512.3	293.7	283.2	273.4	262.0	304.9
	645.2	322.5	256.1	281.2	303.1	293.1
	448.6	366.3	269.7	256.9	310.8	326.1
	458.9	294.6	285.8	286.6	258.2	267.6
	511.6	281.3	364.8	275.3	305.3	293.6
	555.4	306.4	304.8	265.2	256.0	296.1
	326.5	594.6	364.0	309.4	287.9	304.9
	538.9	334.1	263.8	247.7	280.5	327.2
1978-85	695.0	594.4	414.7	325.4	312.2	360.0
	454.9	360.7	344.2	404.2	322.2	324.7
	495.0	337.0	415.1	309.8	367.9	334.5
	663.1	370.4	368.1	370.6	401.2	362.8
	388.9	500.7	455.3	323.7	347.4	380.5
	455.5	327.1	378.9	332.6	330.8	311.1
	524.7	400.3	345.8	306.7	334.5	335.8
	471.8	671.7	360.0	413.6	380.5	336.9
	500.6	438.1	369.7	334.6	362.9	331.1
	476.3	366.9	325.5	277.2	296.1	368.4

Table A5-10 Sensitivity of Genetic Algorithm Performance to the Probability of Mutation using the STDT3 Model (test 10).

Data	m Values					
	0	0.2	0.4	0.6	0.8	1
1970-77	617.8	365.2	364.9	255.6	254.3	251.2
	413.2	279.4	252.3	309.7	260.9	267.5
	780.1	593.5	267.9	261.9	271.9	364.2
	734.1	343.4	305.5	272.8	488.7	316.7
	664.0	374.0	420.5	363.5	347.7	315.0
	797.6	369.1	366.6	272.5	311.3	294.4
	584.3	491.6	340.8	321.8	285.5	367.4
	748.6	345.1	343.3	305.5	317.1	321.3
	394.6	373.8	305.2	251.0	276.1	386.9
	494.0	353.5	344.3	363.3	281.2	284.1
1978-85	554.8	446.4	433.6	334.6	335.0	307.3
	459.6	397.1	336.2	315.3	334.3	338.0
	561.0	505.0	340.6	307.1	337.5	411.4
	560.6	352.1	360.2	346.8	366.4	335.6
	573.4	492.3	502.5	267.9	305.1	400.0
	632.1	522.4	416.9	364.4	329.5	341.7
	636.1	326.7	407.9	326.9	324.1	343.2
	483.7	386.5	415.5	497.3	335.0	323.7
	635.2	376.5	483.4	344.4	421.7	340.5
	550.7	313.6	338.6	331.2	418.7	348.0

Table A5-11 Sensitivity of Genetic Algorithm Performance to the Fitness Scaling Parameter using the STDT3 Model (test 11)

Data	fscale values			
	0	1	2	3
1970-77	237.8	237.9	237.8	238.1
	237.9	237.9	237.9	237.5
	237.8	237.8	237.7	237.8
	237.8	237.8	237.9	237.7
	237.8	237.8	237.9	237.8
	237.9	237.7	237.9	237.8
	237.8	237.7	237.8	238.1
	237.8	237.8	237.9	237.8
	237.9	238.3	237.8	237.7
	237.8	237.9	237.8	237.7
1978-85	253.0	251.6	251.6	251.9
	253.0	251.7	252.5	252.0
	251.8	253.1	252.4	252.2
	252.5	252.4	252.2	251.8
	251.7	251.6	252.4	251.8
	252.1	252.2	252.4	252.0
	251.9	251.9	252.4	252.5
	252.2	252.6	251.7	252.0
	253.2	252.3	252.2	252.1
	251.8	251.8	251.3	252.1

Table A5-12 Sensitivity of Genetic Algorithm Performance to a Convergence Parameter using the STDT3 Model (test 12)

Data	cheperf values			
	0.9	0.93	0.96	0.99
	237.6	237.8	237.8	237.9
	237.8	238.1	237.9	237.3
	237.8	237.9	237.6	237.9
	237.8	237.8	237.8	237.9
1970-77	237.7	238.7	237.9	237.8
	237.9	238.2	237.8	238.1
	238.3	237.8	238.0	238.1
	237.8	237.9	238.1	238.0
	237.2	238.0	237.8	238.0
	237.8	238.0	237.8	237.8
	251.8	251.8	252.6	251.8
	251.9	252.5	252.5	251.7
	251.8	252.2	251.5	251.9
	252.2	252.5	251.7	251.5
1978-85	251.3	252.5	251.9	251.3
	252.3	252.9	252.3	251.4
	251.4	251.8	252.1	252.2
	251.5	251.5	252.6	251.9
	253.1	251.9	252.1	252.7
	251.6	253.3	251.8	251.5

Appendix A5-2 Application of the Traditional Genetic Algorithm to STDT4 Model Calibration

Table A5-13 Traditional Genetic Algorithm Optimization Parameters used in the STDT4 Model Calibration

Optimization Parameter	Symbol	Parameter Value
Population size	P	196
Subpopulation size	p_s	196
Number of subpopulations	n_s	1
Bit length of parameter substring	l	20
Maximum number of generations per optimization	g_{max}	1000
Maximum number of function evaluations	ev_{max}	25000
Probability of crossover	c	1.0
Number of crossover positions	n_{cross}	2
Probability of mutation	m	0.05
Tournament size	t_o	56
Fitness scaling index	f_{scale}	3
Convergence parameter	$cheperf$	0.9999
Maximum number of epochs	ep_{max}	1

Table A5-14 STDT4 Model Parameter Values for Babinda Creek with a Traditional Genetic Algorithm Calibration

Data	eval	p1	p2	p3	p4	p5	p6	p7
	17640	17	0.920	499.5	14.66	0.571	1.256	0.321
	12348	27	0.626	499.7	17.16	1.273	1.882	0.690
	9604	47	0.389	270.0	-95.79	4.220	1.383	0.072
	14112	17	0.156	498.7	2.993	1.335	0.632	0.132
1974-80	11172	21	0.078	499.6	49.77	2.637	0.985	0.125
	7252	27	0.418	496.0	17.07	1.240	0.863	0.109
	15288	27	0.170	499.2	49.87	4.365	2.505	0.281
	13132	20	0.468	499.2	26.57	1.260	0.944	0.152
	13916	20	1.877	499.3	38.14	4.607	4.103	0.753
	12740	17	0.050	499.5	21.95	0.683	0.478	0.015
	12152	17	1.251	238.7	13.30	0.577	1.174	0.313
	10780	15	0.532	224.5	49.46	2.453	0.635	0.109
	23324	24	0.674	358.2	14.45	0.623	0.982	0.094
	9016	36	0.623	407.6	-1.817	1.943	1.885	0.460
1981-87	12152	33	0.783	201.5	30.85	3.162	1.892	0.459
	19404	36	0.637	258.6	3.110	1.112	1.281	0.315
	10976	27	0.622	255.1	23.78	0.946	1.404	0.379
	11368	27	0.550	255.3	28.96	1.103	1.179	0.181
	9604	26	0.626	215.4	-5.819	2.887	2.252	0.564
	10584	27	0.022	314.8	30.27	0.984	0.595	0.012

Data	p8	p9	p10	p11	p12	p13	p14	obf
	1.745	9.007	0.717	1.500	0.704	3.740	2.942	381.3
	0.789	3.722	0.319	1.504	3.274	15.54	2.658	422.8
	0.712	2.189	3.845	1.391	1.447	10.10	3.209	505.1
	0.712	7.646	1.971	1.426	0.333	1.542	1.420	471.8
1974-80	0.559	2.972	1.703	1.504	2.641	26.12	4.693	486.8
	1.017	9.854	2.582	1.407	0.899	3.242	1.258	446.3
	0.331	8.533	0.922	1.369	0.843	1.731	2.753	504.9
	0.998	9.204	1.498	1.471	3.640	1.547	2.209	420.9
	0.176	4.292	0.335	1.414	3.978	10.48	4.629	514.6
	1.899	8.927	15.15	1.461	1.865	1.623	1.875	447.7
	1.739	5.459	0.920	1.576	2.062	3.106	3.594	353.3
	0.712	9.656	2.905	1.500	0.636	4.640	1.945	480.9
	1.933	9.139	3.253	1.498	0.672	2.427	1.796	350.0
	0.559	9.992	0.655	1.499	3.531	2.768	2.542	410.1
1981-87	0.545	9.982	0.655	1.566	3.892	2.843	4.523	415.1
	1.168	9.965	0.953	1.548	1.731	2.891	3.280	338.6
	1.598	5.033	0.567	1.750	2.550	27.616	3.243	358.3
	1.565	9.344	1.481	1.626	0.989	2.879	1.061	329.2
	0.406	9.894	0.555	1.498	1.236	3.063	2.531	455.3
	1.935	8.336	21.564	1.623	3.738	2.821	1.872	416.3

Table A5-15 STDT4 Model Parameter Values for Scott Creek with a Traditional Genetic Algorithm Calibration*

Data	eval	p1	p2	p3	p4	p5	p6	p7
1970-77	11172	42	0.862	185.5	-68.66	1.162	1.259	0.0293
	16660	39	0.312	33.50	-95.46	1.446	1.274	0.6806
	5096	40	0.890	74.59	-47.63	3.307	1.974	0.1454
	10192	22	1.019	444.6	-12.58	1.634	1.061	0.0491
	12152	28	0.235	43.32	-64.25	0.898	1.425	0.3692
	9604	25	0.632	447.0	-0.412	0.667	1.210	0.1133
	6272	23	0.635	480.6	-85.24	1.378	1.242	0.0417
	12152	27	0.627	158.1	0.856	0.465	1.301	0.1569
	10976	39	0.842	388.5	-76.08	2.203	1.664	0.0937
	12740	22	0.431	32.98	-8.198	1.424	1.268	0.1076
1978-85	8232	14	1.882	166.5	-73.09	4.147	0.860	0.0619
	8036	17	1.257	354.2	6.831	2.831	2.243	0.1851
	8820	23	1.804	123.5	-47.48	3.348	1.535	0.1251
	12544	27	1.909	64.18	-82.52	2.163	1.648	0.1198
	6272	47	0.871	72.72	4.282	1.886	2.131	0.2965
	8036	11	0.614	73.49	18.19	4.829	1.281	0.2514
	10388	51	0.467	72.31	-35.05	4.211	1.941	0.2036
	6664	41	1.066	118.5	2.535	0.428	1.693	0.5339
	15680	27	1.647	138.0	-83.16	2.162	1.337	0.0743
	6468	14	0.166	465.1	7.887	0.794	1.283	0.0827

Data	p8	p9	p10	p11	p12	p13	p14	obf
1970-77	0.156	2.028	7.561	1.667	0.268	4.870	1.073	294.8
	1.847	4.692	2.824	1.991	0.171	8.823	1.177	275.0
	0.362	6.633	29.74	1.442	1.407	22.49	1.023	336.0
	0.368	2.447	7.760	1.740	0.406	4.729	4.153	290.6
	2.225	2.401	0.968	1.789	0.075	3.160	3.956	247.6
	2.001	9.191	21.30	1.877	0.090	19.59	2.590	262.7
	0.396	7.605	19.18	1.970	0.172	2.861	4.953	323.4
	4.320	5.588	3.445	1.496	1.205	2.887	1.559	258.7
	0.398	9.968	12.87	1.932	0.636	6.182	2.455	321.4
	0.701	8.549	29.93	1.490	2.393	14.04	0.520	294.0
1978-85	0.311	2.023	7.398	1.989	0.594	5.564	1.702	266.0
	0.728	1.924	6.068	1.967	0.390	5.280	2.584	301.0
	0.404	6.723	14.98	1.997	0.311	6.494	3.082	285.8
	0.383	5.256	5.189	1.739	0.914	2.176	2.498	293.4
	1.012	8.416	28.03	1.790	0.705	22.16	1.307	297.3
	0.811	8.969	19.60	1.924	0.433	16.07	2.640	299.5
	0.729	0.572	1.661	1.853	0.067	17.33	4.498	292.0
	4.300	7.487	2.661	1.496	1.482	4.246	1.279	273.5
	0.395	4.943	27.57	1.997	0.241	8.332	4.972	273.9
	2.883	5.611	29.99	1.991	0.649	8.059	1.103	255.1

Table A5-16 STDT4 Model Parameter Values for Canning River with a Traditional Genetic Algorithm Calibration

Data	eval	p1	p2	p3	p4	p5	p6	p7
	13328	27	1.047	71.56	-53.37	1.259	0.791	0.0364
	12936	39	0.628	80.84	-50.74	0.992	0.946	0.0701
	9212	27	1.251	43.73	-23.09	2.692	0.631	0.5560
	19992	27	1.251	71.29	-31.21	1.413	0.791	0.0743
1977-84	11564	29	1.251	52.17	-52.75	2.159	0.946	0.0810
	13524	28	1.268	74.01	-35.68	1.435	0.795	0.0288
	12740	27	1.329	71.38	-95.25	2.593	1.258	0.0403
	18424	36	1.254	71.25	-25.12	1.396	0.790	0.0649
	7840	39	0.763	48.25	-27.27	1.576	0.907	0.1181
	9604	39	0.625	55.06	-53.77	1.262	0.946	0.0548
	9996	26	2.501	41.17	-10.43	1.882	0.358	0.1184
	12740	24	1.110	48.30	-28.93	2.665	0.478	0.3665
	10584	25	2.503	115.9	-6.253	0.946	0.634	0.0627
	19992	22	1.270	56.43	-87.32	1.705	0.636	0.0333
1984-87	8624	22	0.936	71.25	-76.70	2.505	0.317	0.1254
	8624	31	1.543	48.03	-12.35	1.375	0.637	0.0157
	16660	27	0.938	25.67	-80.96	2.311	1.121	0.1201
	5880	30	0.873	71.22	-46.55	1.311	0.790	0.0254
	16660	31	0.860	55.93	-95.58	1.802	0.807	0.2506
	25088	33	0.763	87.53	-37.74	1.232	0.829	0.1252
	p8	**p9**	**p10**	**p11**	**p12**	**p13**	**p14**	**obf**
	1.908	1.289	5.716	1.858	0.140	12.23	1.072	85.39
	3.254	2.220	1.974	1.905	0.076	8.946	2.125	76.62
	2.186	9.523	14.66	1.124	2.558	14.94	1.458	111.8
	1.711	9.014	26.96	1.377	2.704	14.74	0.631	101.8
1977-84	1.478	4.429	21.80	1.361	4.429	19.47	2.515	118.8
	1.284	1.219	8.779	1.843	0.231	17.55	1.330	101.2
	1.104	8.219	3.395	1.524	4.393	16.02	3.112	145.4
	1.630	3.777	7.314	1.501	0.351	26.38	1.302	96.30
	2.564	9.493	5.865	1.630	4.587	24.60	2.814	100.7
	3.108	2.479	6.139	1.803	2.320	19.11	3.761	100.0
	2.551	3.477	5.673	1.618	3.457	18.43	3.391	77.71
	2.984	4.332	23.78	1.678	2.321	27.27	3.548	71.31
	1.332	4.841	7.495	1.261	4.636	3.020	0.393	89.91
	1.478	1.754	3.679	1.962	0.118	7.793	1.259	59.26
1984-87	4.352	3.360	13.03	1.020	3.194	20.44	1.622	85.54
	1.779	8.850	29.89	1.916	3.579	15.92	3.447	74.13
	1.325	1.143	15.29	1.134	0.343	24.15	4.671	73.08
	2.540	7.672	11.53	1.837	1.121	19.50	2.302	62.10
	3.168	3.849	9.548	1.174	3.849	8.416	2.579	64.99
	3.527	1.352	1.922	1.966	0.018	15.75	2.339	44.29

Table A5-17 STDT4 Model Performance Coefficients for Babinda Creek using the Traditional Genetic Algorithm

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.934	-0.023	0.206	0.763		0.934	-0.023	0.206	0.763
	0.938	0.000	0.212	0.731		0.938	0.000	0.212	0.731
	0.932	-0.038	0.242	0.626		0.932	-0.038	0.242	0.626
	0.926	-0.055	0.244	0.746		0.926	-0.055	0.244	0.746
Calibration	0.932	-0.045	0.245	0.587	Validation	0.932	-0.045	0.245	0.587
1974-80	0.932	-0.031	0.234	0.624	1981-87	0.932	-0.031	0.234	0.624
	0.930	-0.039	0.247	0.569		0.930	-0.039	0.247	0.569
	0.938	-0.045	0.224	0.622		0.938	-0.045	0.224	0.622
	0.934	-0.043	0.247	0.642		0.934	-0.043	0.247	0.642
	0.926	-0.056	0.240	0.682		0.926	-0.056	0.240	0.682
	0.896	-0.046	0.207	0.424		0.581	0.106	0.300	0.702
	0.876	-0.082	0.252	0.370		0.717	0.048	0.317	0.705
	0.895	-0.045	0.209	0.528		0.773	0.082	0.277	0.683
	0.896	-0.036	0.225	0.513		0.775	0.069	0.283	0.593
Calibration	0.885	-0.025	0.226	0.426	Validation	0.516	0.145	0.350	0.676
1981-87	0.902	-0.038	0.194	0.404	1974-80	0.619	0.122	0.301	0.638
	0.887	-0.028	0.214	0.523		0.096	0.168	0.352	0.577
	0.897	-0.027	0.200	0.458		0.417	0.153	0.329	0.601
	0.881	-0.037	0.242	0.303		0.732	0.090	0.322	0.786
	0.879	-0.069	0.238	0.491		0.560	0.093	0.340	0.640

Table A5-18 STDT4 Model Performance Coefficients for Scott Creek using the Traditional Genetic Algorithm

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.610	-0.280	0.469	0.347		0.598	0.043	0.700	0.464
	0.519	-0.150	0.467	0.678		-0.142	0.350	0.846	-0.637
	0.661	-0.149	0.492	0.583		-1.296	0.506	0.917	-0.184
	0.740	-0.167	0.406	0.680		0.665	0.247	0.693	0.300
Calibration	0.799	-0.113	0.341	0.694	Validation	0.697	0.313	0.667	-0.156
1970-77	0.634	-0.230	0.411	0.595	1978-85	0.437	0.278	0.754	-0.246
	0.372	-0.161	0.521	0.555		0.585	0.223	0.769	0.168
	0.784	-0.064	0.365	0.963		0.679	0.495	0.694	-0.225
	0.559	-0.220	0.505	0.552		0.596	0.130	0.759	0.509
	0.663	-0.139	0.426	0.693		0.597	0.191	0.721	-0.109
	0.676	-0.305	0.515	0.478		0.323	-0.587	0.675	0.387
	0.562	-0.277	0.587	0.004		-0.060	-0.510	0.789	0.653
	0.749	-0.182	0.503	0.550		0.049	-0.485	0.669	0.609
	0.787	-0.140	0.470	0.174		0.465	-0.521	0.582	0.517
Calibration	0.633	-0.143	0.570	0.136	Validation	-0.065	-0.449	0.709	0.680
1978-85	0.628	-0.221	0.571	0.360	1970-77	0.115	-0.518	0.712	0.619
	0.625	-0.251	0.567	0.243		-0.101	-0.543	0.775	0.645
	0.706	-0.255	0.512	-0.027		0.272	-0.634	0.670	0.387
	0.715	-0.237	0.503	0.327		-0.049	-0.496	0.654	0.609
	0.658	-0.205	0.510	-0.064		-1.610	-0.309	0.735	0.700

Table A5-19 STDT4 Model Performance Coefficients for Canning River using the Traditional Genetic Algorithm

Data	ce	bias	ade	rmcc3	Data	ce	bias	ade	rmcc3
	0.859	-0.139	0.331	0.741		0.565	-0.195	0.424	0.421
	0.933	-0.066	0.274	0.949		0.619	-0.166	0.400	0.371
	0.537	-0.325	0.553	0.652		0.377	-0.415	0.549	0.440
	0.888	-0.121	0.358	0.900		0.507	-0.303	0.478	0.565
Calibration	0.528	-0.359	0.562	0.505	Validation	0.457	-0.273	0.482	0.465
1977-84	0.791	-0.250	0.402	0.593	1984-87	0.491	-0.282	0.474	0.582
	0.406	-0.335	0.698	0.395		0.242	-0.189	0.703	0.619
	0.742	-0.188	0.420	0.755		0.531	-0.244	0.471	0.432
	0.634	-0.290	0.511	0.640		0.519	-0.153	0.504	0.273
	0.705	-0.233	0.471	0.743		0.551	-0.105	0.496	0.244
	0.357	-0.247	0.563	0.065		0.325	0.449	0.914	0.058
	0.472	-0.263	0.504	0.400		0.505	0.124	0.721	0.677
	0.471	-0.132	0.541	0.733		-0.159	0.351	0.891	0.580
	0.757	-0.147	0.359	0.722		0.603	-0.366	0.524	0.395
Calibration	0.416	-0.334	0.508	0.593	Validation	-	6.128	6.516	-
1984-87	0.541	-0.147	0.476	0.380	1977-84	0.505	-0.321	0.595	0.562
	0.564	-0.194	0.469	0.396		0.258	-0.611	0.695	0.094
	0.544	-0.257	0.431	0.512		0.474	-0.397	0.583	0.461
	0.499	-0.183	0.474	0.336		-0.939	0.246	0.757	0.127
	0.938	0.022	0.241	0.902		-0.323	0.795	0.958	-0.530

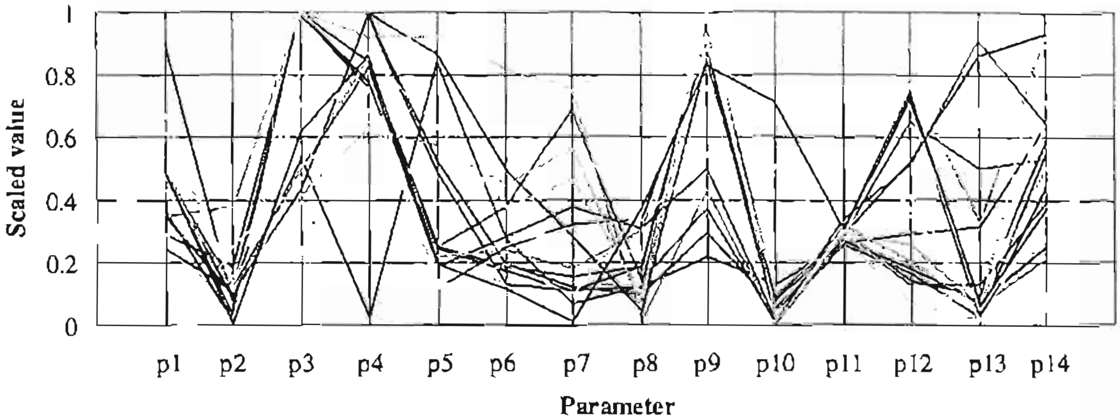


Figure A5-1 STDT4 Model Parameter Identification Plot for Babinda Creek using the Traditional GeneticAlgorithm

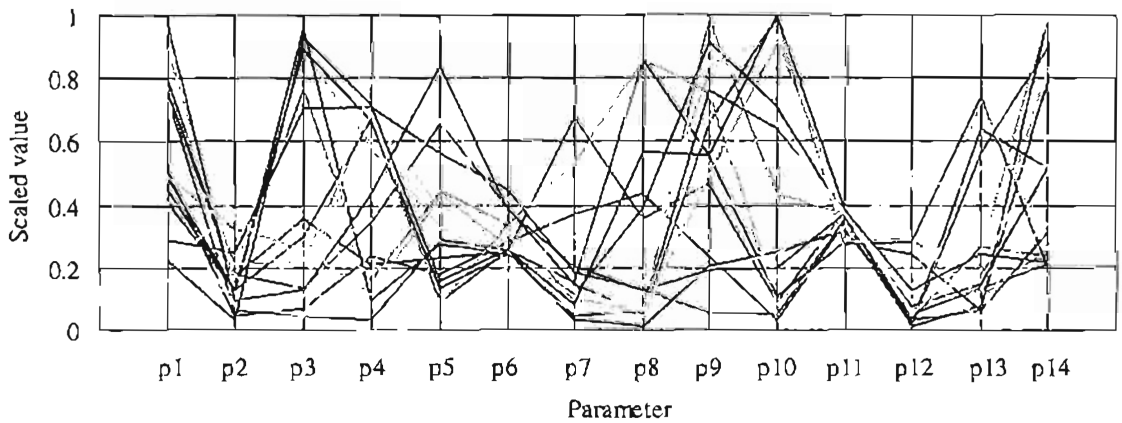


Figure A5-2 STDT4 Model Parameter Identification Plot for Scott Creek using the Traditional GeneticAlgorithm

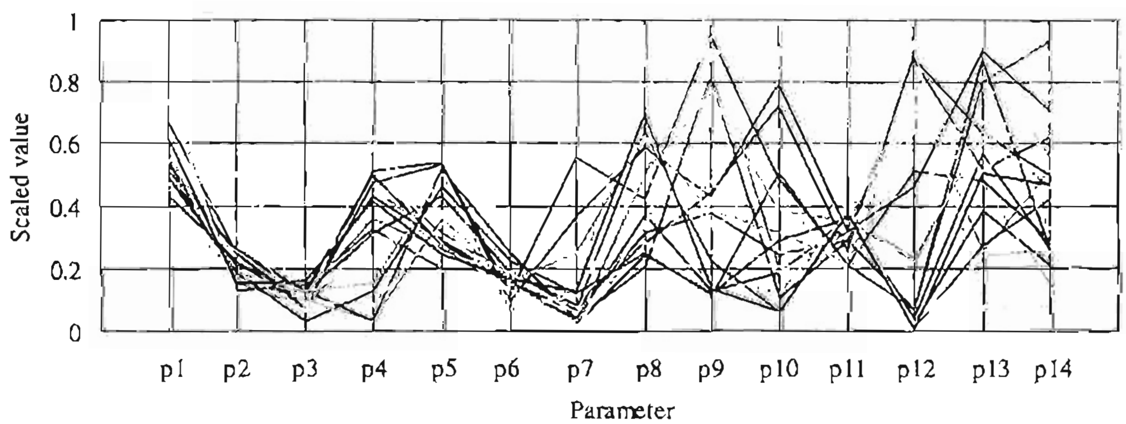
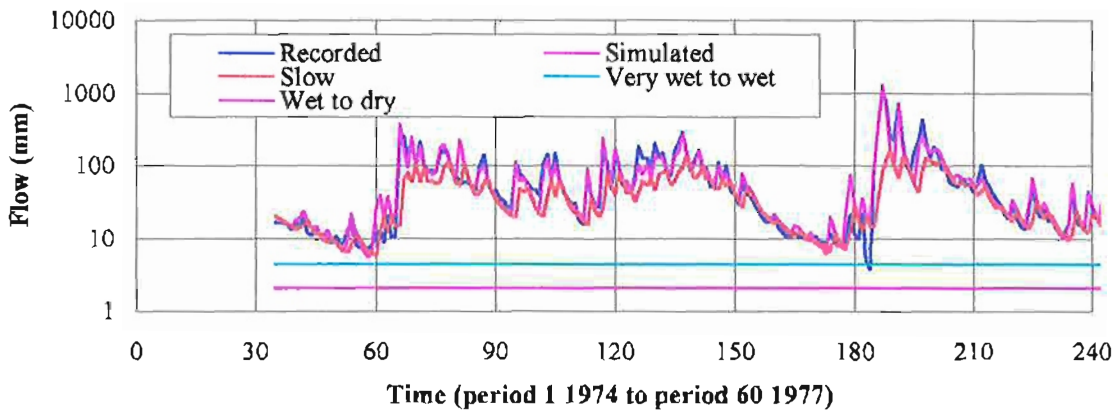


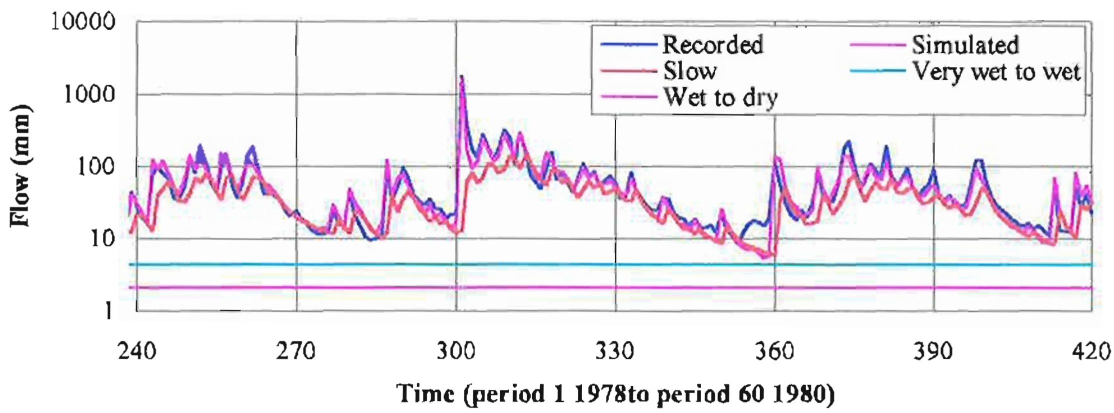
Figure A5-3 STDT4 Model Parameter Identification Plot for Canning River using the Traditional GeneticAlgorithm

Appendix A6

Hydrographs and Errors for STDT4 Model Simulations

The hydrographs and residuals obtained in the calibrations and the validations of the STDT4 model are presented in Figure A6-1 to A6-12 for the three Australian catchments and Figure A6-13 to A6-24 for the three Kenyan catchments. Owing to the higher variability of Australian flows, a logarithmic scale is applied on the flow (vertical) axis in their hydrograph plots. The values of the two parameters *p9* and *p12* are plotted as horizontal lines on the graphs. The STDT4 model uses the slow flow to quantify the antecedent catchment wetness. Parameter *p9* gives the slow flow value at which changes between the very wet and the wet state happen and is denoted as 'very wet to wet' in the plots. Parameter *p12* which gives the slow flow value at which the catchment changes between the wet and the dry state is denoted as 'wet to dry' in the plots.





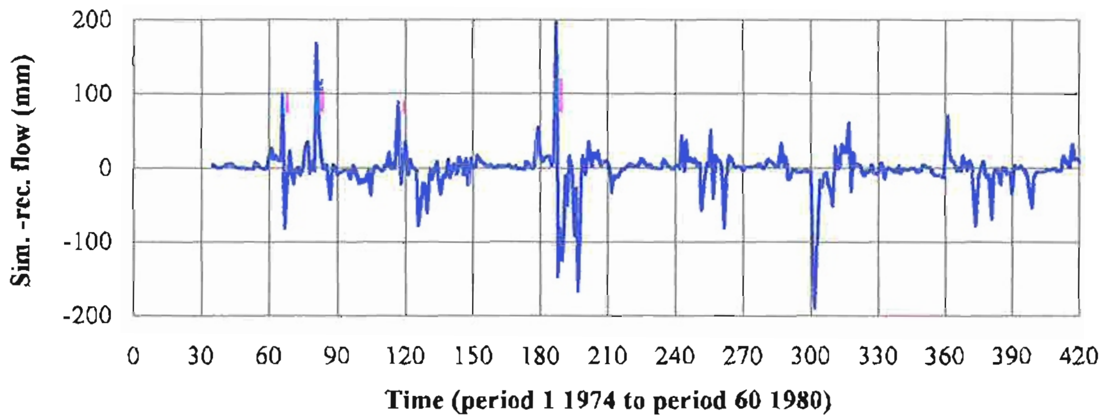


Figure A6-1 Babinda Creek STDT4 Model Calibration Hydrographs

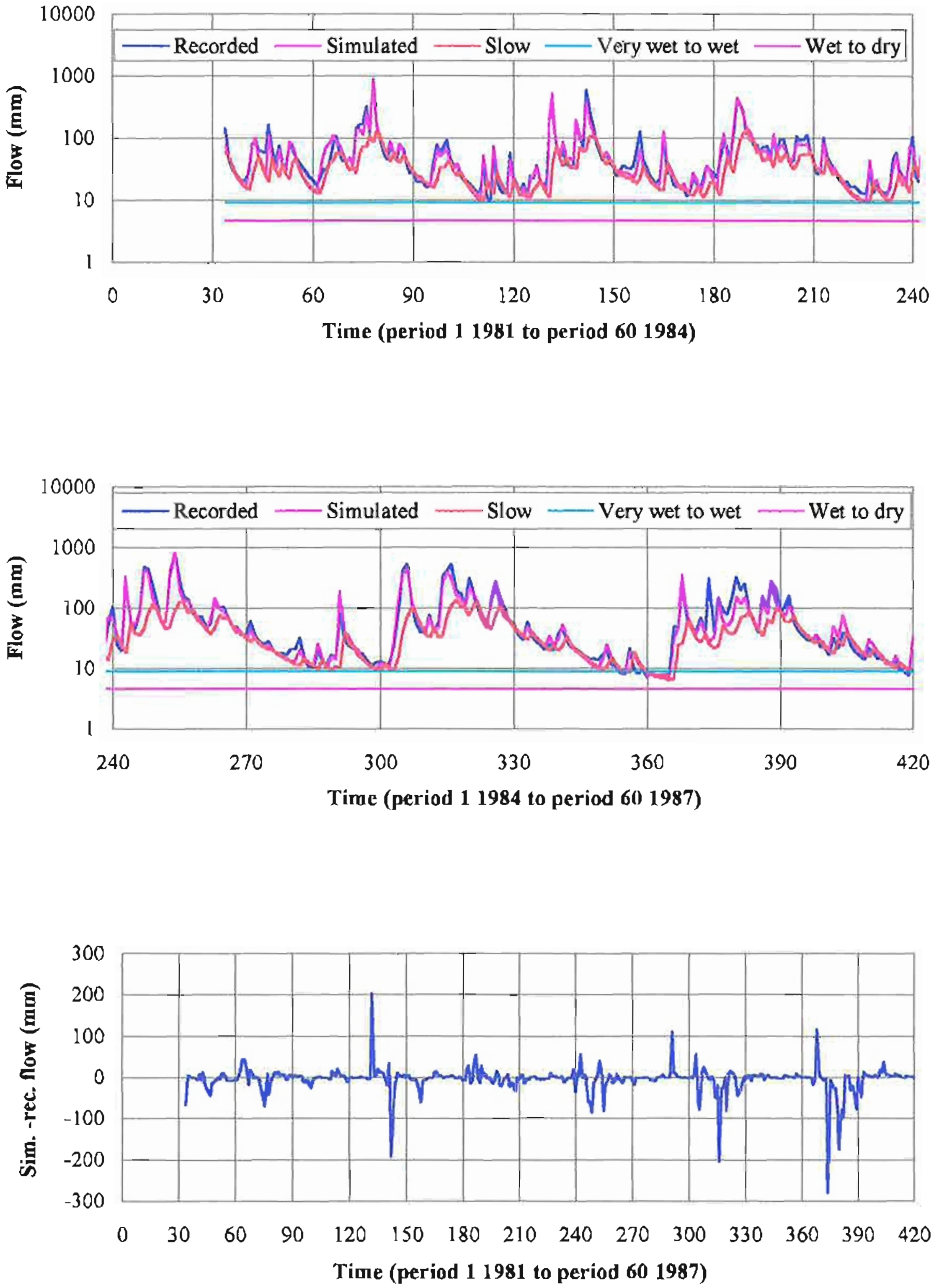


Figure A6-2 Babinda Creek STDT4 Model Calibration Hydrographs

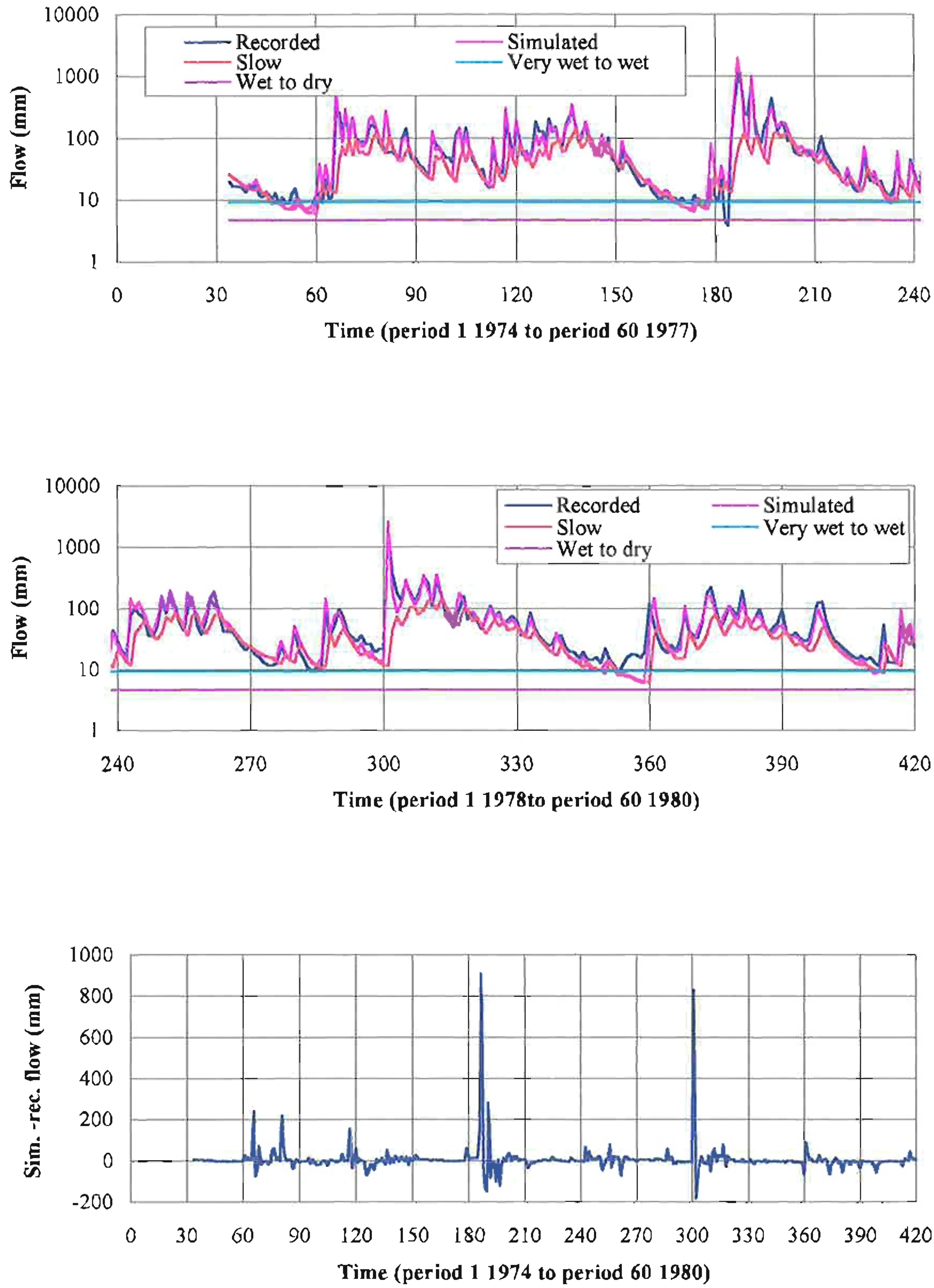
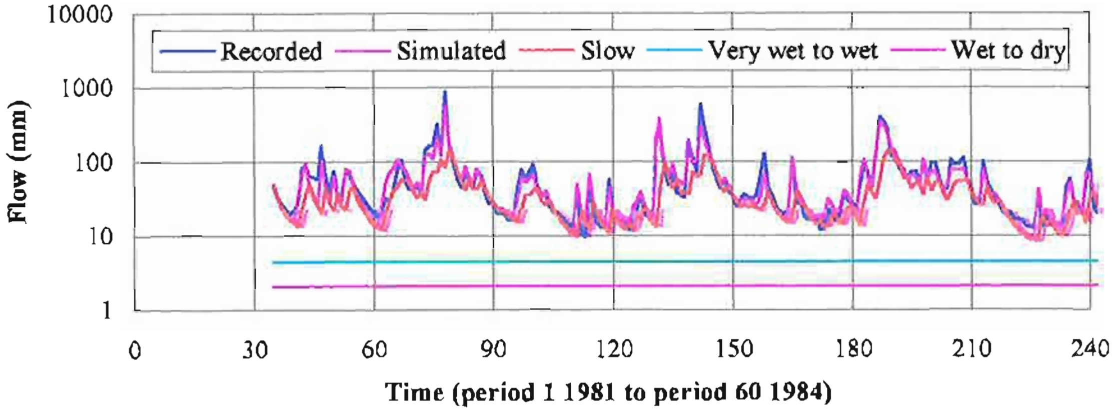
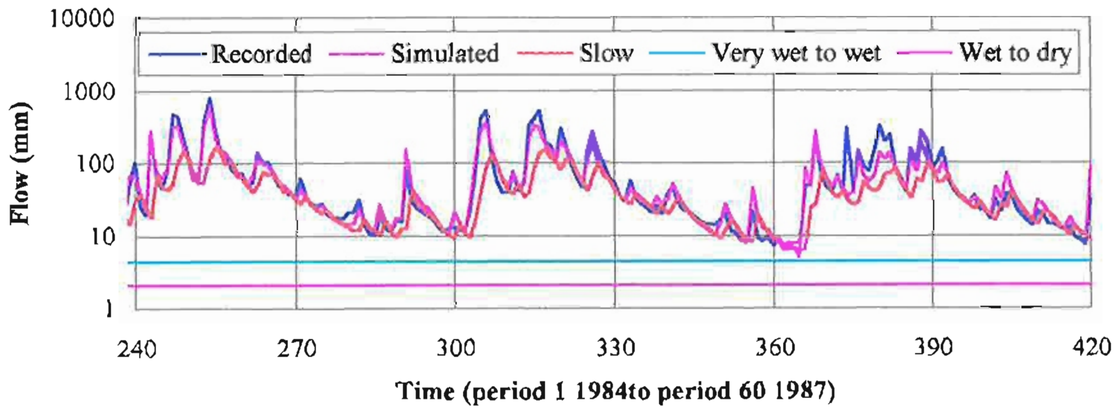


Figure A6-3 Babinda Creek STDT4 Model Validation Hydrographs





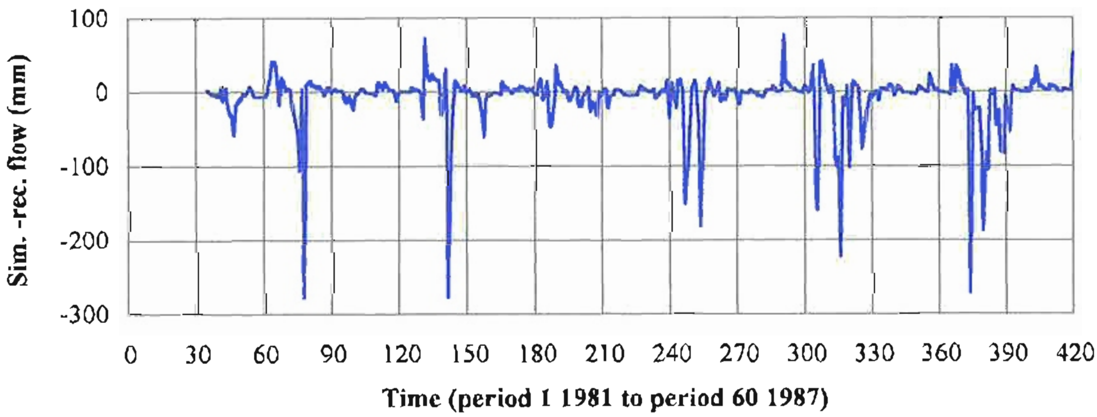
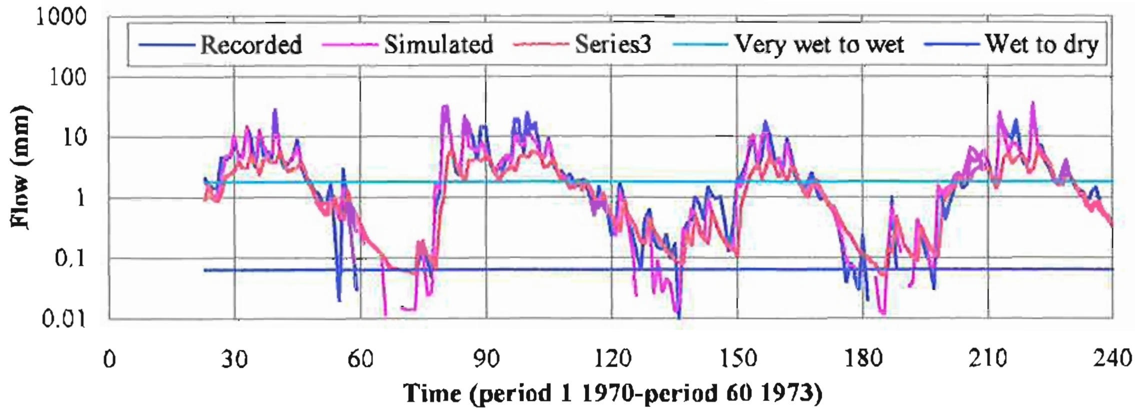
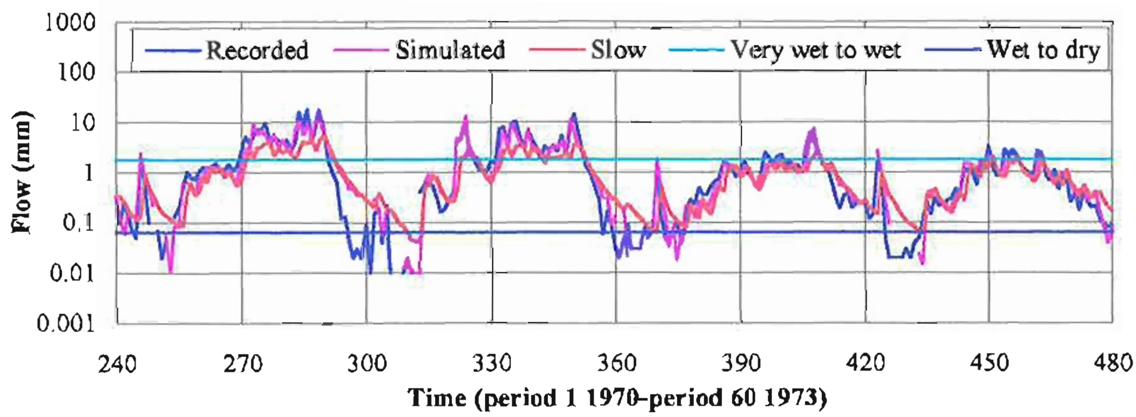


Figure A6-4 Babinda Creek STDT4 Model Validation Hydrographs





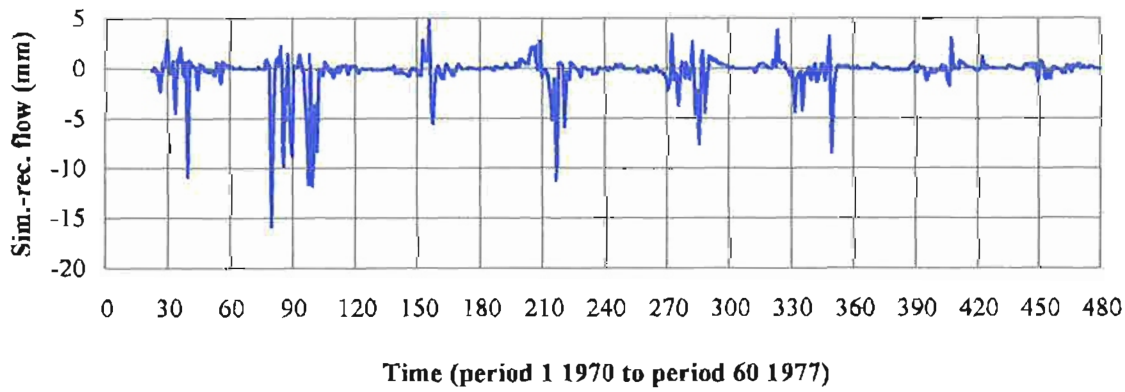


Figure A6-5 Scott Creek STDT4 Model Calibration Hydrographs

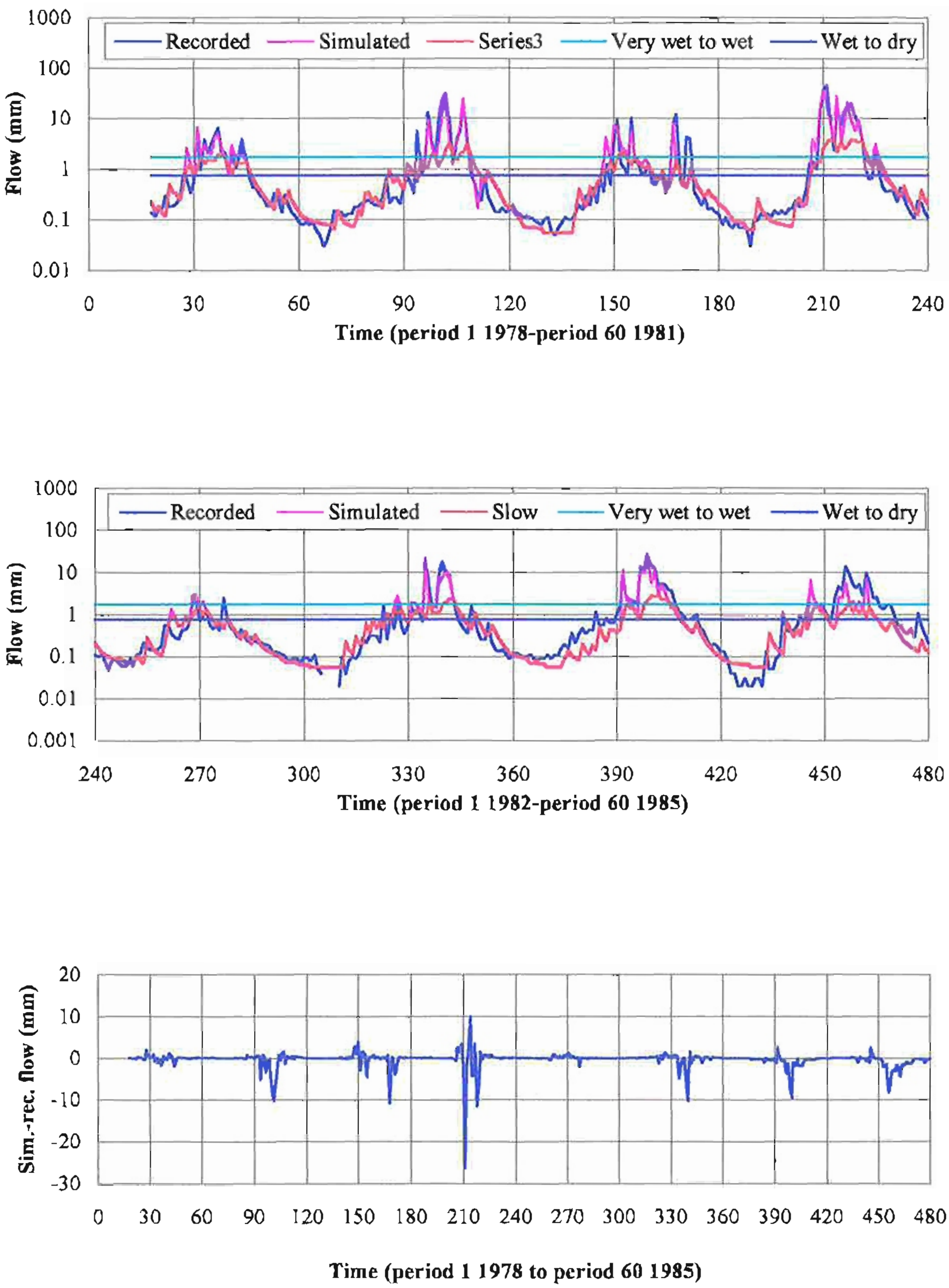
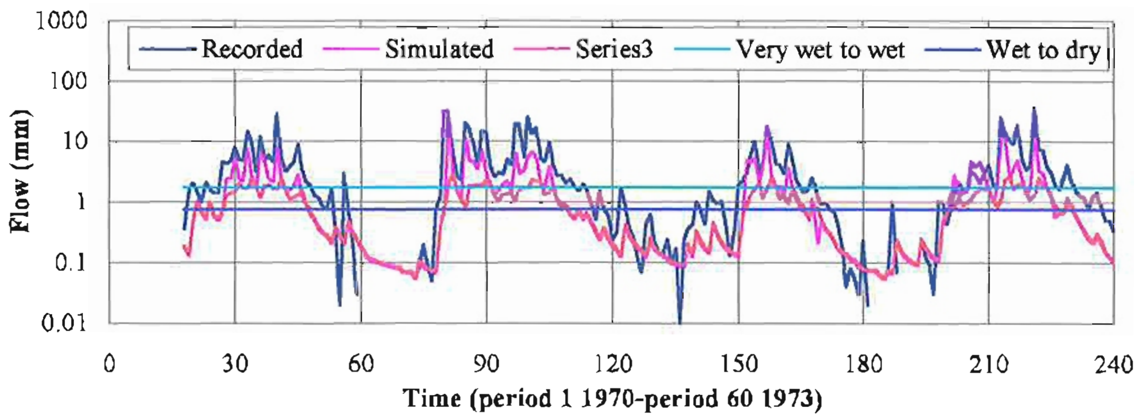
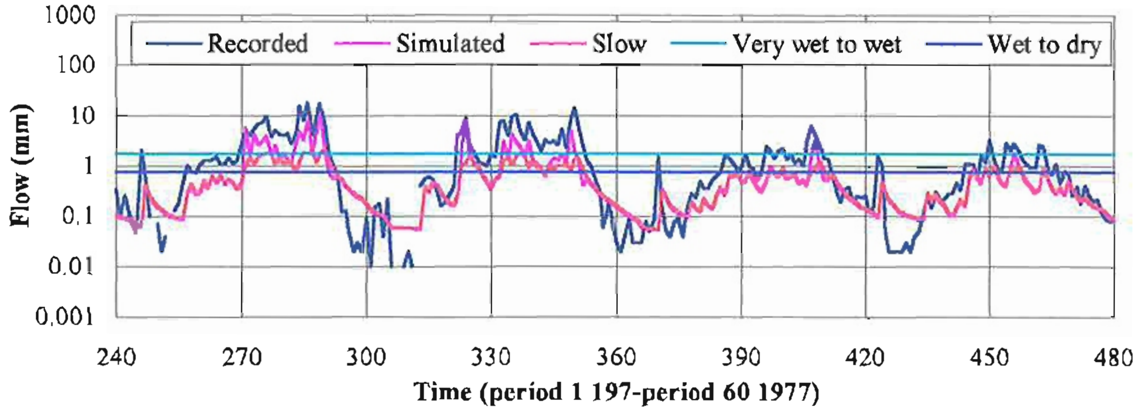


Figure A6-6 Scott Creek STDT4 Model Calibration Hydrographs





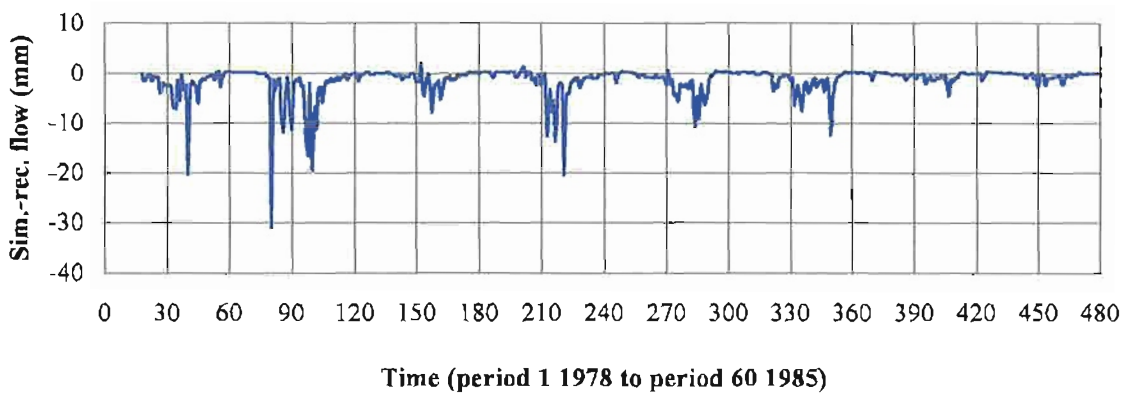


Figure A6-7 Scott Creek STDT4 Model Validation Hydrographs

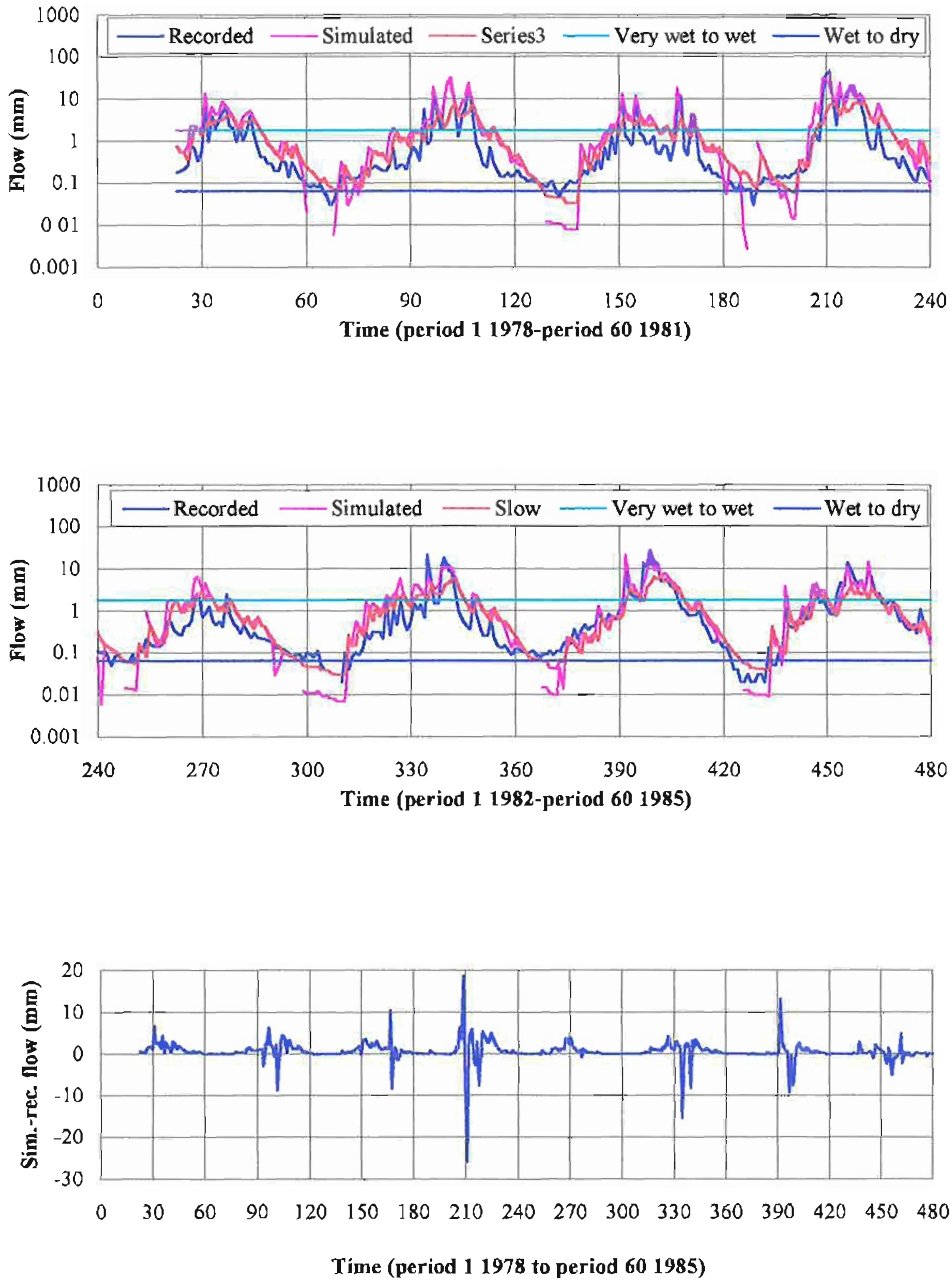
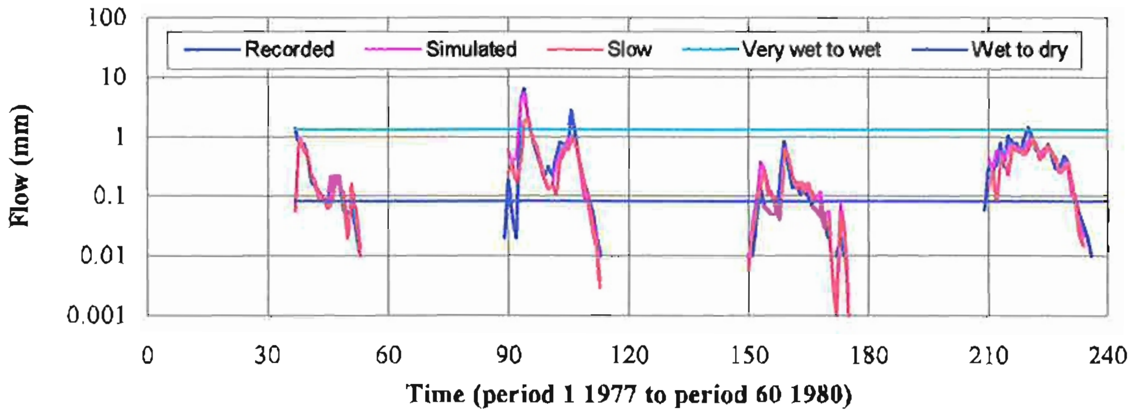
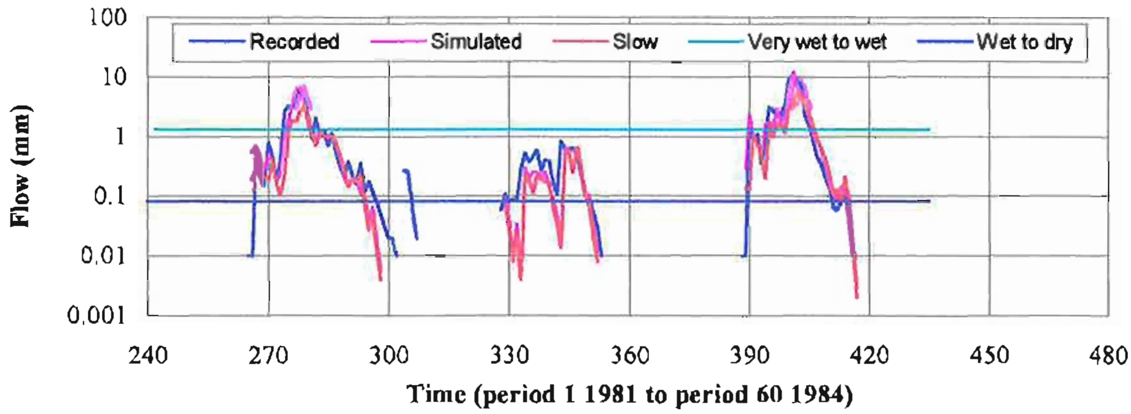


Figure A6-8 Scott Creek STDT4 Model Validation Hydrographs





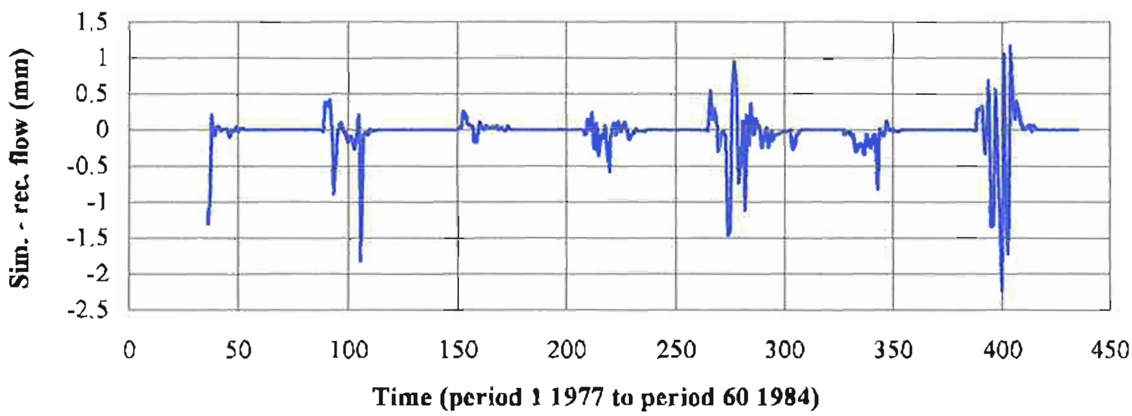
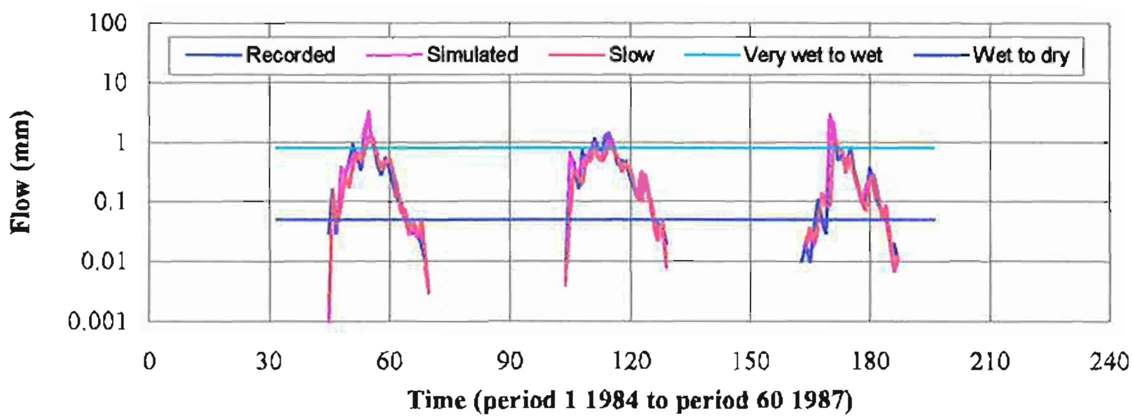


Figure A6-9 Canning River STDT4 Model Calibration Hydrographs



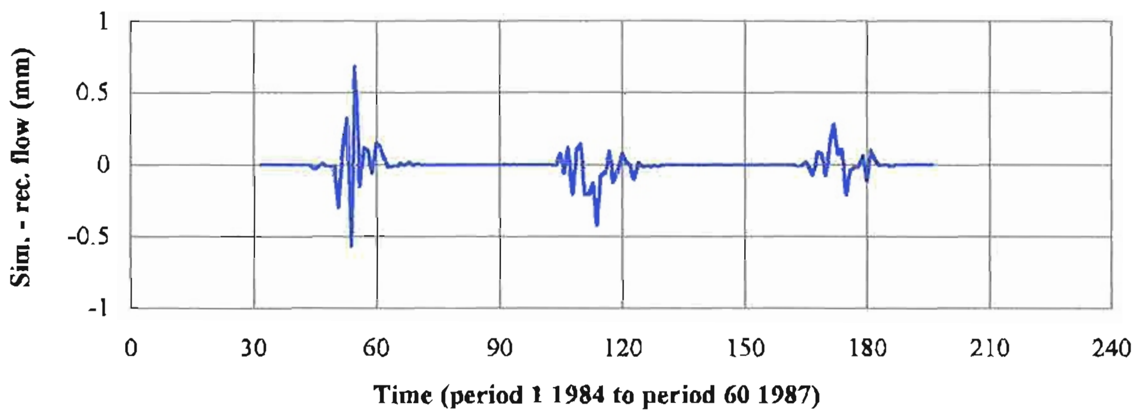


Figure A6-10 Canning River STDT4 Model Calibration Hydrographs

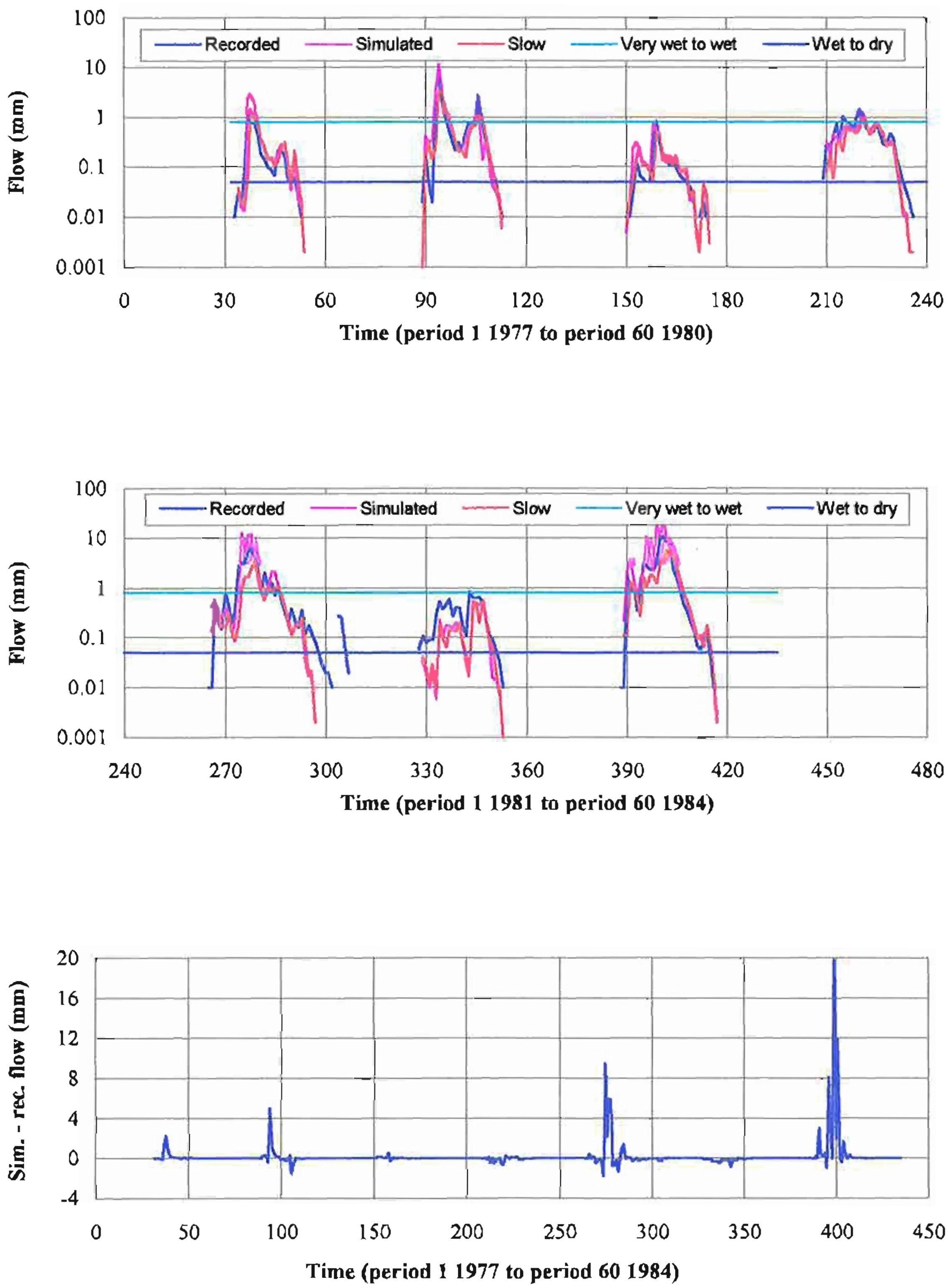
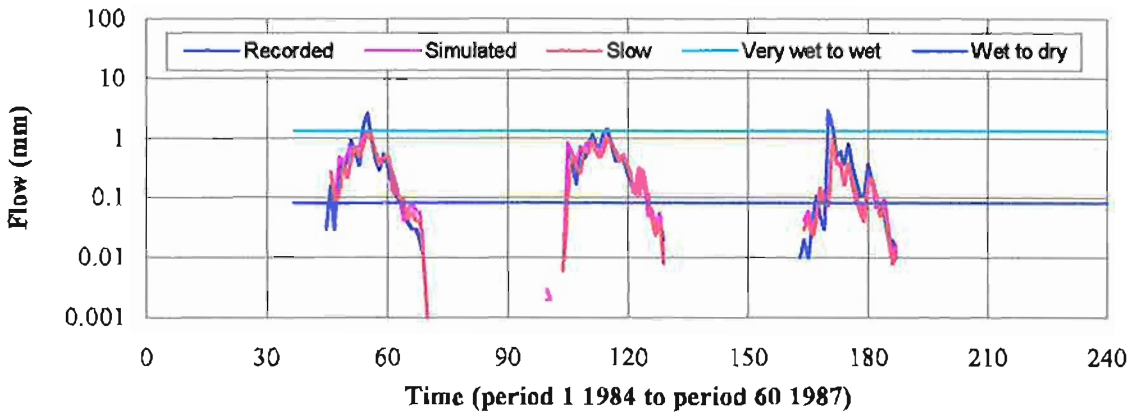


Figure A6-11 Canning River STDT4 Model Validation Hydrographs



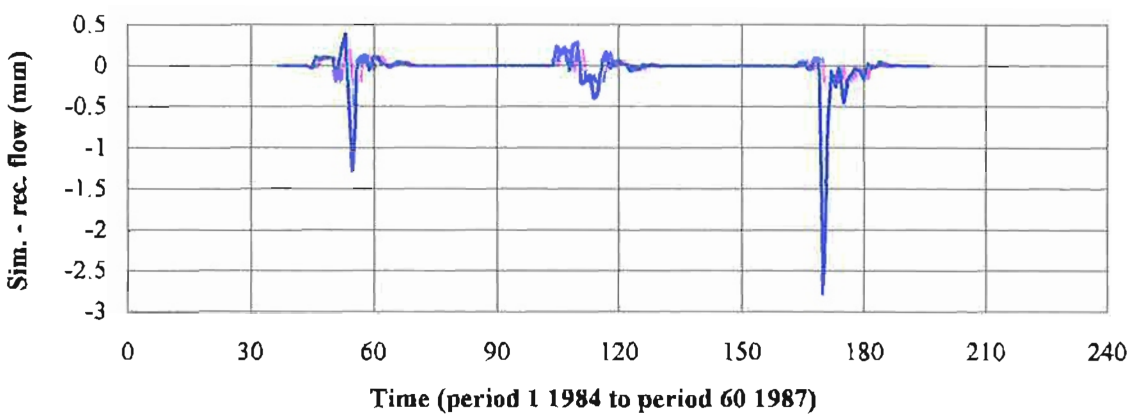


Figure A6-12 Canning River STDT4 Model Validation Hydrographs

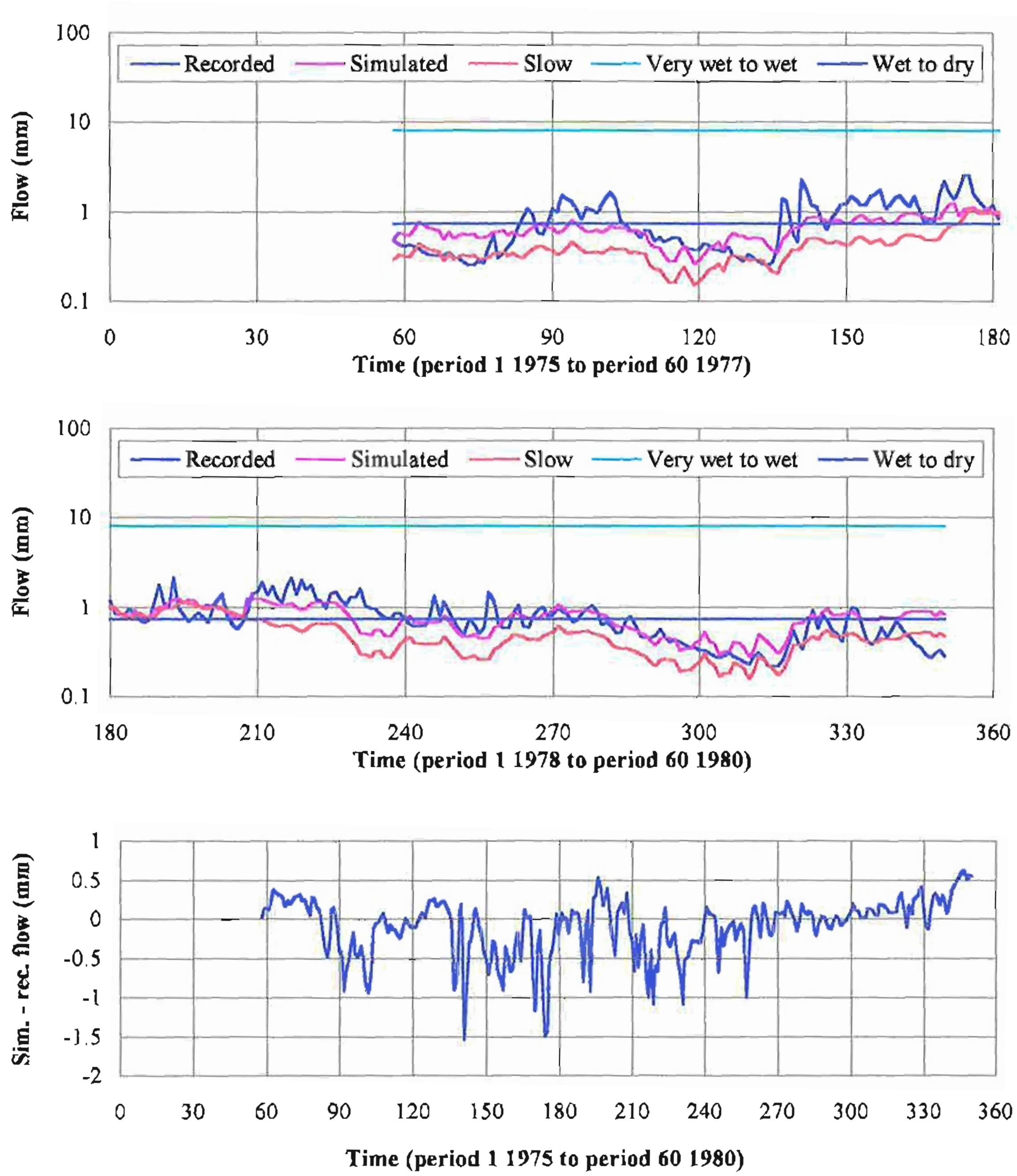


Figure A6-13 Noigameget STDT4 Model Calibration Hydrographs

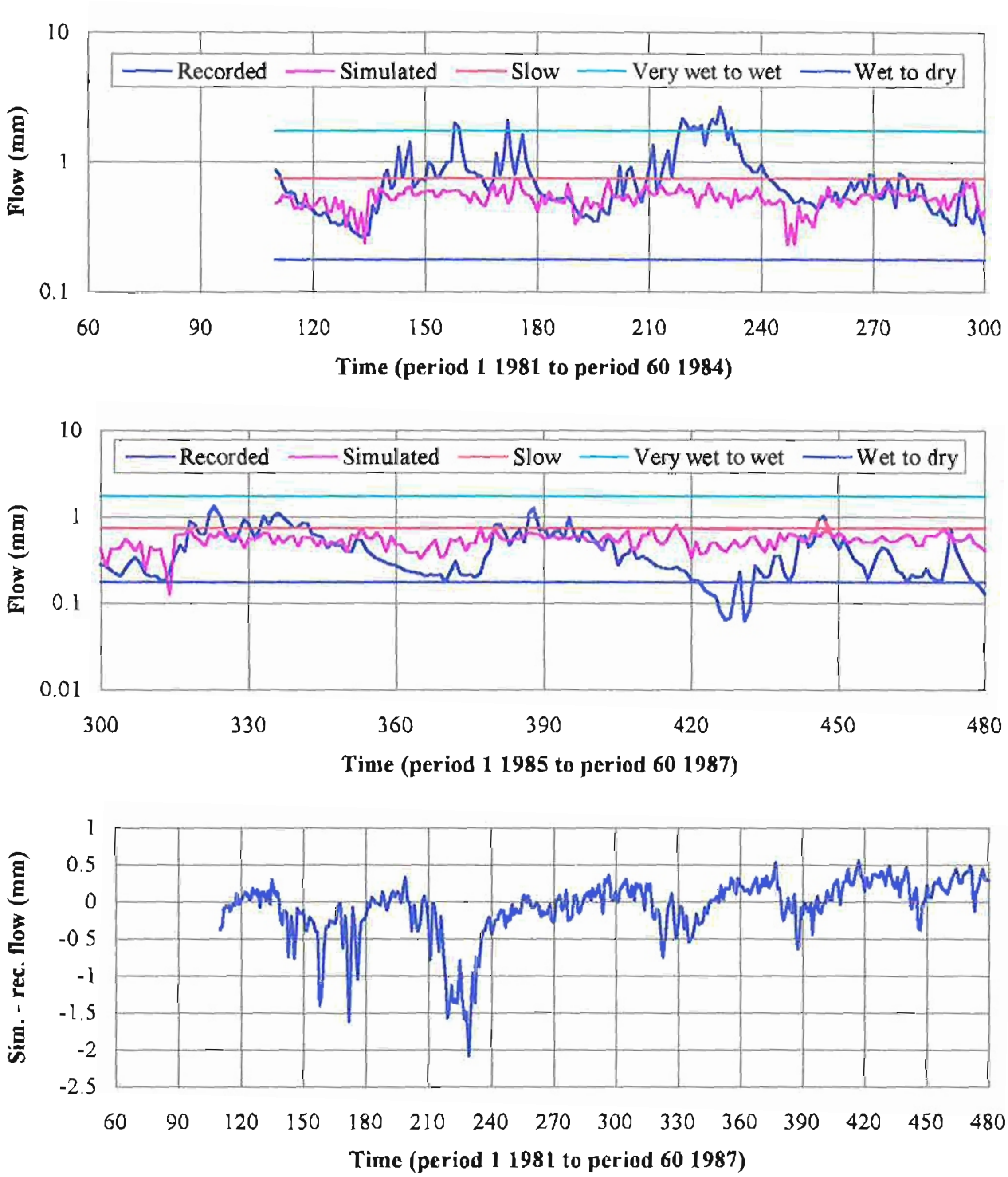
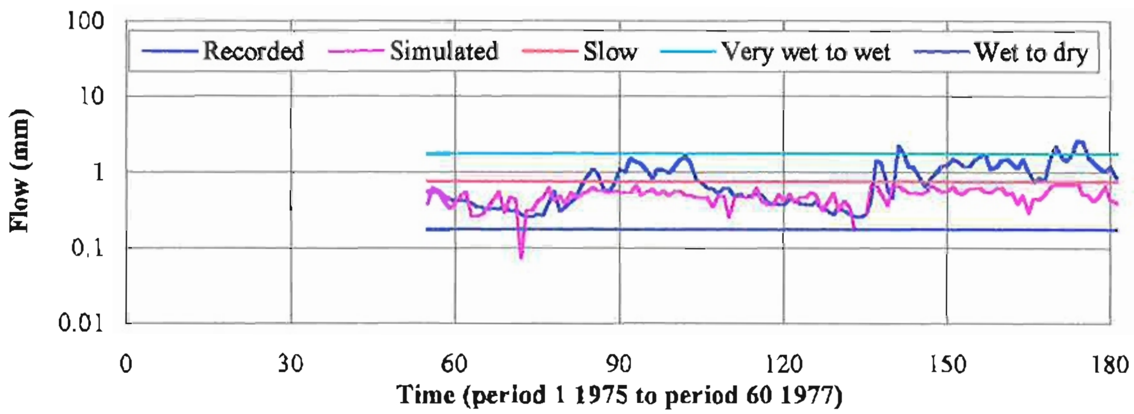
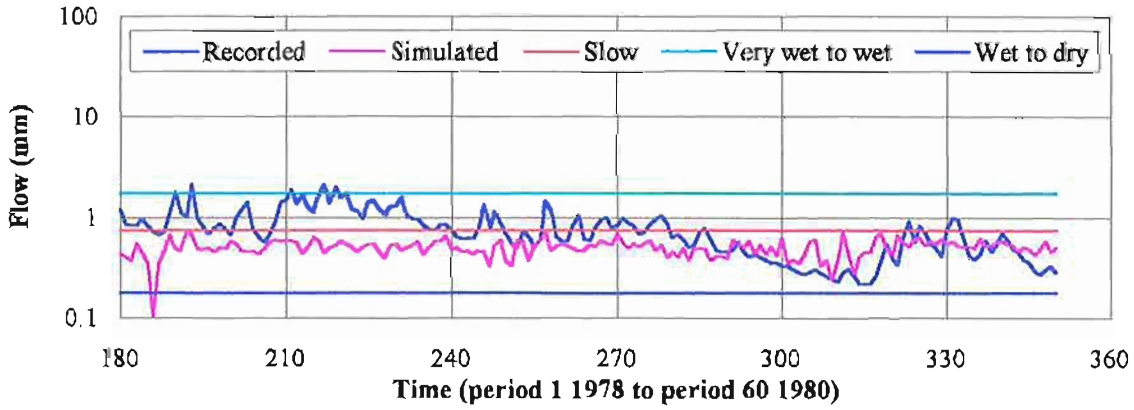


Figure A6-14 Noigameget STDT4 Model Calibration Hydrographs





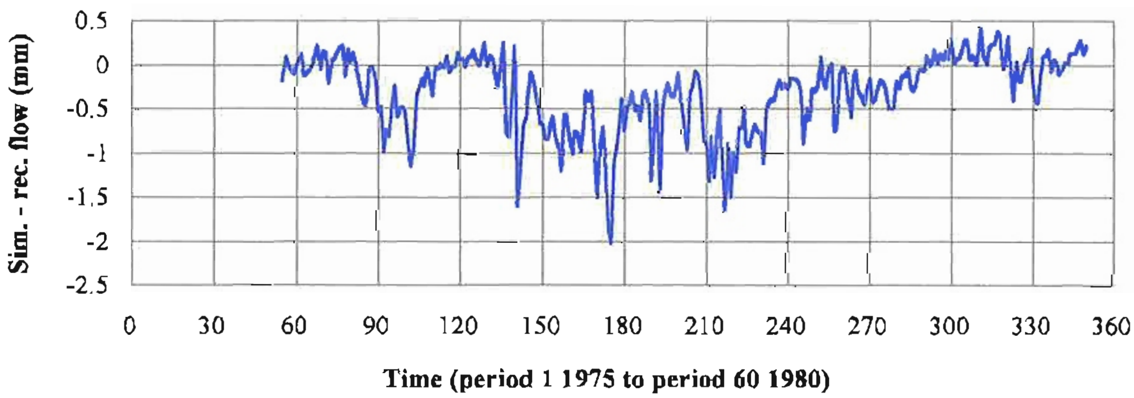


Figure A6-15 Noigameget STDT4 Model Validation Hydrographs

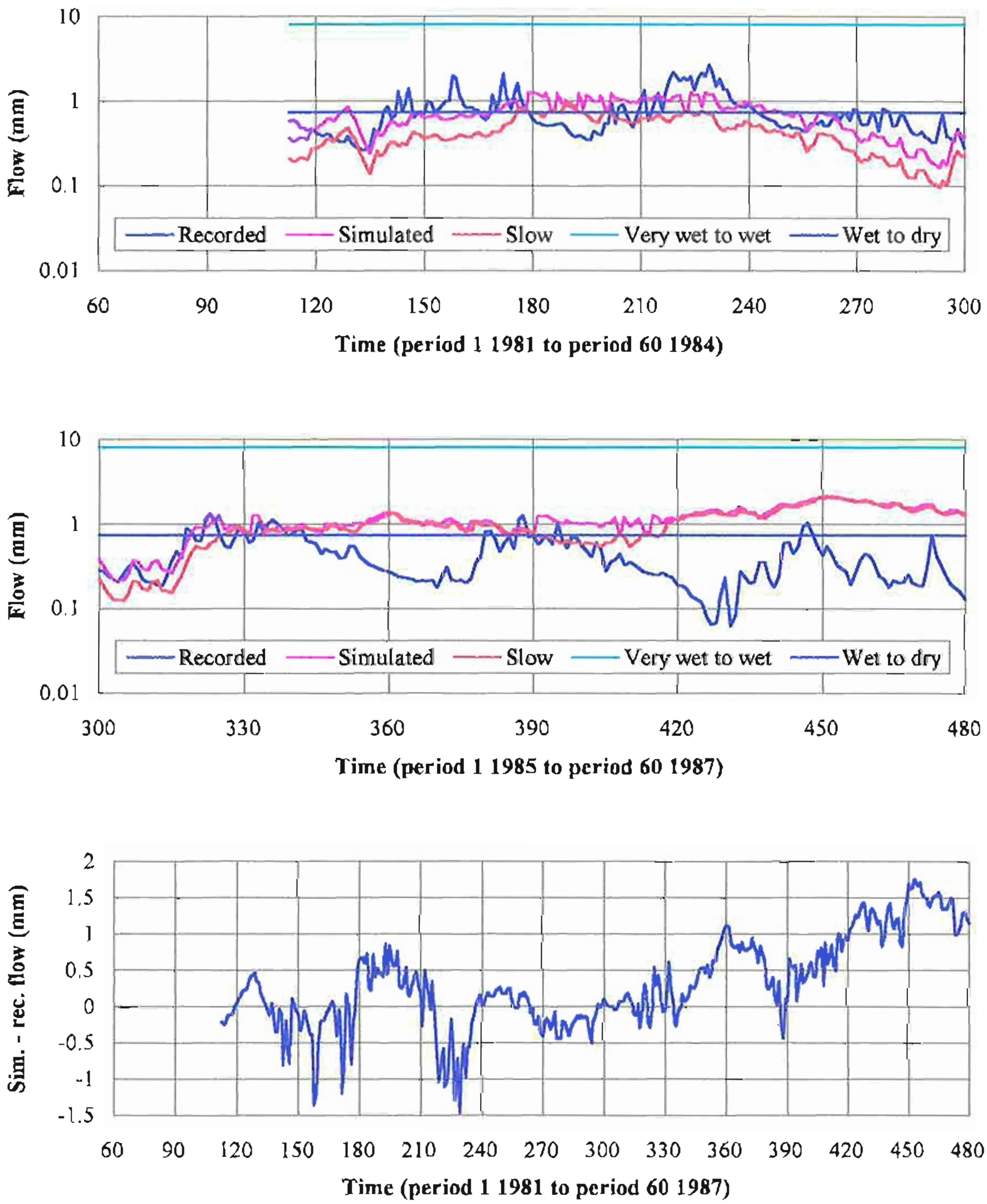
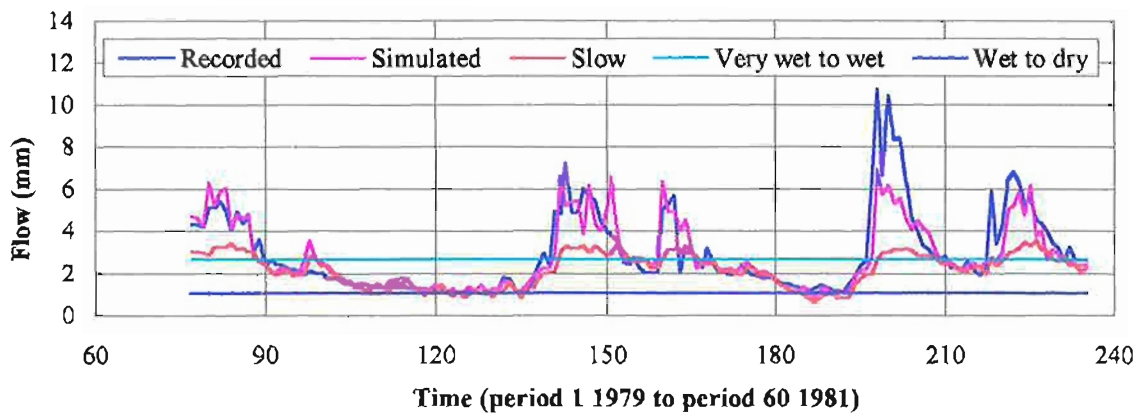


Figure A6-16 Noigameget STDT4 Model Validation Hydrographs



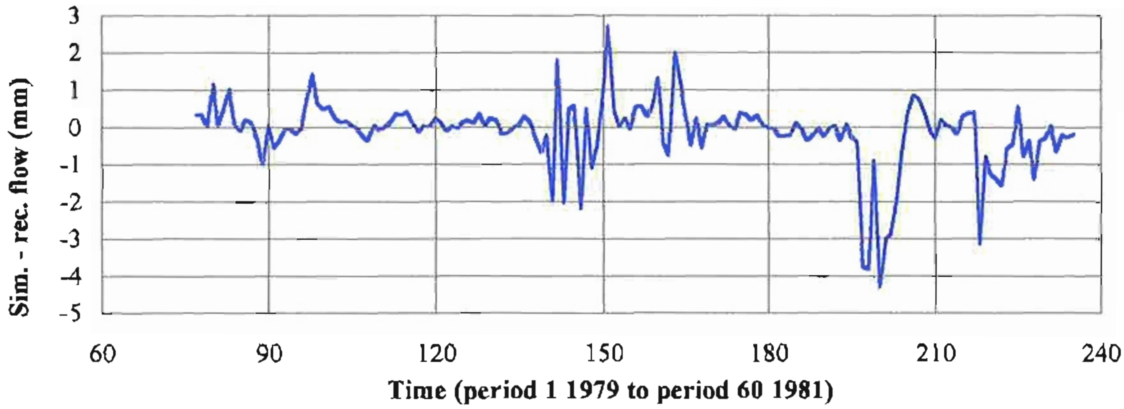


Figure A6-17 Nyasara STDT4 Model Calibration Hydrographs

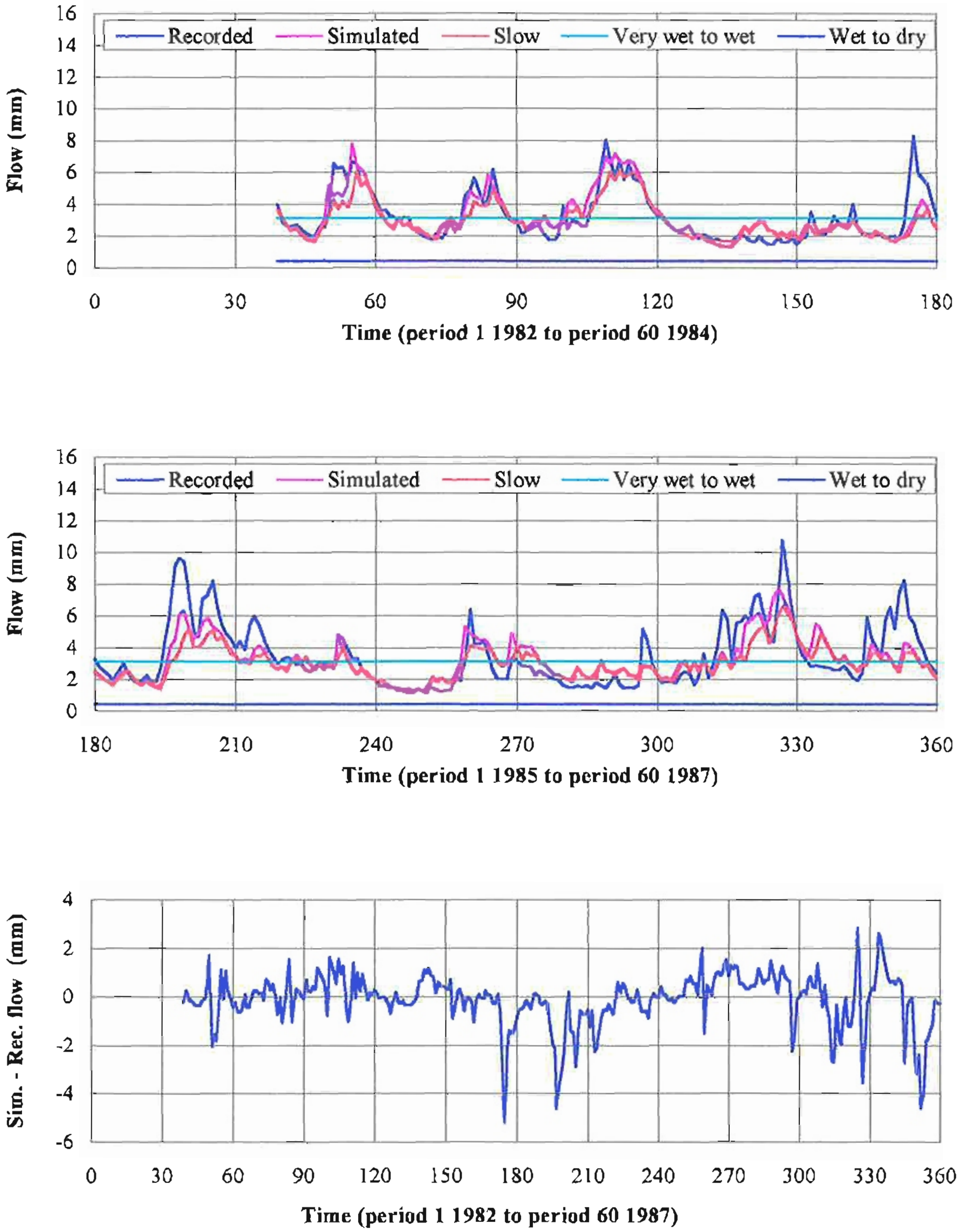


Figure A6-18 Nyasara STDT4 Model Calibration Hydrographs

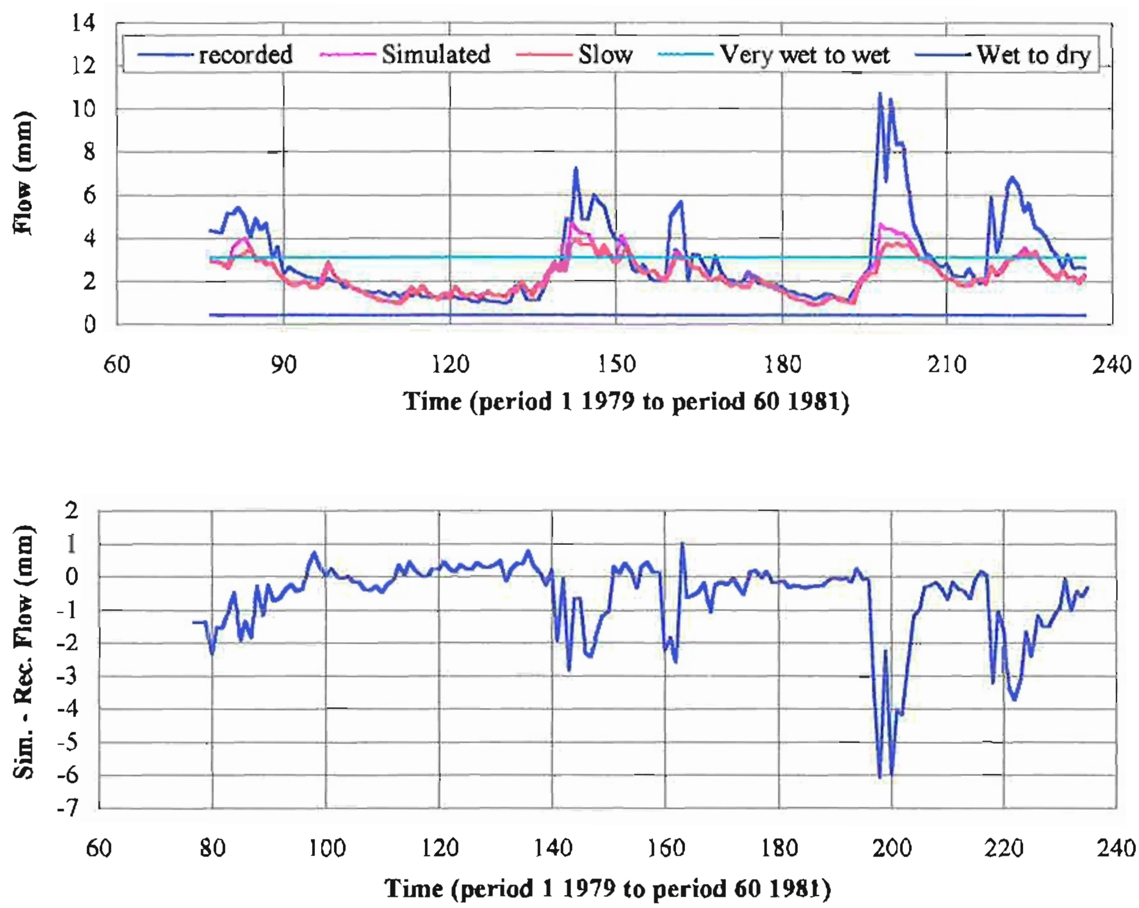


Figure A6-19 Nyasara STDT4 Model Validation Hydrographs

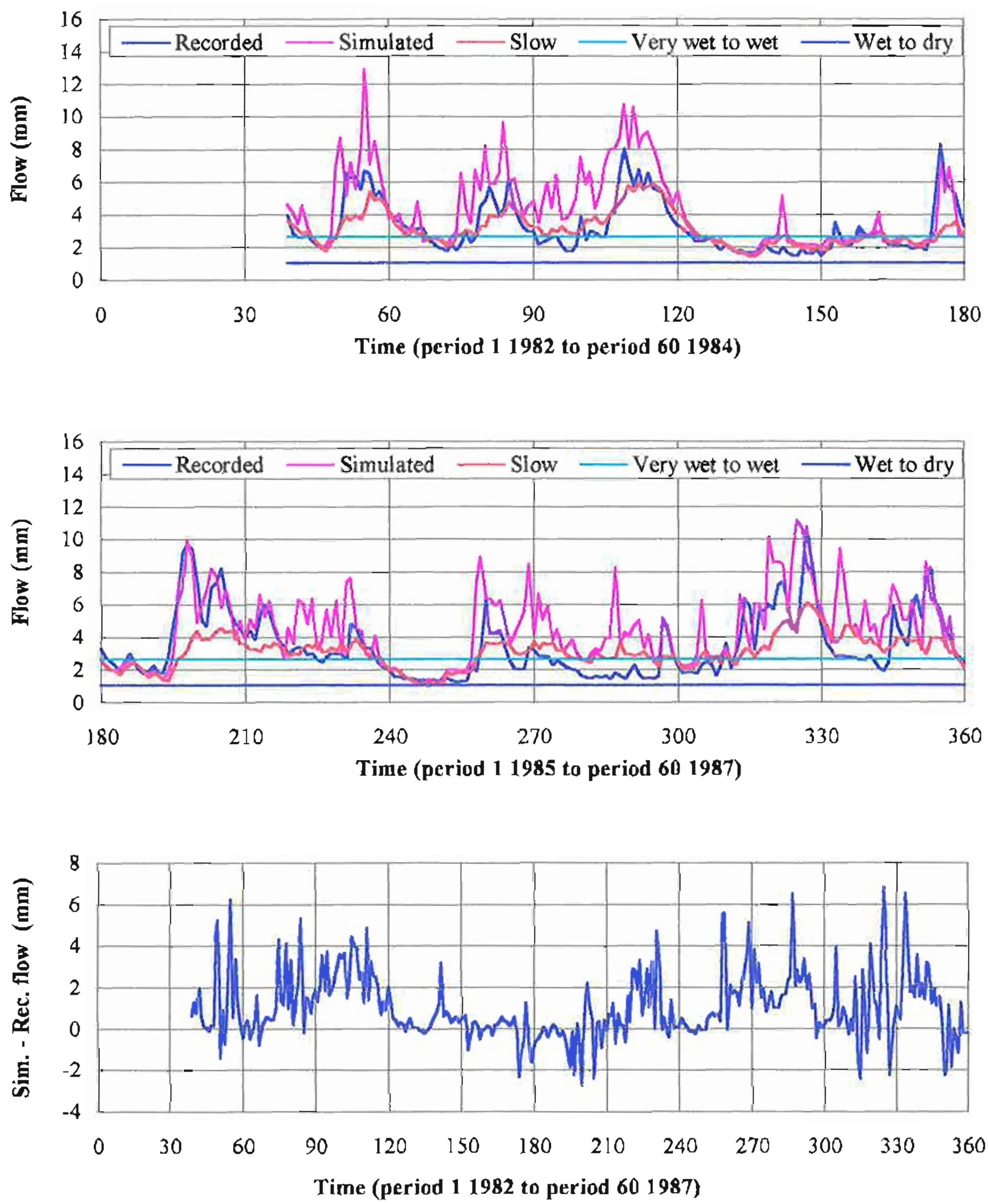


Figure A6-20 Nyasara STDT4 Model Validation Hydrographs

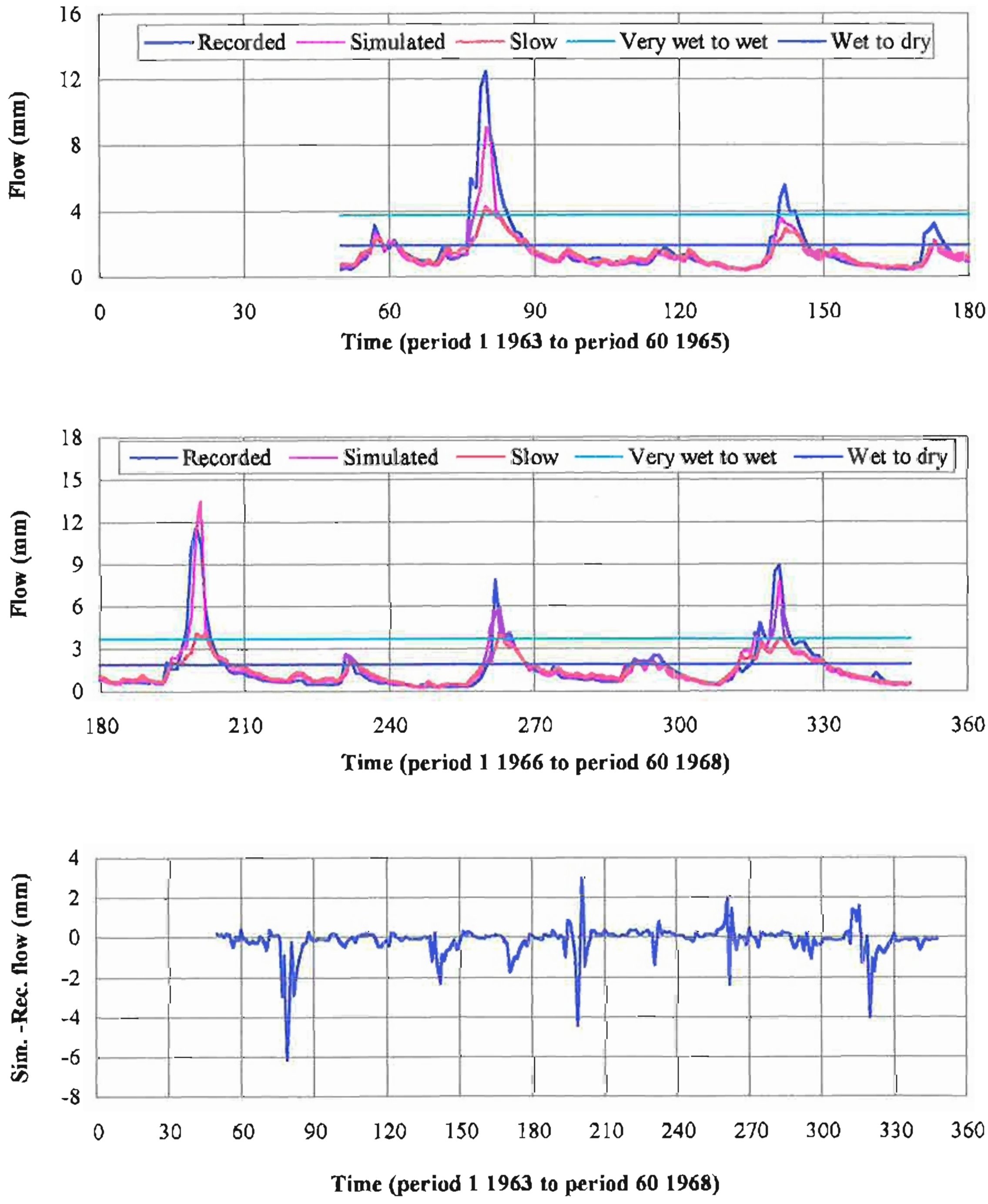


Figure A6-21 Chania STDT4 Model Calibration Hydrographs

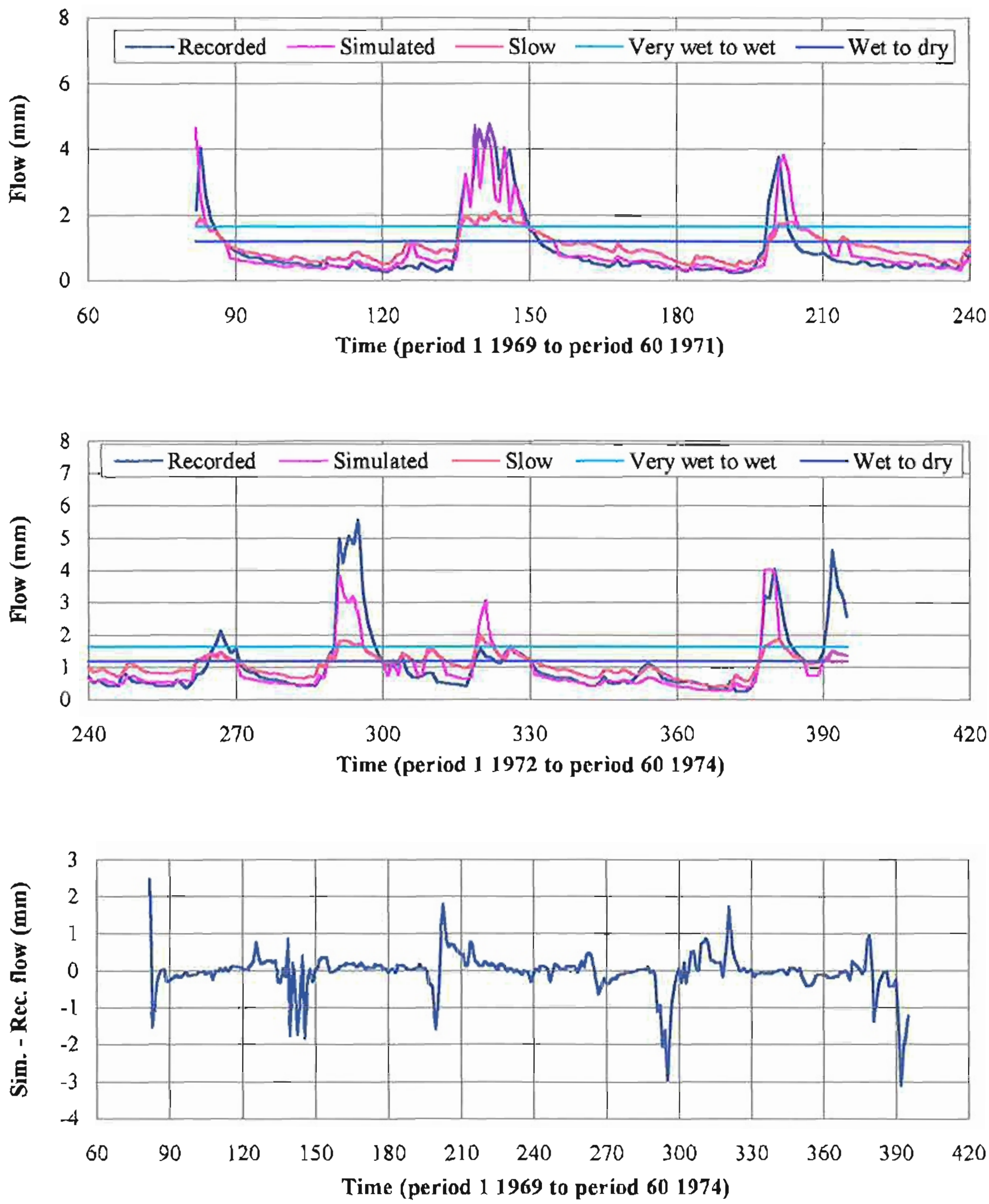


Figure A6-22 Chania STDT4 Model Calibration Hydrographs

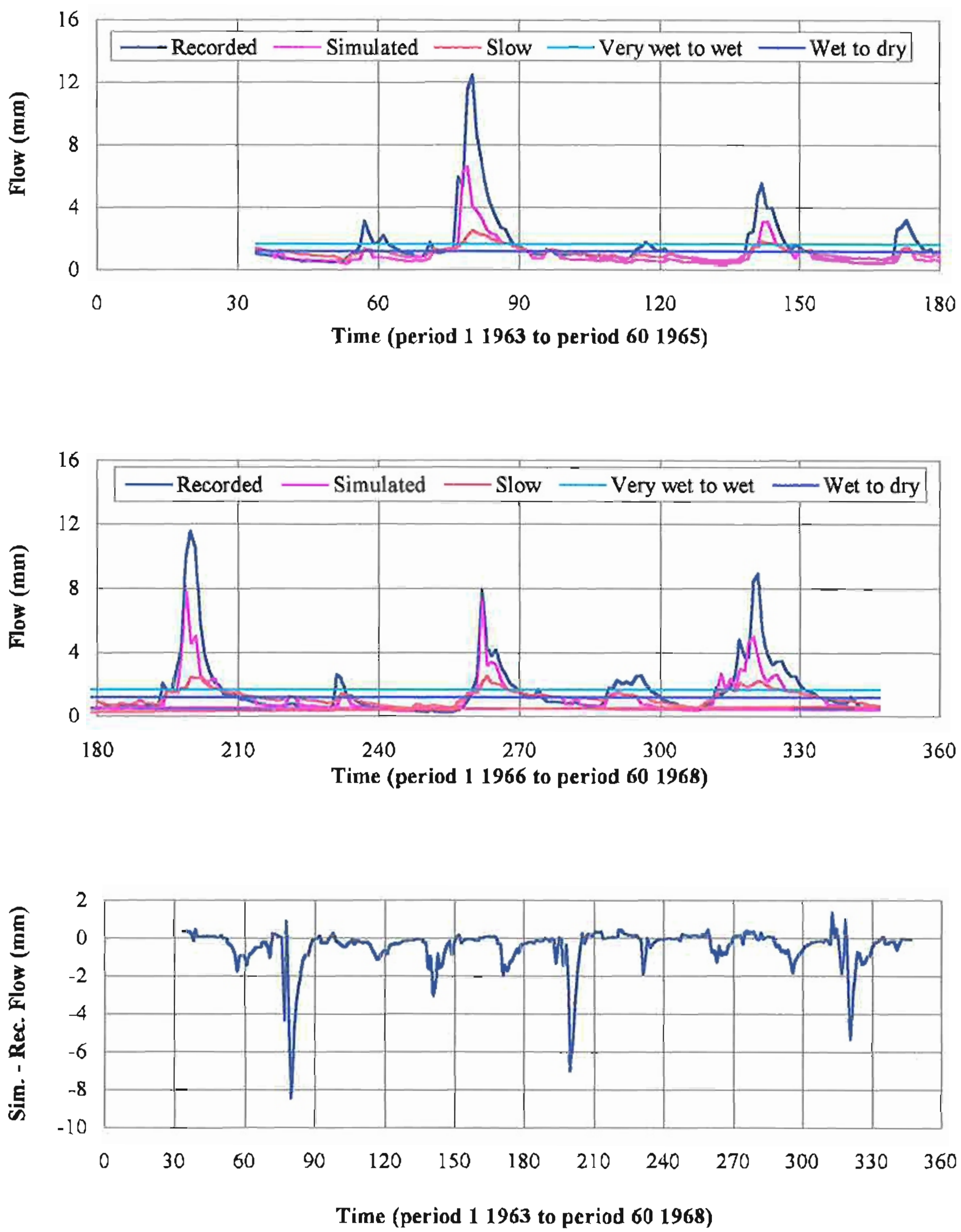
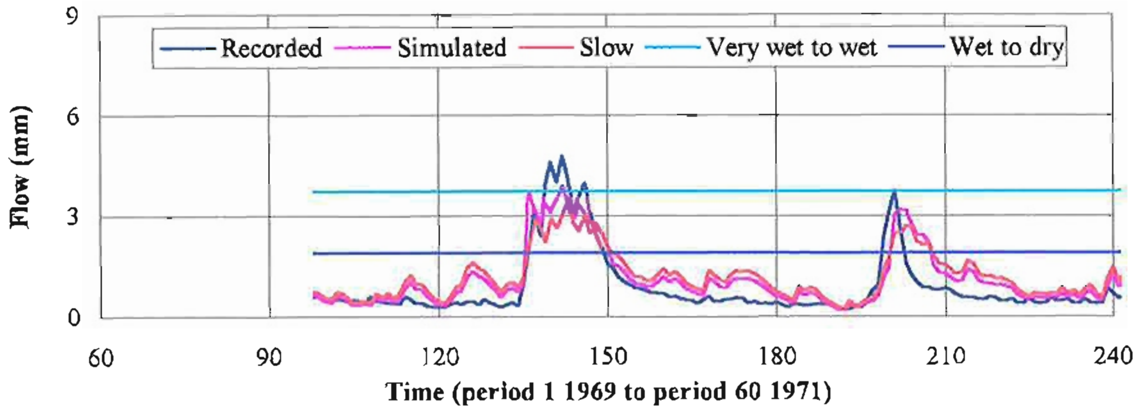
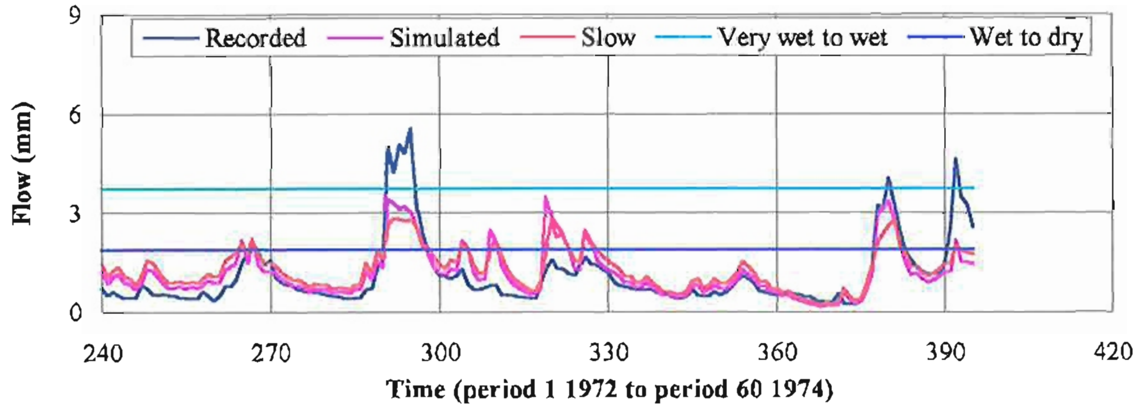


Figure A6-23 Chania STDT4 Model Validation Hydrographs





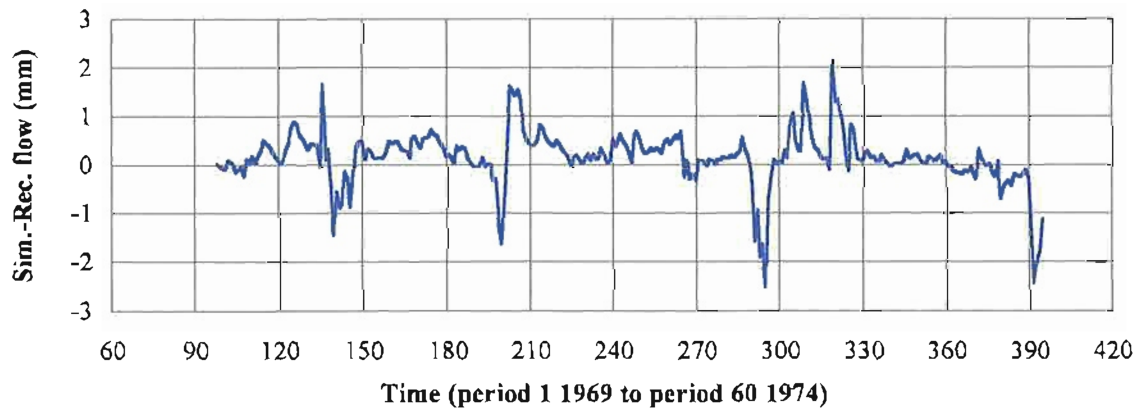


Figure A6-24 Chania STDT4 Model Validation Hydrographs

Appendix A7

Hydrographs for Model Comparisons

The hydrographs obtained from the model calibrations and validations using the STDT3, the STDT4 and the MODHYDROLOG model are presented as Figure A7-1 to A7-3 for Babinda Creek, Figure A7-4 to A7-6 for Scott Creek and Figure A7-7 to A7-9 for Canning River.

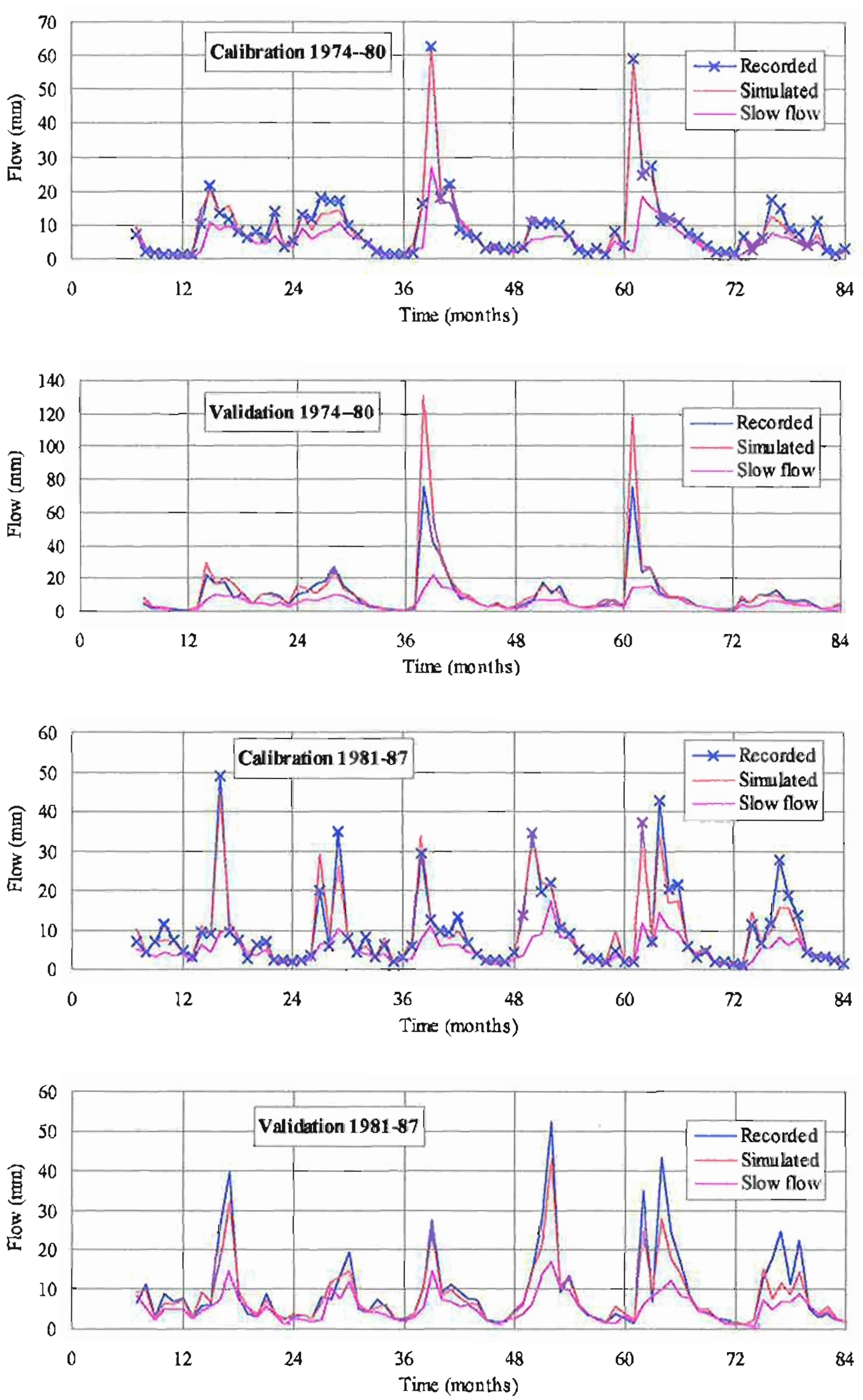


Figure A7-1 STDT3 Model Monthly Calibrations and Validations for Babinda Creek

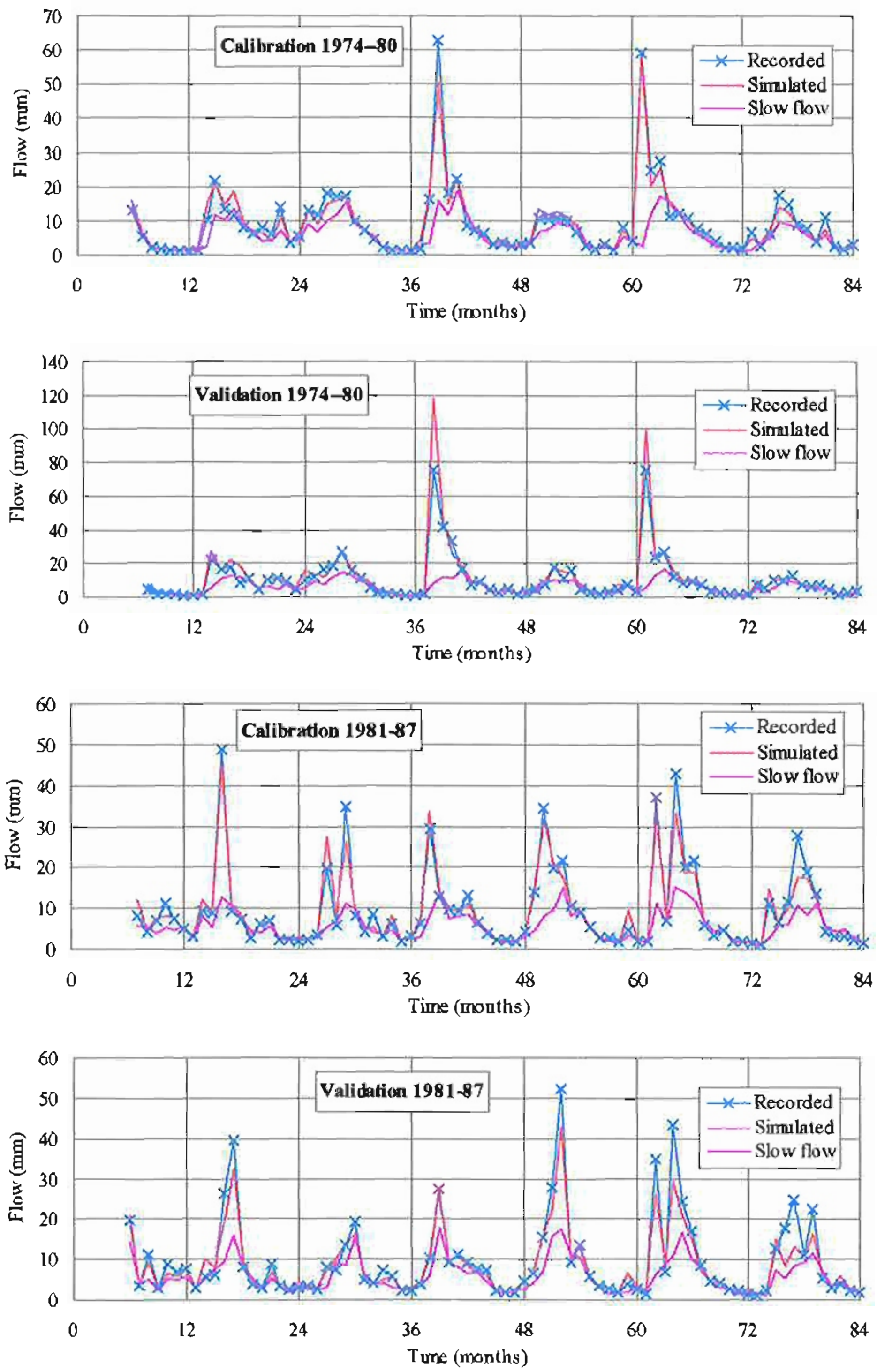


Figure A7-2 STDT4 Model Monthly Calibrations and Validations for Babinda Creek

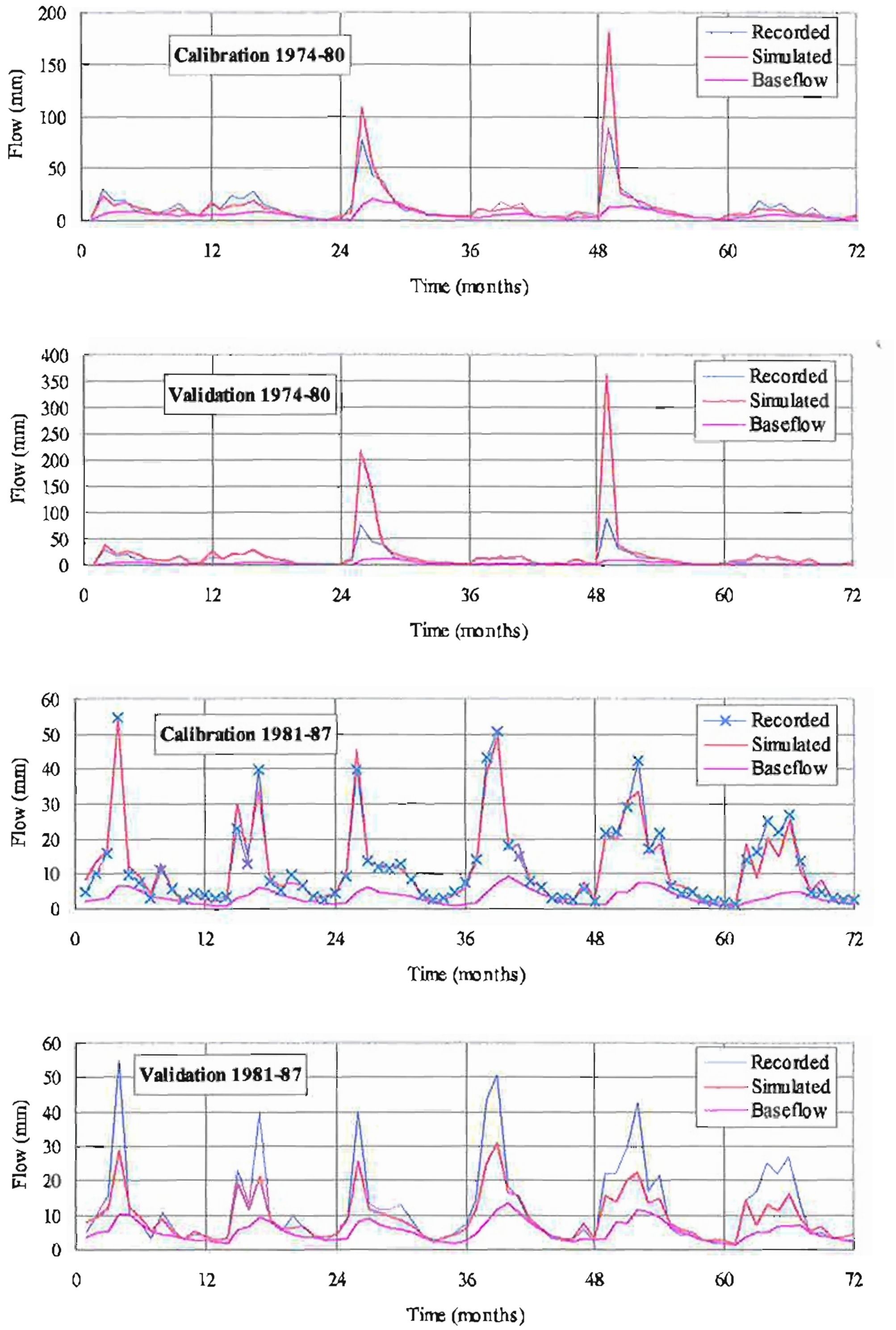


Figure A7-3 MODHYDROLOG Model Calibrations and Validations for Babinda Creek

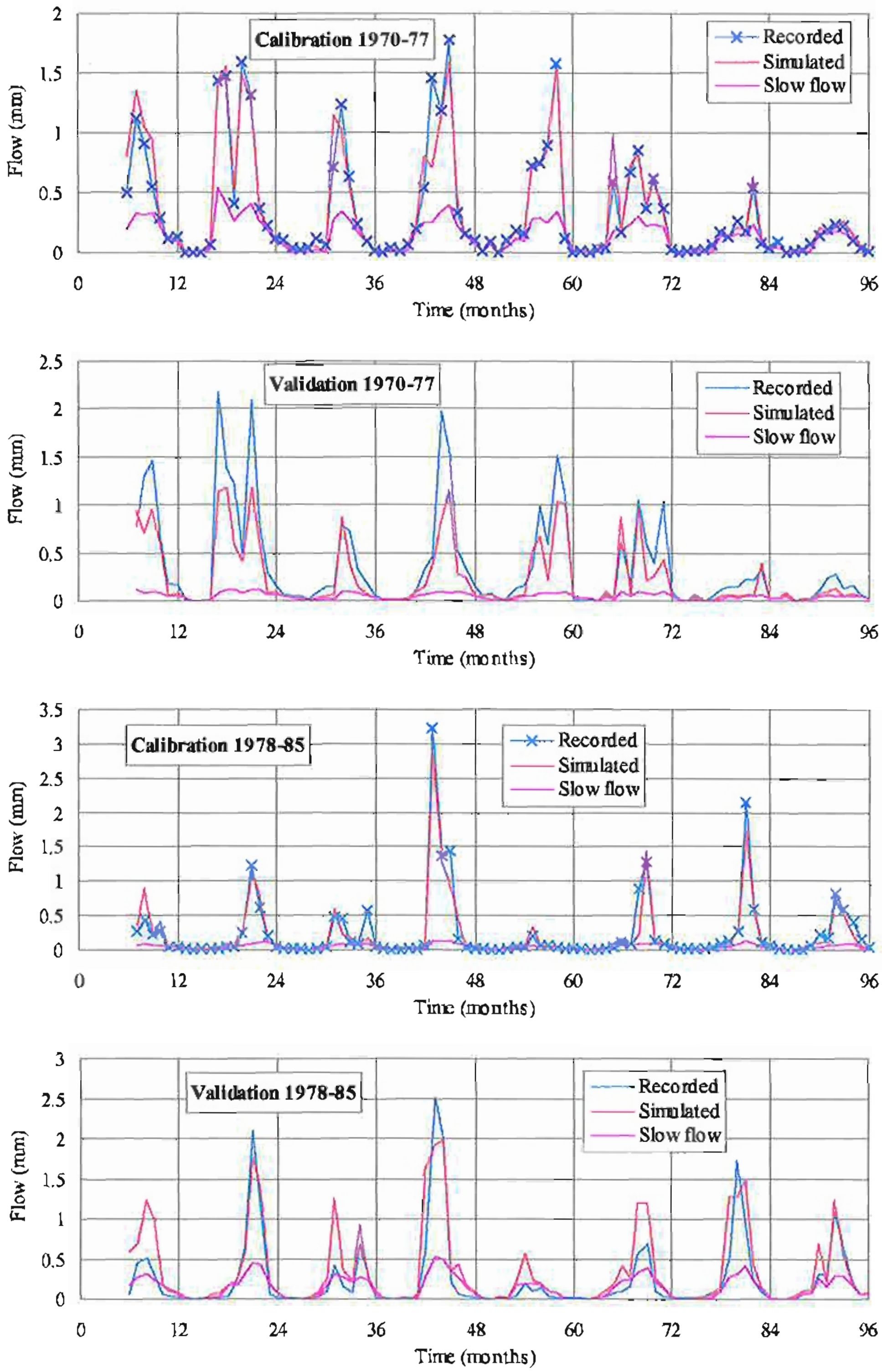


Figure A7-4 STDT3 Model Monthly Calibrations and Validations for Scott Creek

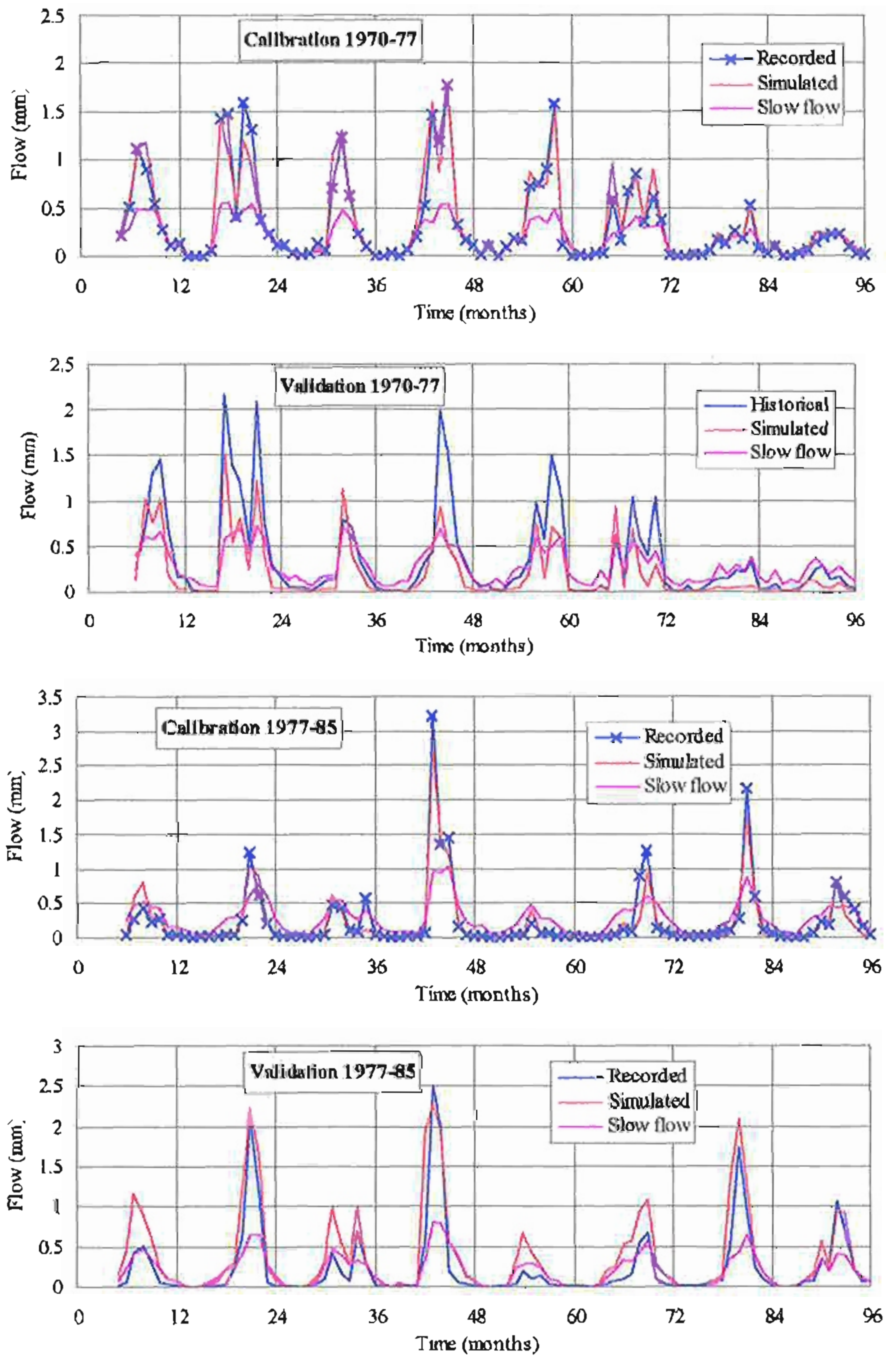


Figure A7-5 STDT4 Model Monthly Calibrations and Validations for Scott Creek

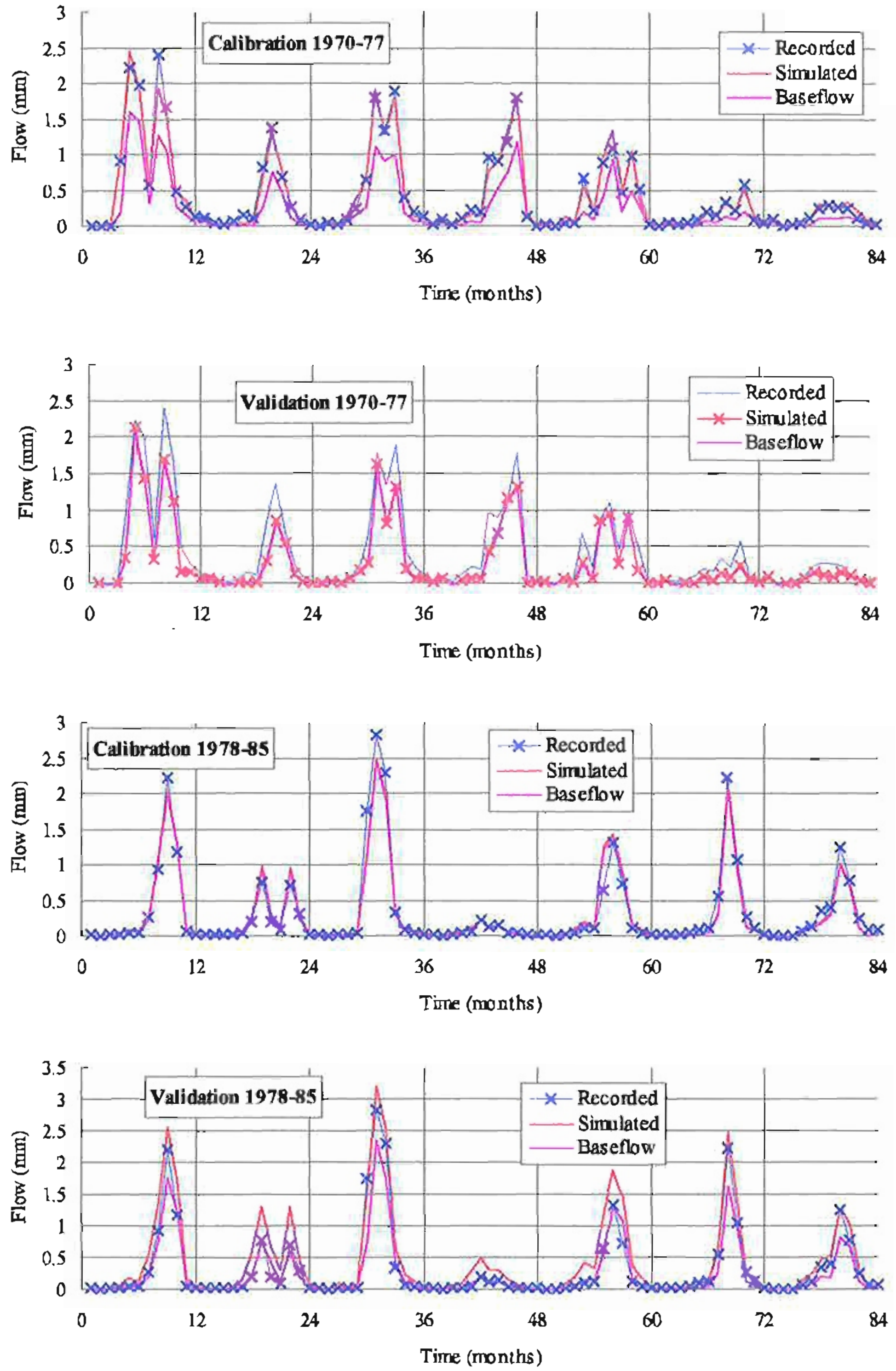


Figure A7-6 MODHYDROLOG Model Calibrations and Validations for Scott Creek

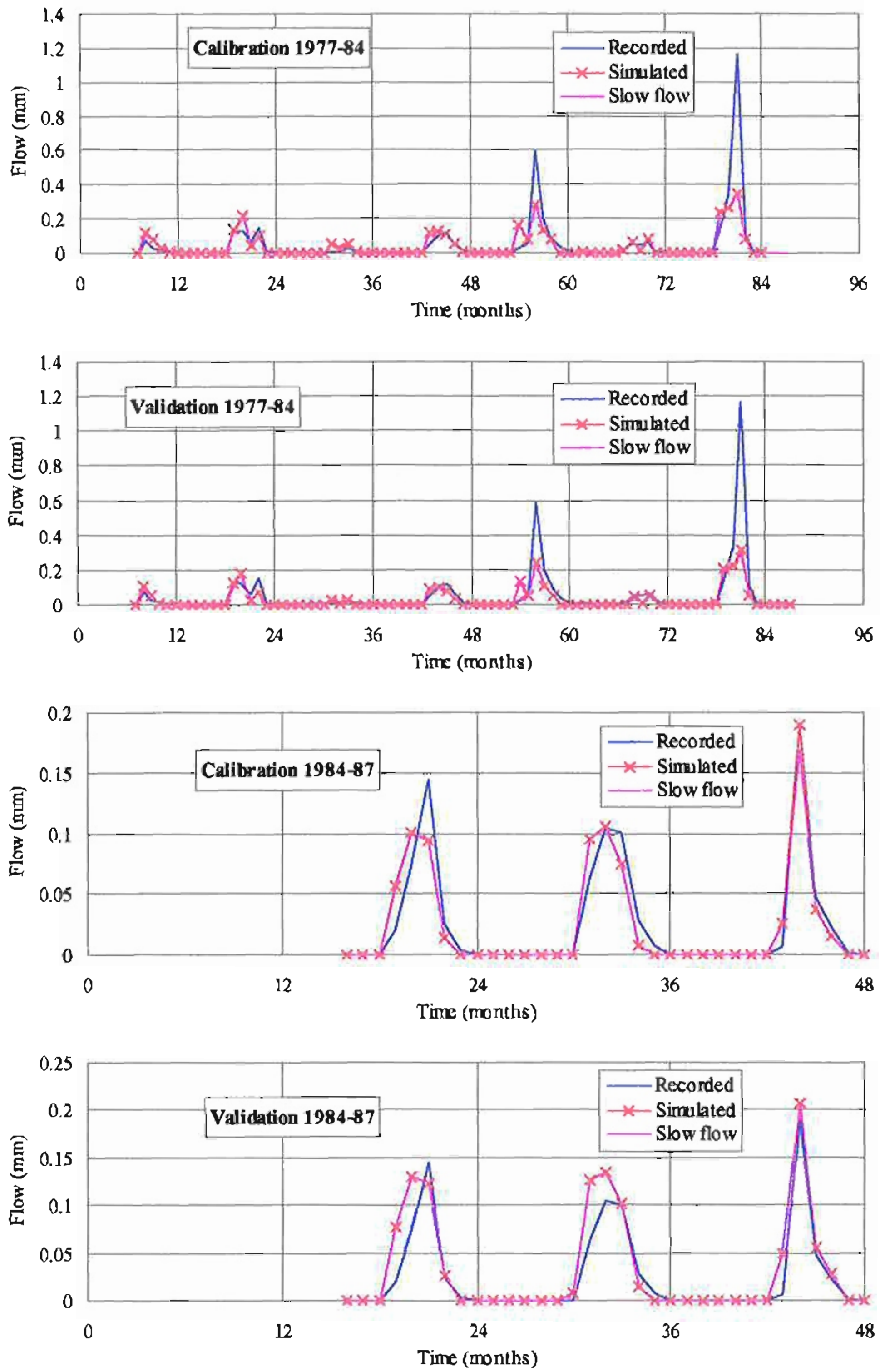


Figure A7-7 STDT3 Model Monthly Calibrations and Validations for Canning River

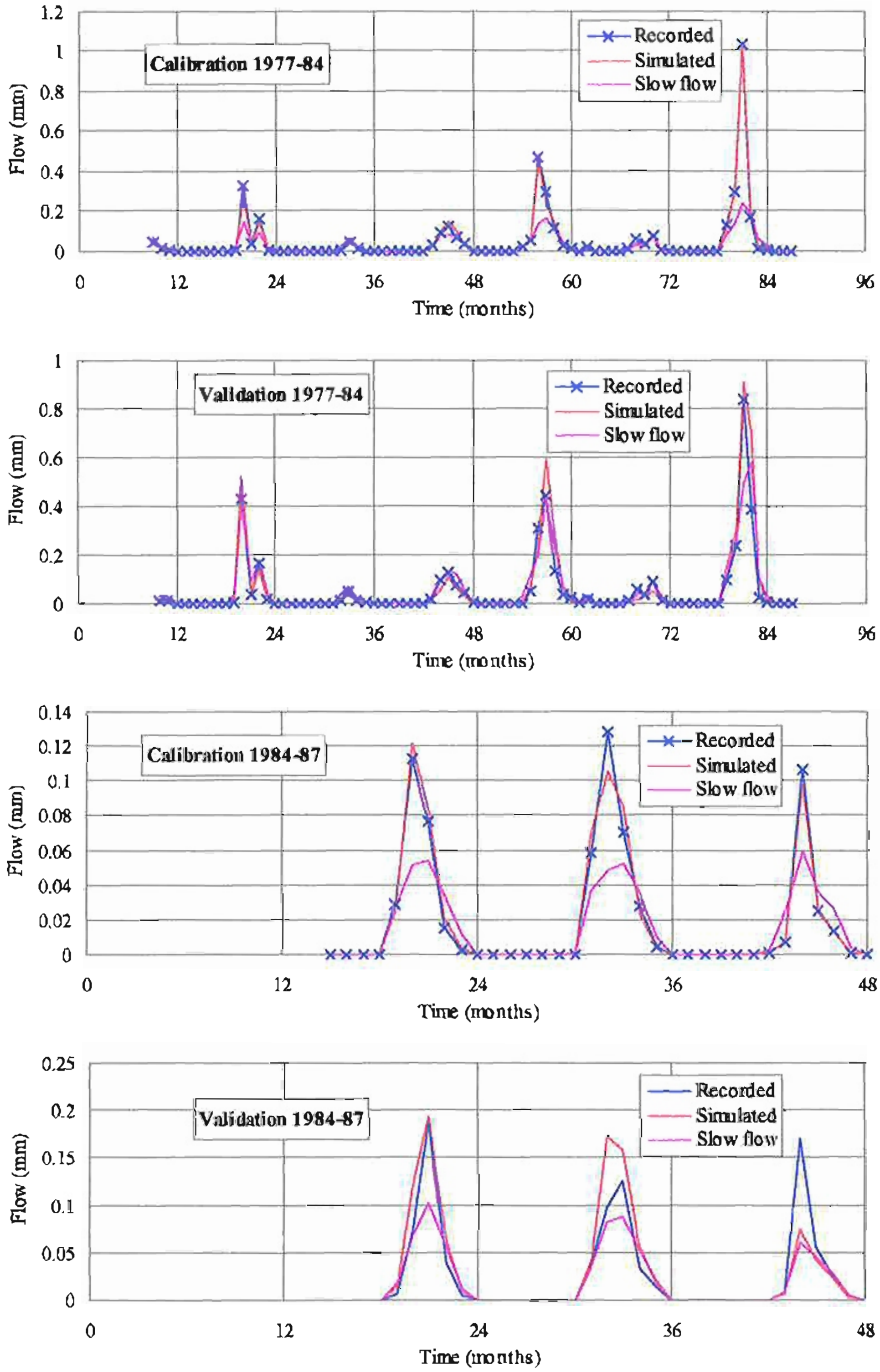


Figure A7-8 STDT4 Model Monthly Calibrations and Validations for Canning River

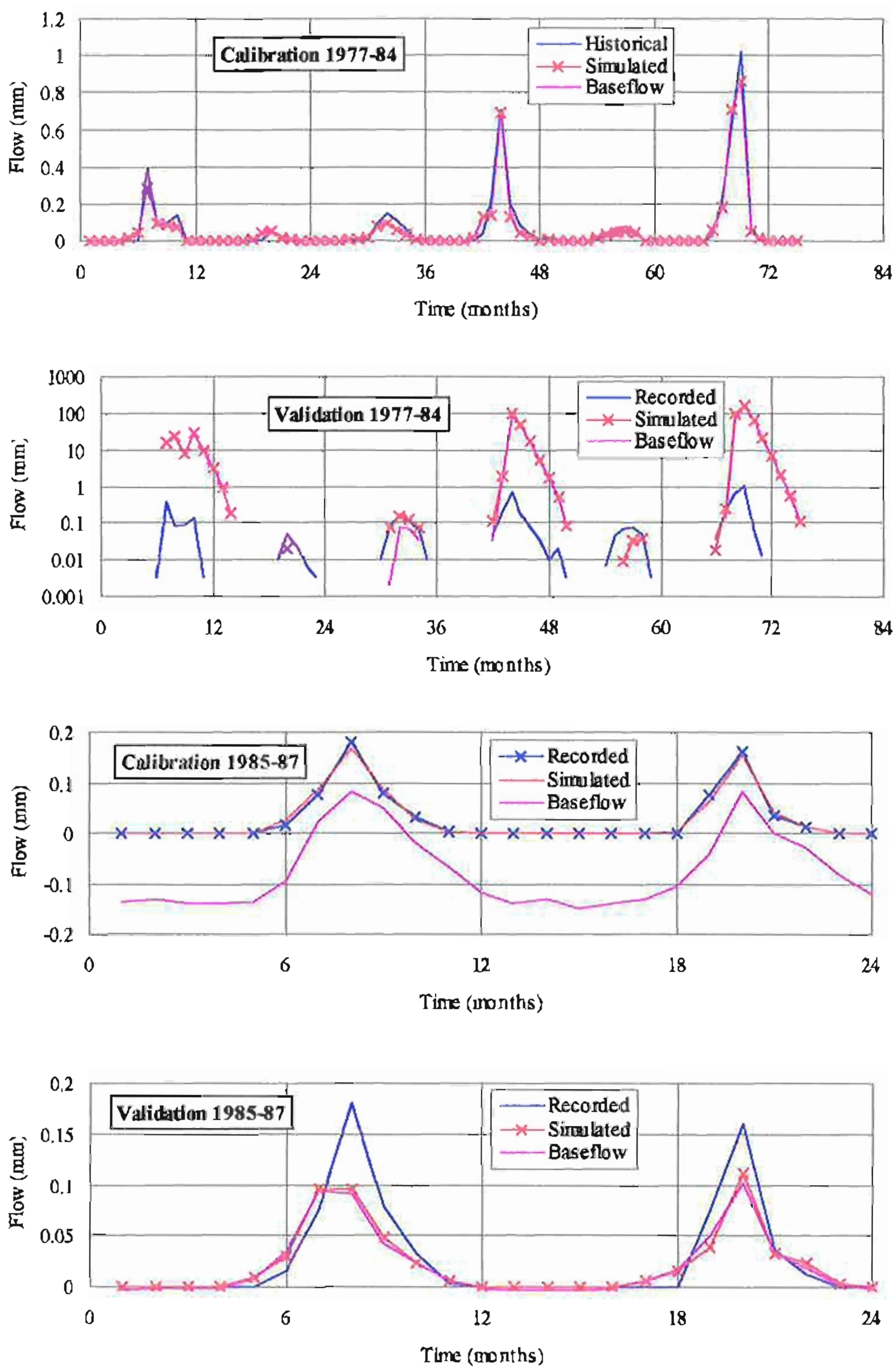


Figure A7-9 MODHYDROLOG Model Calibrations and Validations for Canning River