HYDROLOGIC MODELLING OF THE MFULI WATERSHED IN ZULULAND, SOUTH AFRICA

A Thesis

Presented to

The Faculty of Graduate Studies

of

The University of Guelph

by

LAURA J. BROWN

In partial fulfilment of requirements

for the degree of

Master of Science

April, 2000

ABSTRACT

HYDROLOGIC MODELLING OF THE MFULI WATERSHED IN ZULULAND, SOUTH AFRICA

Laura J. Brown
University of Guelph

Advisor:
Ray Kostaschuk

Two deterministic watershed hydrologic models are applied to the Mfuli subcatchment in KwaZulu-Natal, South Africa, a region characterized by semi-arid conditions, limited accessibility and sparse data. The Hydrological Model Application System (HYMAS), a model designed for application in Southern Africa proved unusable because parameters were inadequately defined and there was insufficient source data to meet the many parameter requirements. The Runoff module in the Storm Water Management Model (SWMM) was selected as an alternative because it has ample documentation and can be modified to accommodate the available data. SWMM proved sensitive to the parameter defining the percent catchment area that was impervious and directly connected to the channel. The thin local soils required higher values of percent imperviousness than would otherwise be expected for a rural area. Eight of the twelve storm events have a computed output between +/- 50% of the observed stormflow volume and the remaining four storms were overestimated by 209% to 416%. Uncertainty analysis showed that the Mfuli region requires more raingauge and streamflow data for reliable model usage and assessment.

Acknowledgements

This thesis would not have been possible without my advisor Ray Kostaschuk, who encouraged me to pursue a secondary degree, and has supported and guided me through the twists and turns this work has taken. I am grateful to Doug Joy for his knowledge and practical approach to problem solving, and Bill James whose knowledge of the SWMM model and the study area were invaluable resources. Thanks are due to Vicky Dainty and Carol Luttmer for their help in researching the project. I would also like to thank the Senior Hydrology Class (1997) of the University of Zululand for their work in the field, and for providing singing and laughter. Talita Germishuyse, Nina Snyman and Bruce Kelbe graciously shared their homes, knowledge and their part of the world with me.

Thanks also to my family and friends who have been a source of encouragement, diversion and laughter. For their support through the highs and lows of this work and for always helping to put things into perspective I would like to thank Shellie Thomas, Jeannette Krabicka, Jane Hudson, Brenda Murphy and Lois Lindsey. Finally, I would like to acknowledge my husband, Mark Laird, whose constant and unfailing support and encouragement has been a source of strength and his belief that I could achieve anything I set out to do was proven true.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Problem Identification

Water planners and managers in South Africa face a serious challenge because the physical availability of water in the country remains fixed, yet water demands steadily increase as the population expands and standards of living improve (Biswas 1990). To provide for these needs, more water will be required for domestic use, irrigation and industry. Low rainfall further exacerbates the increasing demand on water resources, and drought is a possibility in all parts of the country (South African Government, White Paper 1995). Oral tradition in South Africa affirms that as early as the 19th century frequent droughts and poor harvests were common (Nicholson 1996). Meteorological records document major droughts in the 1800s, 1820s, and 1830s which affected summer rainfall in the regions of Ciskei, Transkei and especially Zululand (Nicholson 1996). Water resource management is needed to ensure that an adequate water supply is available, especially during times of drought. Hydrologic models can be used to provide an estimate of present and future resource supply (Jensen and Mantoglou 1992) and serve as a basis for decision making (Bergström 1991).

Hydrologic models are used to predict the hydrological impacts of changes in the environment (Jensen and Mantoglou 1992) and to supply information where data is not directly available (Refsgaard and Knudsen 1996). Jensen and Mantoglou (1992) and Refsgaard and Knudsen (1996) identify several areas where assessments of hydrological consequences are required,

including land-use changes related to agriculture and forestry practices, development potential of ungauged areas, surface and subsurface water exploitation, climatic changes, and the subsurface migration of industrial and agricultural chemicals. Land-use changes such as deforestation, overgrazing and urban or agricultural developments and loss of topsoil are directly influenced by decision makers in planning or management and increasingly the role of hydrologic models is to predict the results of human activity on the quality and quantity of water (Jensen and Mantoglou 1992). Other changes in the environment, such as global warming, have a direct impact on the global hydrologic cycle but are less directly attributable to human activities.

1.2 Water Policy in South Africa: Past and Present

The history of water management reflects the inequality of power and economic development inherent in South Africa. Water law in South Africa developed over the past 100 years to serves the interests of agricultural land owners, industry and urban municipalities (South African Government, White Paper 1995). By the end of the 19th century, irrigation of white-owned commercial farms accounted for most of the water use in the country (South African Government, White Paper 1995). There were few dams, so water for irrigation was usually diverted from rivers. Legislation protected the rights of the white farmer to an adequate water supply (South African Government, White Paper 1995).

By the 1950s, industry was beginning to expand and in 1956 the Water Act (Act 54, 1956) was passed. This Act ensured adequate water for industrial use and authorised strict control over abstraction, use, supply and distribution of water. With the introduction of "Grand Apartheid" (separate development), water resource management that had been previously under the jurisdiction of the central government was fragmented and subsequently there was no coherent water policy (South African Government, White Paper 1995). As a result, the allocation of water rights benefited those in power who could afford water development schemes.

With the end of Apartheid and the election of the Government of National Unity, a new mandate for water resource allocation called for rudimentary changes in water management. The policy of the Department of Water Affairs and Forestry (DWAF) is to ensure that all South Africans have access to basic water supply and sanitation by the year 2001 (South African Government, White Paper 1995). The perspectives of the DWAF in relation to the environment are to establish a culture of water conservation where the local wisdom of communities and other affected parties is essential to ensure the sustainability of both the environment and economic development (South African Government, White Paper 1995).

1.3 Purpose and Objectives

The Department of Hydrology, University of Zululand, is developing a hydrologic decision support system (DSS) for the Mhlatuze River catchment in

KwaZulu-Natal. One component of the DSS is the evaluation of a constituent hydrologic model. The Environmental Capacity Enhancement Program (ECEP) provided funding through the Canadian International Development Agency (CIDA) for collaborations between the University of Guelph and Southern African Universities for research in environmental issues in Southern Africa. In 1997, the Department of Geography at the University of Guelph and the Department of Hydrology at the University of Zululand were funded to evaluate a catchment hydrologic model that would be used as the basis for the DSS.

The purpose of a hydrologic model in the DSS is to calculate the availability of water in the catchment and to serve as a basis for water resource management and planning decisions. The flow in the Mhlatuze is driven by rainstorm events, so the model needs to be able to simulate short time intervals rather than monthly periods.

The purpose of this research is to hydrologically model the Mfuli subcatchment of the Mhlatuze River Basin in KwaZulu-Natal. The objectives of this study are to:

1) Select a rainfall-runoff hydrologic model for use in the Mfuli River Basin;
2) Acquire and assemble all relevant spatial and temporal information needed to run and test the model;
3) Run the model as a stormflow model for several rainfall events;
4) Compare observed versus modelled stormflow;
5) Analyse the uncertainty of hydrologic modelling in Mfuli Basin.

Chapter 2: Background and Literature Review

2.1 Hydrologic Modelling

Hydrology is the study of water. It is a multidisciplinary science that focuses on the global hydrologic cycle and the processes involved in the land phase of that cycle (Dingman 1994). Hydrology strives to describe and predict the spatial and temporal variations of water and the movement of both surface and underground water (Small 1989, Dingman 1994). The basis for hydrology can be found in the sciences of mathematics, physics, chemistry, geology, geomorphology and meteorology.

A model is a simplified representation of reality that combines significant features, relationships or processes in a generalized form (Haggett and Chorley 1967). Therefore models are subjective because they include only the associations, observations or measurements thought by the model developer to be important aspects of the system (Haggett and Chorley 1967). The selection of model components is intended to omit 'inconsequential' details and allow the 'essential' features of reality to appear (Haggett and Chorley 1967). Haggett and Chorley (1967) note that all models are in constant need of improvement as new information appears and concepts develop.

A major task in hydrology, and for hydrologic models, is to explain the relationship between precipitation and streamflow (More 1967). In the hydrologic cycle, precipitation is the 'input' and streamflow is the 'output' and all hydrologic models are variations of this basic conceptual model. The components of the

hydrologic cycle (Figure 2.1) include evaporation, transpiration, precipitation, runoff, infiltration, interflow, percolation into ground water storage, and surface storage in wetlands, ponds, lakes and oceans.

The land phase of the hydrologic cycle can be divided into hydrologic units based on the topographic area that contributes water to a stream (Dingman 1994). These units are called catchments, watersheds, drainage basins or river basins. The routes and rates of water movement within a catchment are controlled by catchment characteristics (Dingman 1994), such as soil type, landcover and topography (O'Loughlin 1981, Beven and Wood 1983, Wolock and McCabe Jr. 1995).

Hydrologic models contain components called parameters and variables. Though these terms are sometimes used interchangeably, a parameter in a hydrologic model generally describes the physical characteristics of the catchment, such as soil type, slope, or vegetation cover (Fleming 1979). Once the parameter values have been assigned and the model has been calibrated, these values remain constant throughout the running of the model. However, if an objective of modelling is to determine the hydrological consequences of land use change, the parameter representing land use would be reassigned after the model had been calibrated under observed conditions. A variable, on the other hand, is a quantity which may have an infinite number of values throughout the running of the model. The amount of infiltration is an example of a variable found in all hydrologic models.

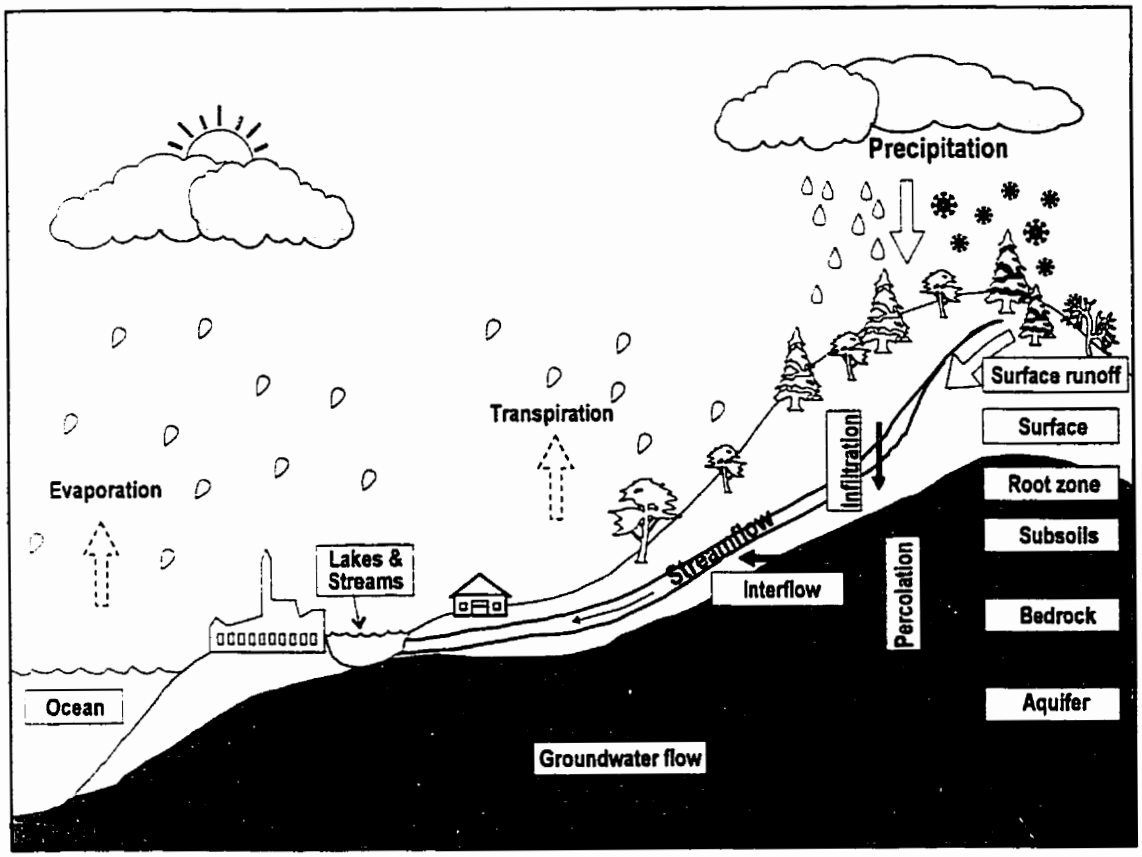

Figure 2.1 The hydrologic cycle (based on Ward and Elliot, 1995)

2.2 Deterministic Hydrologic Models

Over the past century deterministic reductionism has dominated the sciences and as a pattern of scientific investigation it has become well established (Young et al. 1992). Deterministic reductionism assumes that all occurrences are determined by a necessary chain of causation, and that physical systems can be described by deterministic mathematical equations (Young et al. 1992). Hydrologic deterministic models are based on classic mathematical descriptions of the cause and effect relationships among all the processes that impact catchment response (Haggett and Chorley 1967, Fleming 1976, Ward and Elliot 1995).

2.2.1 Model Classification

Hydrologic models can be classified based upon their treatment of physical processes within the catchment as either conceptual or physically-based (Refsgaard 1997). The parameters of conceptual models are often aggregates of physical processes that are largely empirically based (Bergström 1991) and values are model- specific coefficients with no physical meaning (Abbott et al. 1986). In contrast, physically-based models have a theoretical basis and parameters and variables are measurable in the field (Beven 1989). Deterministic hydrologic models can be classified according to their description of spatial catchment processes as lumped, distributed (Refsgaard 1997) or semi-distributed (Hughes and Sami 1994)(Figure 2.2).

Lumped hydrologic models were the first type of model to be developed. A lumped model (Figure 2.3) treats the catchment as a single spatial unit (Fleming 1976) and attempts to achieve a full simulation of catchment behaviour by treating components in a composite manner and simulating the behaviour of processes by largely empirical relationships (More 1967, Fleming 1976, Bergström 1991, Seyfried and Wilcox 1995). Parameters consist of average values over the catchment. A major limitation of the lumped approach is that the entire catchment is treated as a homogenous unit as there is no mechanism to address heterogeneity within the catchment.

Distributed models (Figure 2.4) differ fundamentally from lumped models in that spatial heterogeneity is represented by providing data for a number of points within the catchment. These models place a prescribed grid over the catchment and parameter and variable data are input for either each intersection point in the grid or the centre of each grid cell (Refsgaard 1997). Parameters in distributed models are mainly physically-based (Jensen and Mantoglou 1992) and allow for a change in land use parameter values (Refsgaard and Knudsen 1996, Refsgaard 1997). Therefore, these models can be used to predict a catchment's response to land use change (Abbott et al. 1986, Refsgaard and Knudsen 1996).

Semi-distributed models (Figure 2.5) were developed in response to the limited flexibility inherent in depicting spatial variability in a catchment with a prescribed grid system. Semi-distributed models allow the user to divide the catchment into subareas, which are characterised by homogeneity of several

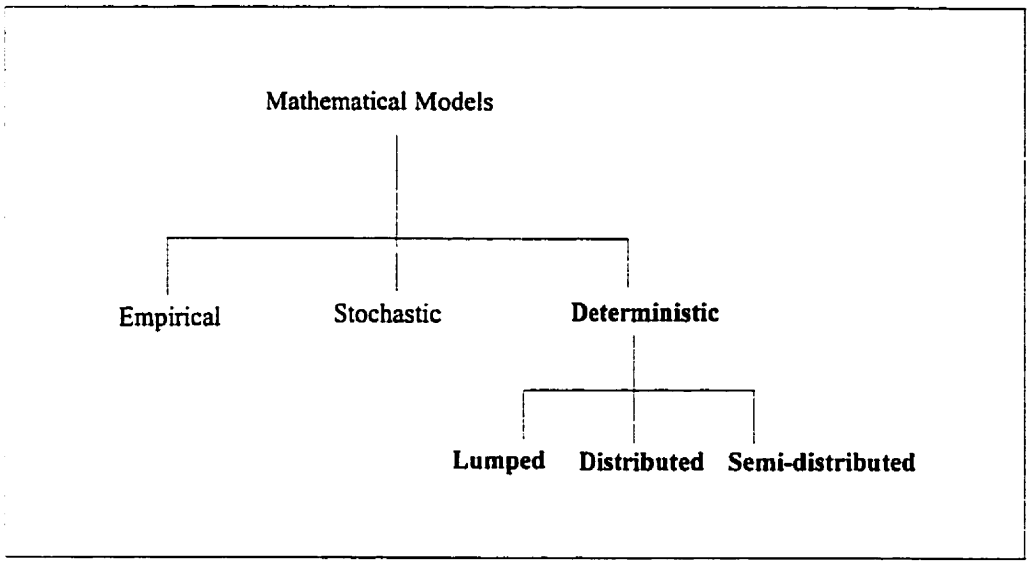

Figure 2.2 Mathematical models

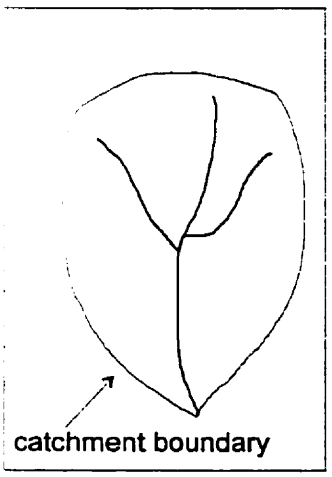

Figure 2.3
Lumped model

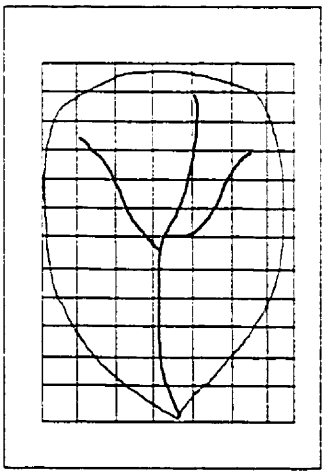

Figure 2.4
Distributed model

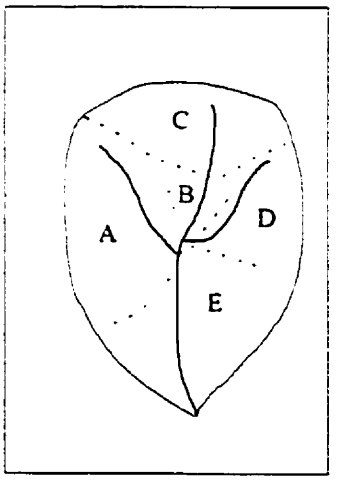

Figure 2.5
Semi-distributed model

parameters (Hughes 1994). Like the distributed model, semi-distributed models use mainly physically-based parameters (Hughes and Sami 1994).

2.2.2 Comparison of Models

Lumped models can perform run-off simulations as well as distributed models, if sufficient calibration data are available for the modelled catchment (Refsgaard 1997). However, the calibration of lumped models involves curve fitting of the parameters until the computed output approximates measured output. The resultant 'curve fitted' parameters have no physical interpretation (Abbott et al. 1986, Hughes 1989). In contrast, physically based parameters are measurable in the field and have direct physical interpretation (Jensen and Mantoglou 1992). If the catchment to be modelled is ungauged, the lumped model cannot be used, because lumped models are dependent on ample meterological and hydrologic records to deduce hydrological processes and make little use of catchment characteristics such as topography and soil type (Abbott et al. 1986, Refsgaard 1997). Physically-based models can be applied in an ungauged catchment as the parameters describing the hydrological characteristics of the catchment are defined by its physical characteristics and not the lumped process response (Refsgaard 1997). In addition, lumped models cannot predict a catchment's response to landuse change (Abbott et al. 1986, Refsgaard and Knudsen 1996), but physically based models allow for a change in landuse parameter values (Refsgaard and Knudsen 1996, Refsgaard 1997).

Lumped models treat the catchment essentially as one homogenous unit. Distributed models claim to address spatial heterogeneity at the catchment scale, but actually assume homogeneity for each of the grid elements within the model. This contradiction has prompted Beven (1989) to note that physically based distributed models are in practice another form of 'lumped conceptual models'. Semi-distributed models use 'subareas' based on parameter homogeneity, but considerable spatial heterogeneity always exists within each subarea because the properties of earth materials are highly variable over space (Refsgaard and Knudsen 1996).

2.2.3 Limitations of Current Models

There are several general limitations associated with deterministic catchment models. Deterministic numerical models contain closed mathematical components that may be verifiable but natural systems are never closed (Oreskes et al. 1994). Modelling a natural system necessitates the input of parameter values that are difficult if not impossible to measure accurately at the scale at which they are required by the model. Examples include hydraulic conductivity, porosity, and storage coefficients (Oreskes et al. 1994). Beven (1989) points out that the descriptive equations underlying physically based models are good descriptors of processes occurring in the simplified 'model' catchments and hillslopes of the laboratory, but asks whether these equations can describe the processes of complex, spatially heterogenous 'real' catchments.

There is no universal theoretical framework for transferring the small scale physics derived in the lab to the scale required by the model (Beven 1989, Jensen and Mantoglou 1992). Even if small scale modelling is quite successful in the lab, the effect on the simulation of small errors, multiplied many times and distributed over the catchment are unknown (Seyfried and Wilcox 1995). The scaling up of non-additive properties of input parameters is a problem, as the scales of model elements (metres to kilometres) are typically orders of magnitude larger than those elements measured in the field (millimetres to centimetres) (Oreskes et al. 1994). Seyfried and Wilcox (1995) note that small scale parameters useful for modelling in the lab may lose their physical significance at larger scales. Even the most rigorous mathematical models describing catchment response are crude representations of reality and while theoretical rigour of some models is impressive, it implies a degree of accuracy that may not exist (Grayson et al. 1996).

2.2.4 Model Assessment

Models are assessed through sensitivity analysis (Melching et al. 1990), calibration and verification (Oreskes et al. 1994, Mroczkowski et al. 1997), and by comparison of model output with observed quantities (Klemes 1986, Michaud and Sorooshian 1994, Refsgaard 1997). Sensitivity analysis involves altering the input value of a parameter, and assessing the resultant change in model output (Melching et al. 1990). A significant change in an output value, such as streamflow, signifies that the model is sensitive to the tested parameter. Hughes

(1994) recommends that model users carry out their own sensitivity tests as parameter sensitivity will vary based on the nature of the catchment's hydrologic response. The results of this type of analysis provides information on the importance of specifying each parameter correctly. Parameters which are relatively insensitive can be estimated with less rigour and more energy and resources can be devoted to assigning the sensitive parameters.

Calibration involves manipulation of parameter values (independent variables) in order to improve model output until computed values (dependent variables) approximate measured values (Oreskes et al. 1994). A two-step calibration scheme, where a data set is divided into two parts, is often used in hydrological modelling (Oreskes et al. 1994). In the first step, model parameter values are manipulated to reproduce the first half of the data set, then the model is run, and results are compared with the second half of the set (Oreskes et al. 1994). The first step is called the calibration step and the second is verification (Oreskes et al. 1994). The model is also said to be verified if the model output accurately simulates observed data, such as stream flow, collected at another time period than that of the calibration data set (Refsgaard and Knudsen 1996). In theory, physically-based models do not need the calibration step, because the parameters have physical meaning and are not 'curve-fitted' like those of lumped models. For this reason physically-based models are often used in situations where calibration data is not available, such as ungauged catchments or to simulate future hydrologic response to environmental change. However, Beven (1989) and Melching et al. (1990) note that in practice physically-based models

are calibrated and verified when data is available. Usually the parameters that are most difficult to accurately measure are manipulated during the calibration process (Mroczkowski et al. 1997). The validation procedure for both lumped and distributed models is similar but the validation requirements are much more comprehensive for distributed models because of its greater complexity (Seyfried and Wilcox 1995, Refsgaard 1997).

Uncertainty analysis identifies the sources of model error, which is the difference between the computed response of the model and observed data. James (1994) states that the purpose of uncertainty analysis is to identify and rank the principal sources of uncertainty in the computed response, so that these uncertainties can be managed and the amount of confidence one has in the model's simulated hydrologic response can be accessed. Three broad categories of uncertainty can be defined as errors pertaining to the model's structure, the user's input, or the data itself. Numerical error within the mathematics in the model's code would be an example of uncertainty associated with the model (James 1994). The erroneous estimation of input parameter values would be an example of uncertainty attributable to the user. Error associated with the location and sampling time of field equipment is an example of uncertainty related to the data.

Chapter 3: Research Approach

3.1 Study Area

The Mhlatuze River catchment (Figure 3.1) in KwaZulu-Natal, South Africa, was selected for hydrologic modelling and was subdivided into five project regions (Table 3.1) for the DSS study. The upper reaches of this catchment are settled by subsistence-farming Zulu families who use the river and its tributaries as their domestic source of water. The Mfuli sub-catchment (Figure 3.2, 3.3 and 3.4), with a total of 660 km^2, is the focus of this research. This relatively undeveloped region is mainly inhabited by Zulus and is expected to have an uncomplicated hydrologic regime, with few dams and little irrigation. In the Nkwaleni Valley, downstream of the Goedertrouw Dam, irrigated crops such as citrus fruits and sugar cane are grown commercially. At the river's outlet into the Indian Ocean lies Richards Bay, an urban centre which has an industrial base that requires a reliable source of water to expand. Richards Bay and Eshowe also draw water from the Mhlatuze River for their domestic water supply.

3.2 Model Selection

The HYMAS (Hydrological Model Application System) catchment model (Hughes and Sami 1994) was initially chosen for this study because it purportedly met all the DSS requirements and was developed in South Africa for southern African conditions. HYMAS is a semi-distributed model developed at the Institute of Water Research, Rhodes University, South Africa. Some of its

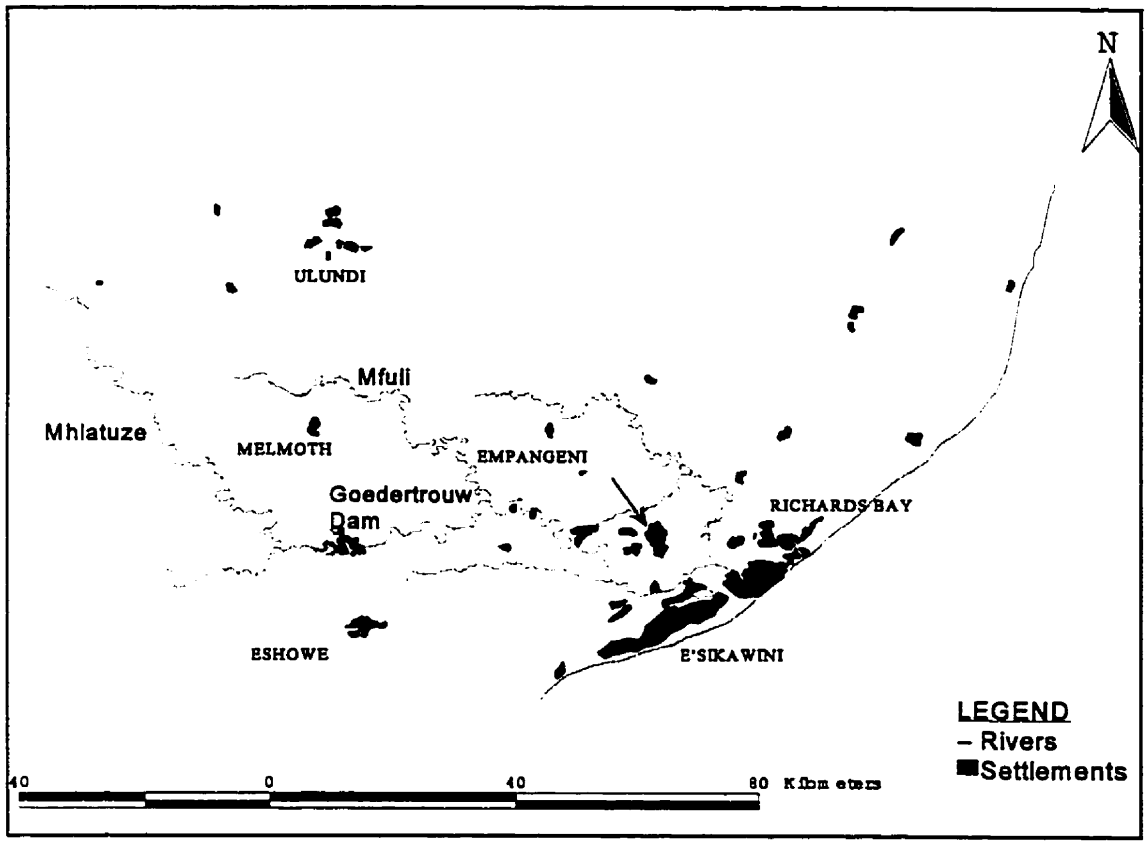

Figure 3.1 The Mhlatuze Catchment

Table 3.1 Mhlatuze Hydrological Project Regions

#	Code Name	Description
1	Goedertrouw	catchment from headwaters of Mhlatuze to Goedertrouw dam
2	Mfuli	Mfuli River catchment
3	Nsezi	catchment of Lake Nsezi
4	Nkwaleni	Mhlatuze catchment in Nkwaleni valley to DWAF weir W1H009
5	Richards Bay	Mhlatuze catchment downstream from weir W1H009 to outlet into Mhlatuze Lagoon, Richards Bay

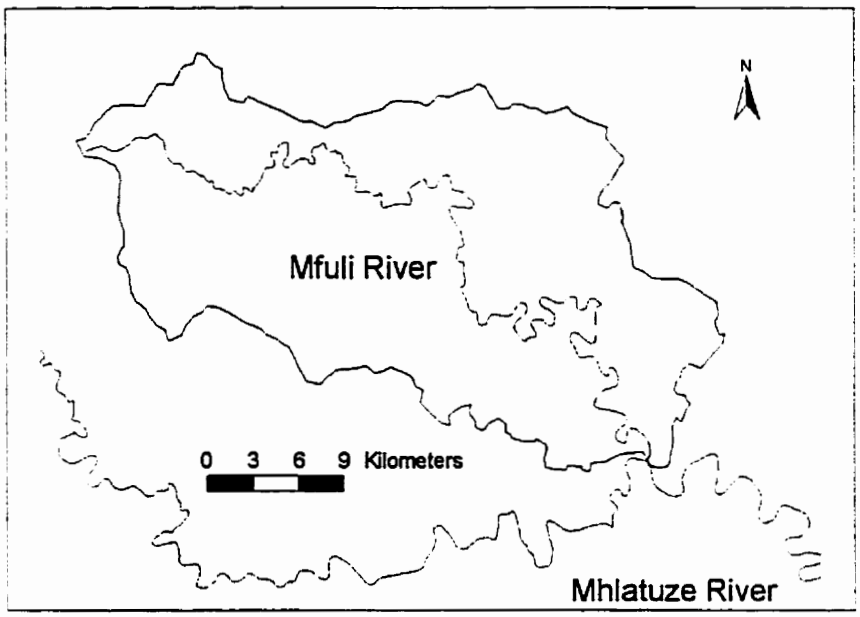

Figure 3.2 The Mfuli Subcatchment

Figure 3.3 Hillside subsistence farming in the Mfuli Subcatchment

Figure 3.4 Erosion gully (donga) in the Mfuli Subcatchment

parameters are physically-based, others are empirical relationships derived from physical indices, and a few are entirely empirical (Hughes and Sami 1994). For example, the percent area with sandy soils is a physically based parameter, in channel vegetation is assigned a value between 0 and 2 to assess one factor of channel roughness and the coefficients for an area-volume relationship used to estimate dam storage are derived from empirical relationships. The system is modular, presently offering nine models with specific capabilities and is designed so that other models can be incorporated into it. Several rainfall-runoff models are included, such as the Variable Time Interval Model (VTI), the PITMAN monthly runoff model and a reservoir simulation model (RESSIM). All three of these models will be utilized by the DSS, but the VTI was chosen for this study.

3.3 The VTI Model

HYMAS requires a set of 94 standard physiographic variables (SPV) which describe the physical characteristics of the catchment. These variables can also be used by the other models included in the HYMAS package. Of these 94 parameters, the user must define 60 while the rest are either calculated by the model or considered redundant. The VTI model within HYMAS converts the SPV into the parameter values (PAR) specific to the VTI model and an additional 14 parameters must be defined. HYMAS also requires rainfall data.

The variable time interval (VTI), refers to the temporal resolution of the model, it is capable of shifting between coarse iterations during periods of low intensity or infrequent rainfall and to a finer time resolution during periods of high

intensity or frequent rainfall (Hughes and Sami 1994). HYMAS uses a pre-modelling program which calculates the rainfall input based on spatial interpolations from individual raingauge data using an inverse square weighting procedure (Hughes 1994). When raingauge data is of a high enough resolution to define intensity adequately, the VTI model is capable of modelling at intervals between 5 minutes and 24 hours. The exact resolution required will depend on the nature of the rainfall regime (Hughes 1993). However, rainfall data in this region is recorded daily and the variable time option afforded by this model could not be used. Since rainfall data was not available in 'break point' format, the model instead disaggregates daily rainfall into shorter fixed time intervals when rainfall exceeds a threshold defined by a summer and winter average storm duration parameter.

The VTI model (Hughes and Sami 1994) contains 9 interlinking elements, all representing different functions in the model:

1. Potential evapotranspiration (PEVAP)
2. Interception (INTCP)
3. Runoff controlled by rainfall intensity and infiltration rates (IROFF)
4. Runoff controlled by soil moisture accounting (MROFF)
5. Evapotranspiration (AEVAP)
6. Groundwater - surface water interactions and recharge (GWATER)
7. Sub area (catchment) routing, including depression storage, small dam runoff storage and sub area (land phase) routing (respectively DEPST, DAMST and SAROUT)

8. Channel transmission losses (TLOSS)

9. Channel phase runoff routing (CHROUT)

3.3.1 Model Input

Once the initial PAR file has been established, the individual parameter values can be manually edited without affecting the original SPV file used to create them. The initial parameter values derived from the SPV are retained as default values.

HYMAS was designed to accept the rainfall file format of the CCWR, so the files can be input directly. In total 31 rainfall stations were assigned to the grid covering the Mhlatuze catchment. The SPV can be subdivided into location and topography, channel characteristics, soil characteristics, groundwater characteristics and vegetation cover. Location and topographic parameters require georeferenced-spatial data which can be managed by using a Geographic Information System (GIS) (Drayton et al. 1992, Lu et al. 1996, McDonnell 1996). A GIS can manage spatial coordinates, topological information and attributes associated with geometric objects (McDonnell 1996). GIS also gives the model user the capability of manipulating, analysing and displaying data (Drayton et al. 1992). Most of the location and topographic parameters for this study were derived from the WR90 GIS data set (Water Research Commission Report No 298/6.1/94). The WR90 GIS data set includes information such as stream networks and streamflow gauging stations, soil types and vegetation cover for the entire country. This data set was converted into a compatible ARC-VIEW GIS format and the information pertinent to the Mfuli

project was extracted. The boundaries of the projects and their subareas were also converted into digital format and imported into the GIS. The Shreve channel order, drainage density, channel length and the area of each subarea are examples of parameters derived from the GIS. Slope parameters for the main channel and subarea are the only parameters which were not part of the GIS data set and were determined from topographic and orthographic maps.

Channel characteristics are based on field observation. The parameters that describe the roughness of the channel require values on a scale of 0 to 2 that are assigned by the user. For example, a very 'rough' channel is assigned a value of 2 and a hydraulically smooth channel value of 0 (Hughes 1994).

Soil characteristics constitute 21 of the 60 physiographic variables defined by the user. These variables are usually input as percentages, such as the percent area with soils of a specified texture. The soil information contained in the WR90 data set is too generalized for this application, so a detailed landtype map obtained from the Institute of Soils and Irrigation was digitized, in Atlas-GIS, and an additional GIS layer for land type was added to the GIS database. Soil variable values were assigned based on the soils found in the landtype and corresponding field observations. Other soil variables in this section require the user to assign values ranging from 0-2 for characteristics such as surface roughness, organic content and macropore development, which were determined from field notes and photographs.

Groundwater characteristics such as depth to the aquifer, transmissivity and storativity were to be obtained from geology and borehole data. However,

this data for the Mfuli region was insufficient to estimate groundwater parameters and values suggested by the HYMAS developer (Hughes) were used instead.

Vegetation cover in the model is input seasonally as percentage of area covered by various types of ground cover. Vegetation cover was derived from the Landsat Thematic Mapper (TM) image (April 22, 1996) of the region.

3.3.2 Satellite Image Classification

The Landsat image consists of 7 spectral bands, 3 in the visible range, 3 in the infrared range and 1 in the thermal range (Table 3.2) (Lillesand and Kiefer 1994). The spatial resolution of this image is 25 m^2. The original map format of the image was SA_TM31, but the WR90 GIS data set along with the GPS readings and the topographic maps and orthophotos of this region all use some form of a latitude longitude system. Idrisi for Windows Version 2.0 was used to analysis the LANDSAT image and the image maps and GPS coordinates were converted to decimal degrees. The LANDSAT TM scene was then rubbersheeted using Idrisi's RESAMPLE function and the section containing the Mfuli project was then windowed out, creating a new rectangular image with an area of 3100 km^2.

Initial classification employed Principal Component Analysis (PCA) to indicate more specific information on the spectral response of the Mfuli project area. PCA revealed that two component bands could explain 95.13% of the variance in the original seven bands. Component 1 explains 73.44% of the variation of the image and is composed of (in order of importance) bands 5, 7,

and 2. Component 2 explains 21.69% of the variation and is composed primarily of band 4.

Bands 5 and 7 are based on the mid-infrared of the spectrum. The principle applications of band 5 are to indicate vegetation moisture content and soil moisture (Lillesand and Kiefer 1994) and band 7 is useful for discrimination of mineral and rock types but is also sensitive to vegetation moisture content (Lillesand and Kiefer 1994). Band 2 is based on the green part of the spectrum and it is designed to measure green reflectance for vegetation discrimination and vigour assessment. It is also useful for identifying cultural features (Lillesand and Kiefer 1994). Band 4 samples from the near infrared part of the spectrum and can differentiate between vegetation types, vigour and biomass content, as well as delineate water bodies and soil moisture (Lillesand and Kiefer 1994).

The main application of image analysis in this study is to assign land cover, especially vegetation, so bands 2,4 and 5 were combined into a composite image to be analysed by unsupervised classification. Although band 7 ranks high in contributing to Component 1, it was excluded because its function is similar to that of band 5 and discrimination of mineral or rock types is not important in this study. Band 4 was substituted for band 7 because it is more useful in this application.

Unsupervised classification uses cluster analysis to group cells into spectral classes. After the image has been separated into classes, these classes are compared with another source to determine which landuse they represent (Lillesand and Kiefer 1994). The cluster analysis procedure used both

fine and broad classification techniques. The fine classification technique identified 23 clusters and the resultant image was a mosaic of colours, particularly in the more hilly terrain. The fine classifier is designed to pick up subtle peaks in the data's spectral attributes (Campbell 1996) and it appears as though the classification of such a large number of clusters is a function of landcover types being classified into more than one cluster. Landcover spectral signatures are clearly being affected by the various slopes and aspects produced by this complex terrain. The broad classification technique produced a more generalized output and resulted in 12 spectral classes, although illuminated vegetation and shadowed vegetation, are classified separately.

Spectral ratioing was used to reduce the effect of differing illumination conditions within the image (Lillesand and Kiefer 1994). A ratioed image compensates for the variation in brightness caused by the varying terrain which characterizes Zululand. The normalized difference vegetation index (NDVI) which was produced using the green band (band 2) and the near infrared spectra (band 4) (Lillesand and Kiefer 1994) was most successful in reducing the effects of topographic relief. Vegetated areas yield high values in the NDVI image, while water gives negative values, and bare soil or rock outcrops result in values close to zero (Lillesand and Kiefer 1994).

Supervised classification involves two steps. The first defines 'training sites' and the second classifies the pixels in the image (Lillesand and Kiefer 1994). In the first step the user identifies areas of known landcover and uses the computer to generate training sites containing unique spectral signatures

associated with each landcover class. All seven bands were included in this classification process when defining the spectral signatures. In the second step each pixel is classified into a landcover class based on the representative training cells. The model input requirements of HYMAS guided the classification. The HYMAS SPV related to landcover pertains to the percentage of each subarea which is covered with dense trees, sparse trees, dense crop/ground cover, sparse crop/ground cover and bare ground. Surface water such as reservoirs and rivers were included as classes and a shadow class was defined. The shadow class was needed for areas of deep shadow for which there was no spectral response. The landcover features included in each of the 8 classes are outlined in Table 3.3. The same composite image of bands 2, 4 and 5 used for the unsupervised classification was used to delineate polygons for the training sites in the supervised classification. The NDVI image was displayed simultaneously and served to help identify landcover cover boundaries. Once the training site polygons were defined, all seven bands were included when identifying the spectral signatures.

Orthophotos and ground-truthed data collected in the field recorded with the GPS identified the training sites. Some of the field observations were reserved to create a second image with the same landcover classes represented. An error matrix (Table 3.4) was then generated using both images to test the accuracy of the classification. The error matrix produced an acceptable overall Kappa value of 0.7143. This value indicates that 71% of the pixels were classified as the same landcover in both images. The final image

Table 3.2 Spectral Bands

band	1 (blue-green)	2 (green)	3 (red)	4 (near infrared)	5 (mid infrared)	6 (thermal)	7 (mid infrared)
spectral range (μm)	0.45-0.52	0.52-0.6	0.63-0.69	0.76-0.9	1.55-1.75	10.4-12.5	2.08-2.35

Source: adapted from Campbell 1996

Table 3.3 Training Site Classes

HYMAS SPV	Class	Landcover features included
dense tree cover	trees	plantations
bush/sparse tree cover	bush	orchards and native brush
dense crop cover/ ground cover	cane	sugar cane
sparse crop/ ground cover	sparse	grassland and aloe scrub
bare soil	bare	tilled fields, clear cuts, sand deposits, roads, Zulu kraals
	deep	large reservoirs
	shallow	rivers and small reservoirs
	shadow	deep shadow

(Figure 3.5), created using the supervised classification technique, was used as the landcover map from which the SPVs for vegetation cover were quantified.

3.4 Problems with the Application of the HYMAS VTI Model

The application of the HYMAS VTI model in the Mfuli basin was challenging on many levels. Parameter estimation was difficult for several reasons. First, many of the parameters are linked to others and it is not always clear which parameters are calculated from other information and which have to be specified individually. There are also several parameters which are difficult to estimate from the on-line manual because of a lack of understanding of their conceptual role in the model and the brevity of their description. It was necessary to consult with the model developers at Rhodes on a regular basis to overcome some of these difficulties. Another obstacle in parameter estimation was the lack of sufficient source data in the Mfuli catchment to meet the many parameter requirements of the model. The HYMAS structure is data intensive and prohibits the model user from scaling down the model's complexity to compliment the data availability for the Mfuli system. For example, groundwater data for this area is lacking and yet the parameters pertaining to groundwater still had to be defined for the model to run.

HYMAS is a new and developing system that is not 'user friendly'. More importantly, the internal code appears to be unstable. When using the model the computer would freeze at times and had to be rebooted. Once the computer was restarted the model would run without any alterations. At other times the model

Table 3.4 Summary of Error Matrix

landcover	trees	bush	cane	grass	bare	deep	shallow	shadow
error of omission	0.387	0.199	0.109	0.070	0.406	0.000	0.471	0.834
error of commission	0.080	0.161	0.154	0.178	0.485	0.130	0.057	0.080

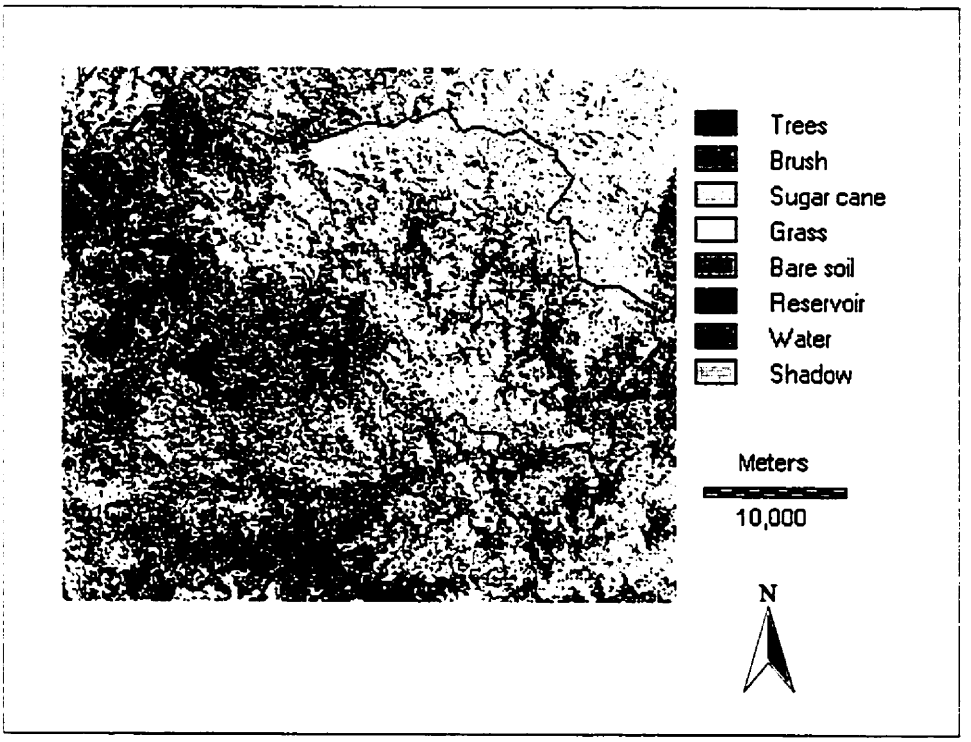

Figure 3.5 Classified satellite image of the Mfuli Catchment

wouldn't run for reasons ranging from a missing or misspelled path name in one of 20 required files to an unexpected parameter value entered in one or more of the 370 parameters. Technical support for this program was insufficient and several problems were encountered and went unanswered. Finally the model would not run at all, so it was abandoned by both the University of Guelph and the University of Zululand. Uncertainty analysis of the HYMAS model is presented in Chapter 6.

3.5 Adoption of SWMM

When the HYMAS package became unusable a model was searched for that satisfied all the things lacking in HYMAS. It had to be a model that offered technical support, was cited in the literature, had been used successfully by people other than the model developers and was able to use the data collected for the HYMAS project. The Storm Water Management Model (SWMM) with the PCSWMM interface met all these requirements.

SWMM is a public domain program originally developed with United States Environmental Protection Agency funding between 1969-1971 (James et al. 1999). It was originally developed to simulate urban runoff but has been used for other applications. Since the first version was released the model has undergone continual improvements and development. Version 4.31, released in 1995, is PC based (DOS-compatible) and uses FORTRAN in its code (James et al. 1999). This version offers four hydrology/hydraulic modules: Runoff, Transport, Extran and Storage. Several user interfaces have been developed

over the years, among them is PCSWMM, a windows-based, user-friendly interface developed by Computational Hydraulics International (CHI). PCSWMM provides additional options not offered in SWMM, such as output hydrographs along with sensitivity analysis and calibration components.

Of the four hydrologic/hydraulic modules offered in SWMM, the runoff module was used for this study. This module simulates the runoff quantity and quality and routes the flow through the catchment (James et al. 1999).

Chapter 4: SWMM Methodology

4.1 Catchment Discretization

Discretization allows a better description of the watershed being modelled than is possible when the watershed is lumped into one set of characteristics. The Mfuli catchment was divided into six subcatchments based on vegetation, geology, settlement and subwatersheds defined by tributary drainage (Table 4.1). All six subcatchments intersect with the Mfuli river (Figure 4.1). Subcatchment 1 contains the headwaters of the Mfuli River but was modelled without a channel segment. The overland flow from Subcatchment 1 becomes the input for the first channel segment found in Subcatchment 2, and so on until the Mfuli merges with the Mhlatuze. A flow chart of the surface flow routing is provided in Figure 4.2.

4.2 Data Sources

Three basic types of data are required for the SWMM model (Table 4.2): sequential-temporal, geographically-referenced spatial information and field observations. Sequential-temporal data refers to data sets collected at specific points, including daily rainfall depth and stream discharge. Geographically-referenced spatial information, such as soil characteristics, describes the characteristics of the subcatchments. Field observation data serve several purposes, including direct input parameters describing stream channel characteristics, familiarity with the site and photographs of soil profiles, stream

Table 4.1 Project Subdivision, Criteria and Size

subcatchment	downstream subcatchment	geology	vegetation	size (ha)
1	2	intercalated arenaceous and argillaceous strata	plantations, natural grassland and bush	11890
2	3	intercalated arenaceous and argillaceous strata	plantations, sugar cane, natural grassland and bush	19996
3	4	intercalated arenaceous and argillaceous strata	sugar cane, natural grassland and bush	12998
4	5	intercalated arenaceous and argillaceous strata	Nhlozane tributary, natural grassland and bush	8033
5	6	intercalated arenaceous and argillaceous strata, Assemblage of till and shale	natural grassland and bush	7167
6	Into Mhlatuze River	intercalated arenaceous and argillaceous strata	sugar cane, orchards and natural grassland and bush	6200

Sources: WR90 (Water Research Commission Report No 298/6.1/94), topographic maps, satellite image

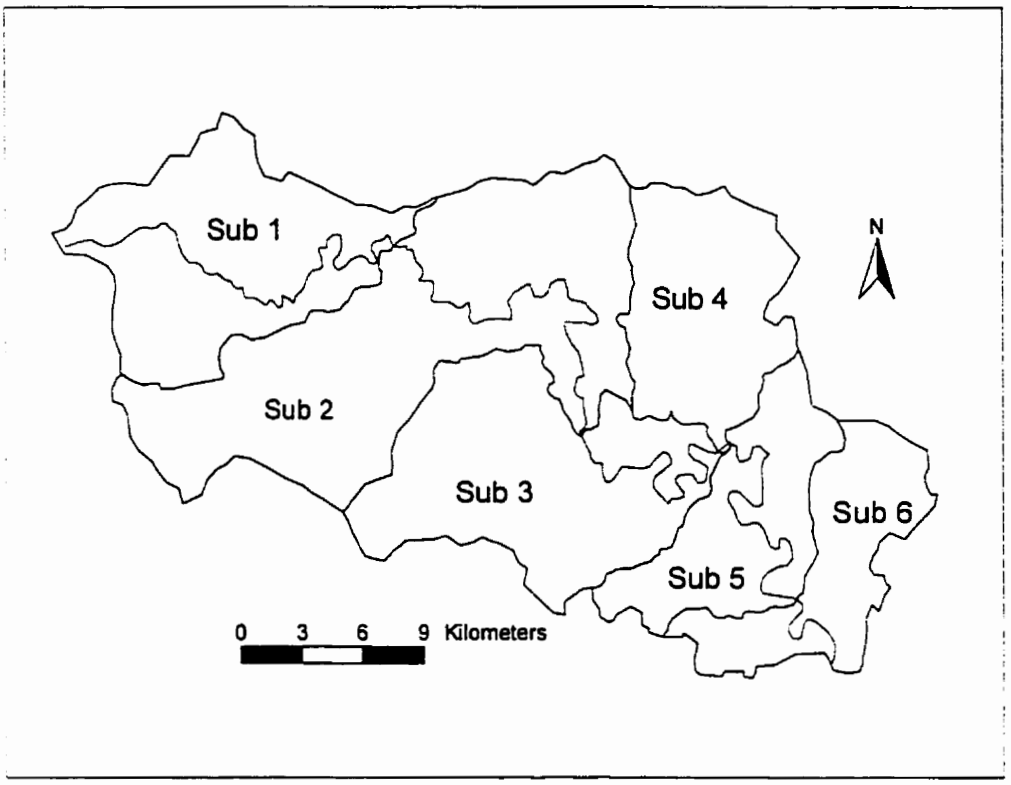

Figure 4.1 Six subcatchments of the Mfuli Basin

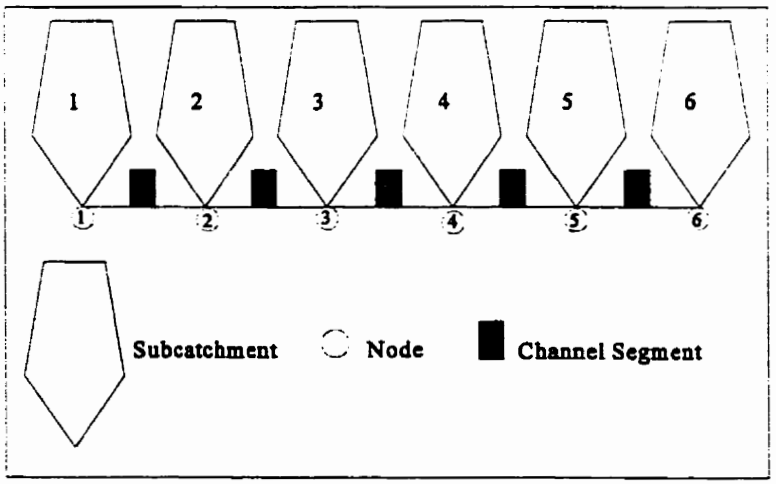

Figure 4.2 SWMM model schematic

channels and landuse and supplement field notes. These notes and photographs capture observations that cannot be directly measured or obtained from other sources, such as channel hydraulic roughness.

The availability of sequential-temporal data for the Mfuli catchment determined the type of modelling which could be done. The spatial sparseness and the coarse temporal resolution of both the raingauges and the weirs for discharge measurements in this area restricted the years that could be modelled, the temporal modelling style and the type of rain event that could be modelled. Data limitations are summarized in Table 4.3.

4.3 Model Input

The model input for the runoff module of SWMM requires channel and subcatchment physiographic parameters, evaporation and rainfall. The input parameters assigned for the channel and subcatchment characteristics are summarized in Appendix 1. Channel segment physiographic parameters include, shape, width and length, slope, Mannings roughness coefficient, the initial depth and the maximum depth. James et al. (1999) in the absence of better data suggest that natural channels be modelled with a parabolic shape, therefore all channel segments were assumed to be parabolic. Cross-sections from the field provided segment width. Observations and photographs taken at cross-section sites were used to estimate maximum depth and to assign Mannings roughness coefficients (Figure 4.3). Each segment's slope was determined by dividing the difference in elevation, using 1:50,000 maps topographic, by the flow length.

Table 4.2 Data Required and the Sources

Data	Type	Information and Source
sequential-temporal	daily rainfall	6 station series from CCWR (Computing Centre for Water Research) at University of Natal, Pietermaritzburg
	daily streamflow	weirs WH1009 and W1H028 daily discharge series from DWAF (Department of Water Affairs and Forestry)
	daily evaporation	from DWAF databases
geographically referenced	soil type information	maps and profile descriptions from the Institute of Soils and Irrigation
	land use	LANDSAT TM (March 1997) image
	topography	1:50,000 topographic maps, 1:10,000 Orthographic maps
field observations	ground truth	used GPS (Global Positioning System) to identify coordinates of landcover features, to verify satellite image classification
	channel characteristics	observation of instream vegetation, structures and bed material, surveyed cross-sections

Table 4.3 Data Limitations

Data	Limitations
Precipitation and flow data	few gauges, finest time interval is daily
Rainfall data	only Subcatchment 2 has raingauges within catchment, numerous data gaps
Flow data collected at weirs	numerous data gaps
1:10,000 orthographic maps	incomplete set for Mfuli
Field observations	limited road access into interior of Zululand
Cross-section measurements	limited road access to stream channels

The length of each channel segment was determined using a Geographic Information System (GIS). The boundaries of the subcatchments which were converted into a digital format and imported into the GIS combined with the Mfuli channel data included in the WR90 data set allowed determination of channel segment length.

Subcatchment characteristics include area, width of overland flow, percent of imperviousness directly connected to the channel, soil properties, Mannings roughness coefficients, and depression storage. Depression storage was not used in this study as it was felt that its impact would be negligible. The Mfuli Basin has steep slopes without many places for water to pond before it infiltrates or is evaporated also there was insufficient data to assign values to these parameters. ARC-VIEW was used to determine each subcatchment's area in hectares. The width of overland flow was derived by dividing subcatchment area by the maximum length of overland flow (James et al . 1999). The maximum length of overland flow is the distance from the furthest point on the subcatchment boundary perimeter to the channel plus the distance from that intersection point on the channel to the outlet node (Figure 4.4). The calculation of subcatchment slope also used the maximum flow length. The difference in elevation between the furthest point on the catchment boundary and that of the outlet node were used to derive the 'rise' of the slope and the 'run' of the slope was equal to the maximum flow length. The percent of imperviousness directly connected to the channel was derived by using the classified satellite image and IDRISI. The number of hectares of bare ground, assumed to represent an

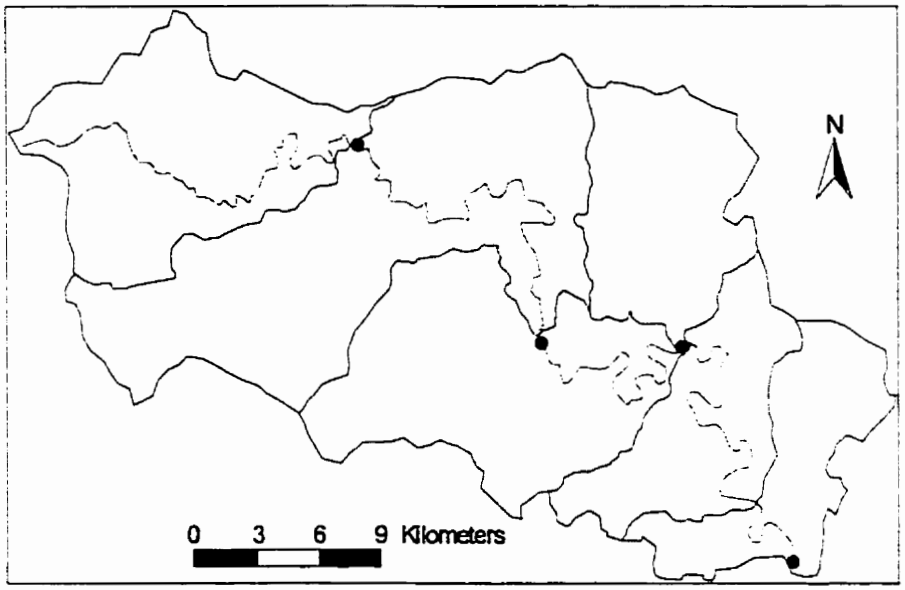

Figure 4.3 Location of field survey cross-sections

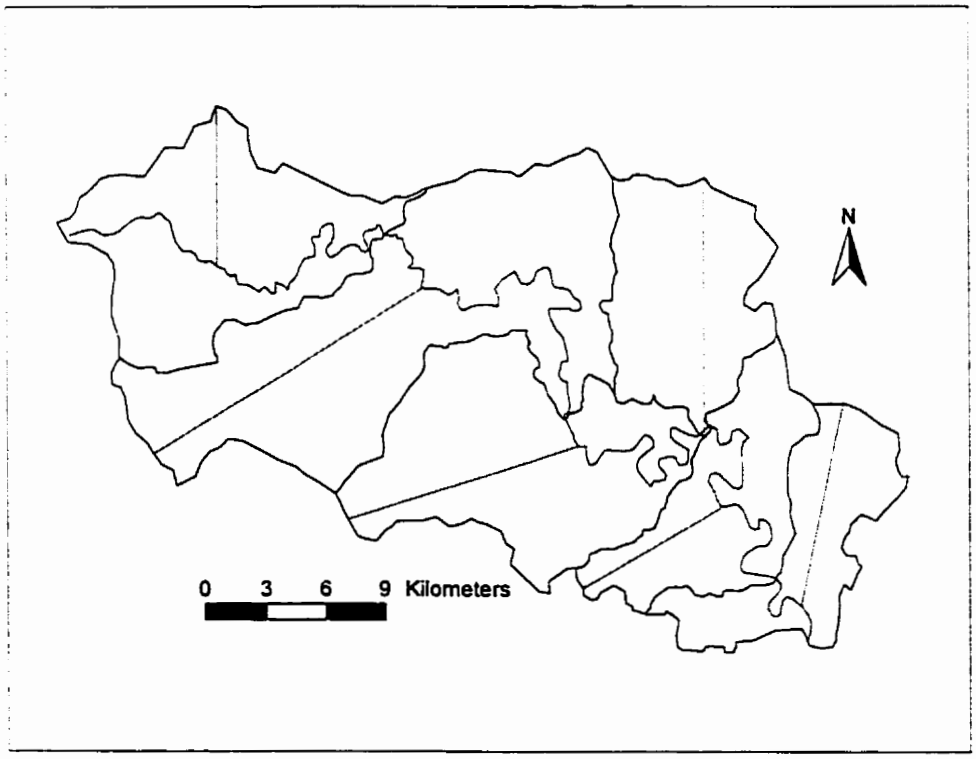

Figure 4.4 Maximum overland flow lengths

impervious surface in contact with the channel, was determined for each subcatchment.

Soil properties such as capillary suction, saturated hydraulic conductivity and initial moisture deficits (volume of air/volume of voids) were needed for the Green-Ampt infiltration equation. However, before values for each of those parameters could be assigned the soil of each subcatchment had to be determined. There is no soil map for this region, so soil classification involved cross referencing between photographs taken in the field (Figures 4.5 and 4.6), a landtype map and its associated catalogue (Land Type Survey Staff 1988) and a soil identification book for the sugar cane industry (South African Sugar Association 1984). There are several categories of landtypes based on uniformity of terrain, soil pattern and climate (Land Type Survey Staff 1988). The catalogue lists several soil types likely to be found within each landtype, and occasionally a detailed soil profile analysis had been done. The landtype map was digitized and the boundaries of each subcatchment were added. The identification codes for the landtypes within each subcatchment were identified and referenced in the catalogue.

A total of nine detailed soil profile analyses had been recorded within the Mfuli catchment (Figure 4.7). To determine the rest of the soil types, the locations of field photographs, based on GPS coordinates collected in the field, were added to the landtype map and the soils in these photographs were identified using photographs from the South African Sugar Association's (1984) manual. After visual identification of the soil in the photograph, the name of that

Figure 4.5
Mispach soil in Subcatchment 3

Figure 4.6
Inanda soil in Subcatchment 1

soil type was cross-referenced with those listed in the catalogue for that land-type. The soil type occupying the greatest area of each subcatchment was determined and the properties of that soil type were used to derive the values for capillary suction, saturated hydraulic conductivity and initial moisture deficits based on tables from the SWMM user's guide (James et al. 1999).

Mannings roughness coefficients were required for both impervious and pervious areas and were determined based on field notes and photographs of the subcatchments. Mean monthly evaporation values measured at Melmoth (W1E012) were used for the Mfuli catchment (Table 4.4).

Long periods of dry weather punctuated by occasional rainfall characterize the Mfuli area, so event-based modelling was chosen over continuous modelling. The time periods between rainfall events are sufficient such that a total 'dry out' of the system occurs, so event-based simulations are appropriate. The type of rain event that could be modelled was also limited by the sparse raingauge coverage found in this area (Figure 4.8). Most of the catchment has no raingauge coverage, with only two gauges within the catchment and four near its boundaries. Streamflow in the Mfuli River is driven by rainstorm events but modelling convective storms is impractical because these localized occurrences of rainfall would not be captured by the raingauges. As a result, frontal events were chosen for modelling because rainfall would occur throughout the catchment and the storms are of longer duration. In order to identify frontal storms, the catchment was initially modelled as a single area and rainfall from the one of the gauges within the catchment was selected.

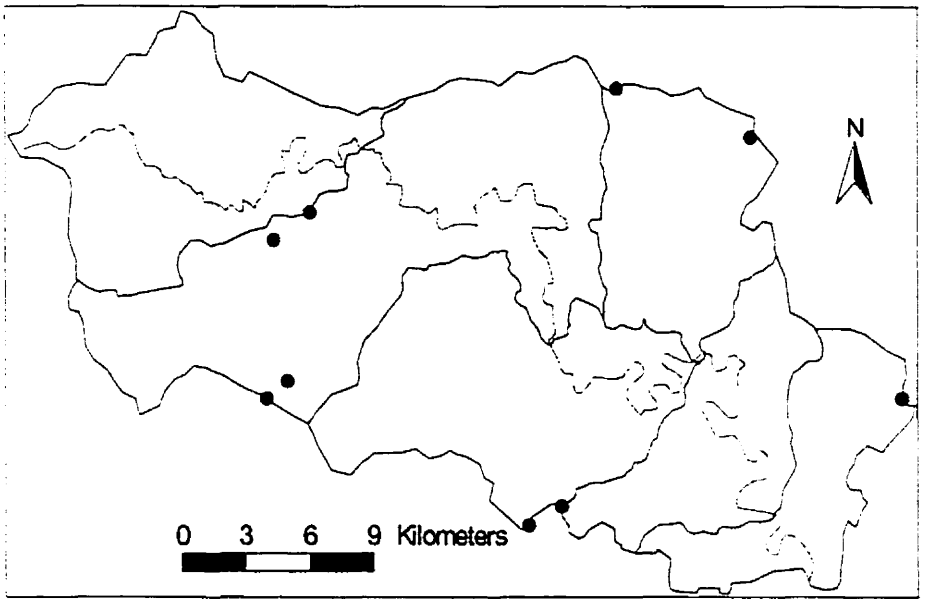

Figure 4.7 Location of soil profiles (Source: Land Type Map)

Table 4.4 The Mean Monthly Evaporation Values (Source: DWAF)

Month	Evaporation	Month	Evaporation	Month	Evaporation
January	158.0 (mm)	May	156.0 (mm)	September	106.0 (mm)
February	157.0 (mm)	June	159.0 (mm)	October	115.0 (mm)
March	168.0 (mm)	July	123.0 (mm)	November	127.0 (mm)
April	185.0 (mm)	August	117.0 (mm)	December	131.0 (mm)

Generalized parameters were entered and the model's output was compared with observed flow from weir W1H009 on the Mhlatuze River (Figure 4.9) to locate simultaneously occurring peak flows. Every concurrent peak flow event was investigated to determine whether other raingauges recorded rainfall the same day. If precipitation had occurred at most of raingauge stations, it was assumed that a frontal event had occurred. The adjacent period was examined for rainfall occurrence and duration of the frontal storm was determined. Rainfall was distributed to the subcatchments using the inverse distance weighting method (Lynch and Schulze 1995). This method is based on the centre of each subcatchment and the distance from each raingauge to those centres. These values were determined using ARC-VIEW. Rainfall for the whole subcatchment is determined from:

$$TR = \frac{\Sigma\left(\frac{1}{D^2} \times R\right)}{\Sigma \frac{1}{D^2}} \qquad \text{Eq. 4.1}$$

where: TR = rainfall assigned to subcatchment (mm)
D = distance from raingauge to subcatchment centre (m)
R = rainfall depth measured at raingauge (mm)

TR is total daily depth but had to be disaggregated into hourly rainfall for modelling purposes. A uniform rainfall intensity was assumed and the daily total was divided by 24 to give hourly depths in millimetres.

4.5 Streamflow Separation

Few weirs measure streamflow in this area and none in the Mfuli catchment (Figure 4.9). The Goedertrow dam controls the flow into the Mhlatuze River and a weir (W1H028) measures streamflow below the dam. The 'Rivers Bend' weir (W1H009) downstream of the confluence of the Mhlatuze and the Mfuli measures the combined streamflow of the two rivers. Farmers in the Nkwalani Valley located in between the Goedertrow Dam and the Rivers Bend weirs have water rights which allow them to extract water from the Mhlatuze for irrigation, but this type of extraction would not be necessary during frontal storm events so the Rivers Bend data will not be affected. Flow from the Mfuli catchment during frontal storms is therefore estimated by subtracting the Goedertrow weir discharge from the Rivers Bend flows.

The Mfuli hydrograph was divided into storm runoff and baseflow using the concave baseflow separation method outlined by McCuen (1989). This method requires drawing a line from the peakflow down to the time axis and determining the inflection point of the recession curve. The inflection point is defined as the point where the recession limb changes from a concave to a convex curve (Figure 4.10). The area under the curve is storm runoff volume, V:

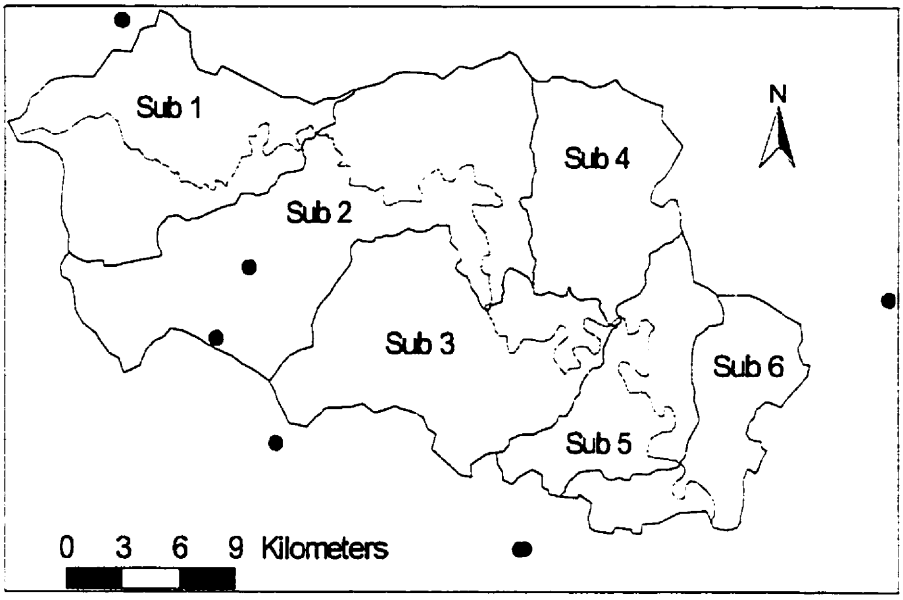

Figure 4.8 Location of raingauges (Source: WR90)

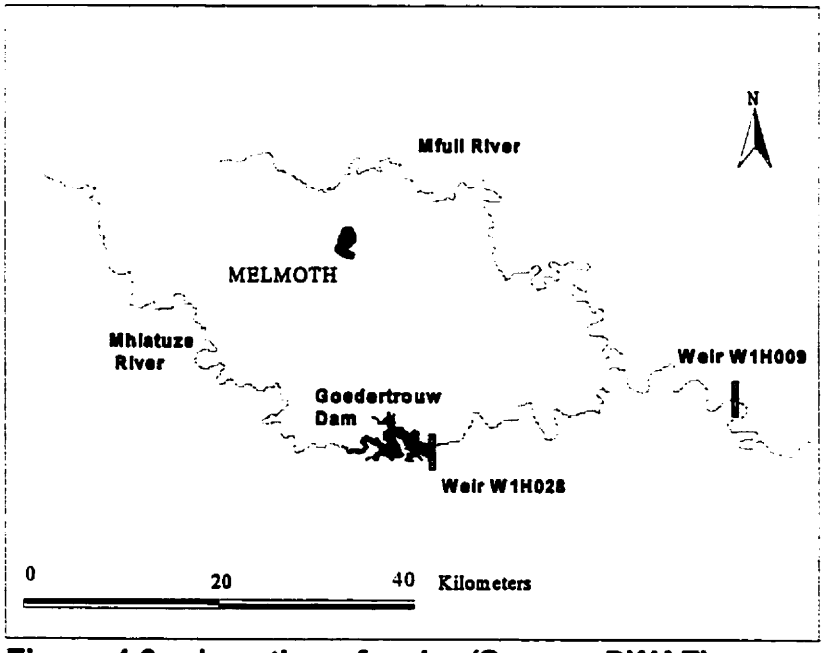

Figure 4.9 Location of weirs (Source: DWAF)

$$V = \left(\sum \frac{Q_n + Q_{n+1}}{2} \times \Delta t \right) - \left(Q_{pt} \times \frac{1}{2} \times \Delta tb \right) \qquad \text{Eq. 4.2}$$

where: V = volume m^3

$n = t_0, t_1, t_2 \ldots$

Q_n = discharge at t_n

Δt = change in time from t_n to t_{n+1}

Qpt = discharge at inflection point

Δtb = change in time from *peak discharge to Qpt*

Storm runoff volume determined in this manner can be compared to the modelled storm runoff volume computed by the SWMM model.

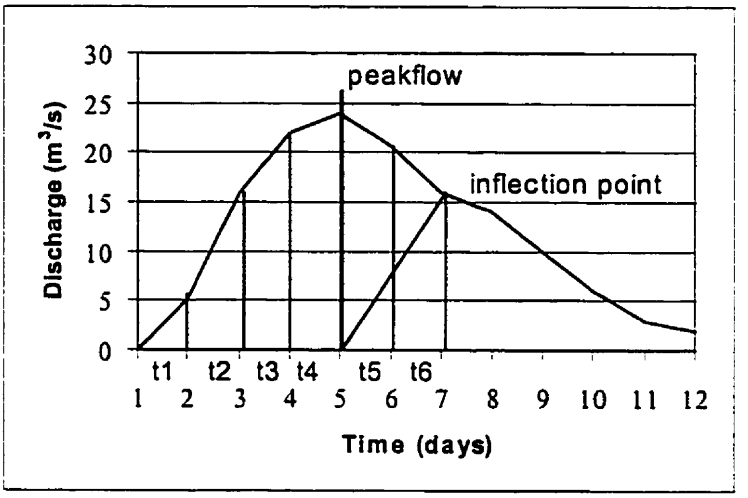

Figure 4.10 Example of hydrograph separation

Chapter 5: SWMM Results

5.1 Storm Events

The Mfuli catchment lies within a region where the winter months are predominantly dry and most rainstorms occur during the summer. Between September 1980 and March 1987 twelve frontal rainfall events were identified, eight of which occurred during the rainy season between December and March. Raingauge coverage throughout the catchment decreased during the modelling time period and only one of the twelve storms had six gauges of coverage, eight storms had five gauges and three storms had four gauges. The duration of these storms varied from two to four days. Table 5.1 lists the date each storm began, the number of days it rained, the number of gauges for which rainfall data was available and the total depth of rain over the catchment. Appendix B contains hyetographs for each storm event.

5.2 The Initial Run

The SWMM runoff module was run for each of the 12 storm events by altering only the rainfall input and maintaining all evaporation values and channel and catchment parameters. Stormflow volume for each event was generated directly by SWMM. Figure 5.1 is a graphical depiction of the model's output for each individual channel segment. The output for channel segment 6 is the cumulative total of the routed runoff for the whole Mfuli catchment generated by the storm.

Table 5.1 Twelve Storm Events

Storm number	Date	Days of rain	Number of gauges	Total rainfall depth (mm)
1	Sept. 7/80	3	6	43
2	Sept. 8/81	4	5	42
3	Nov. 22/81	3	5	15
4	Mar. 21/82	4	5	25
5	Jan. 16/83	2	5	30
6	Dec. 17/83	2	5	24
7	Jan. 29/84	3	5	172
8	Oct. 28/84	2	5	11
9	Feb. 7/85	4	5	98
10	Jan. 7/87	4	4	22
11	Jan. 19/87	2	4	19
12	Mar. 5/87	2	4	19

The cumulative total volume of stormflow generated by the SWMM model was compared with the runoff volume from the baseflow separated weir hydrographs. An example of the baseflow separation technique for the weir data is displayed in Figure 5.2. Appendix C presents a complete set of the baseflow separation graphs. The runoff volumes separated from the hydrographs represent observed stormflow volume.

The initial volume of computed runoff for the Mfuli catchment and the observed direct stormflow runoff separated from each of the twelve storm hydrographs are listed in Table 5.2 and illustrated in Figure 5.3. The difference between the computed volume and the observed volume is expressed as a percentage (Table 5.2):

$$(Qc - Qo) / Qo \times 100 \qquad \text{Eq. 5.1}$$

where: Qc is computed stormflow volume (m^3)
Qo is observed stormflow volume (m^3)

In Figure 5.3, the observations close to the 'line of perfect agreement' represent good agreement between observed and computed runoff. The computed volume underestimates the observed volume by -88% to -99% with the initial parameter values. Figure 5.4 is an example of the relationship between the computed and the observed hydrographs and a complete set of hydrographs can be found in Appendix D. The low computed discharge values illustrated in these hydrographs indicate that the amount of water entering the Mfuli River needs to be increased.

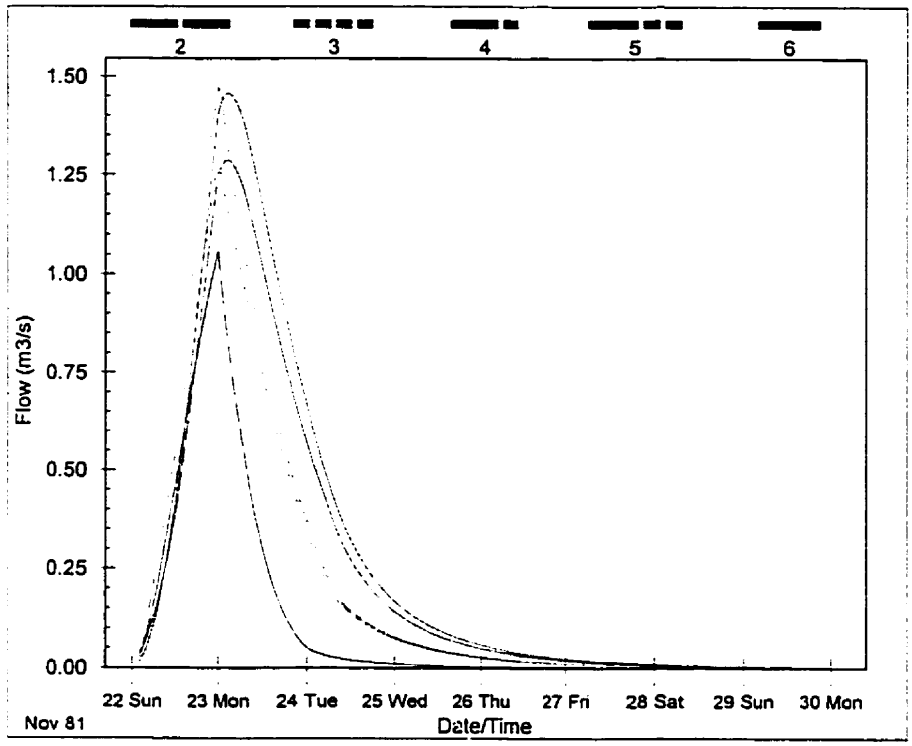

Figure 5.1 SWMM Runoff module output for all channel segments, Storm 3, November 1981

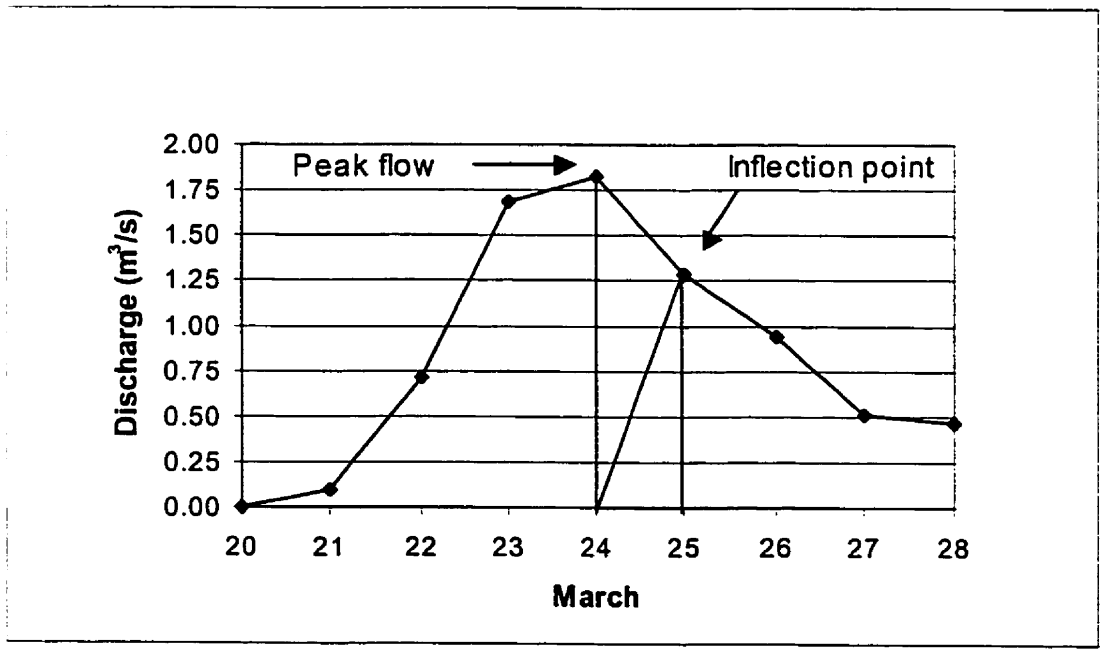

Figure 5.2 Baseflow separation for Storm 4, March 1982

Table 5.2. **Observed Streamflow Volume and Initial Computed Volume**

Storm number	Computed (1×10^4 m^3)	Observed (1×10^4 m^3)	Percent difference
1	14.6	220	-93
2	13.2	709	-98
3	2.02	64.8	-97
4	4.65	37.4	-88
5	10.9	118	-91
6	6.72	87.1	-92
7	78.3	8700	-99
8	0.988	15.9	-94
9	34.5	1520	-98
10	2.89	112	-97
11	3.29	107	-97
12	1.48	211	-99

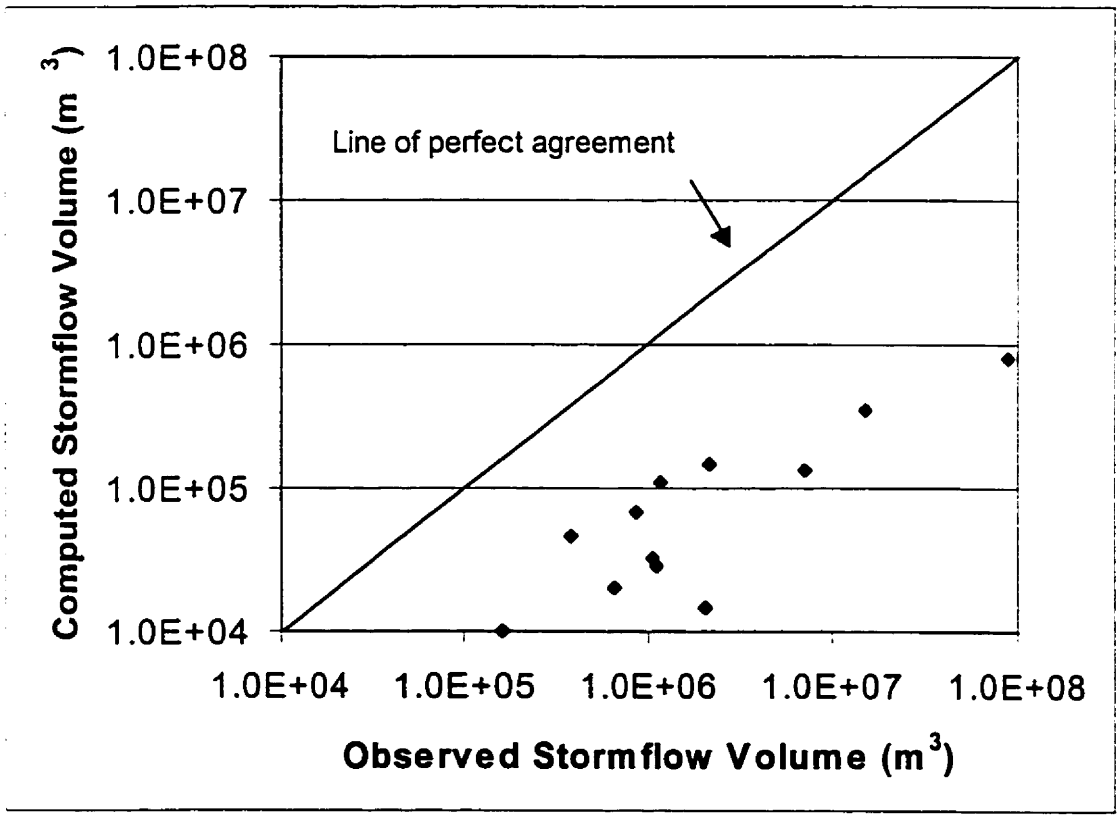

Figure 5.3 **Initial stormflow runoff**

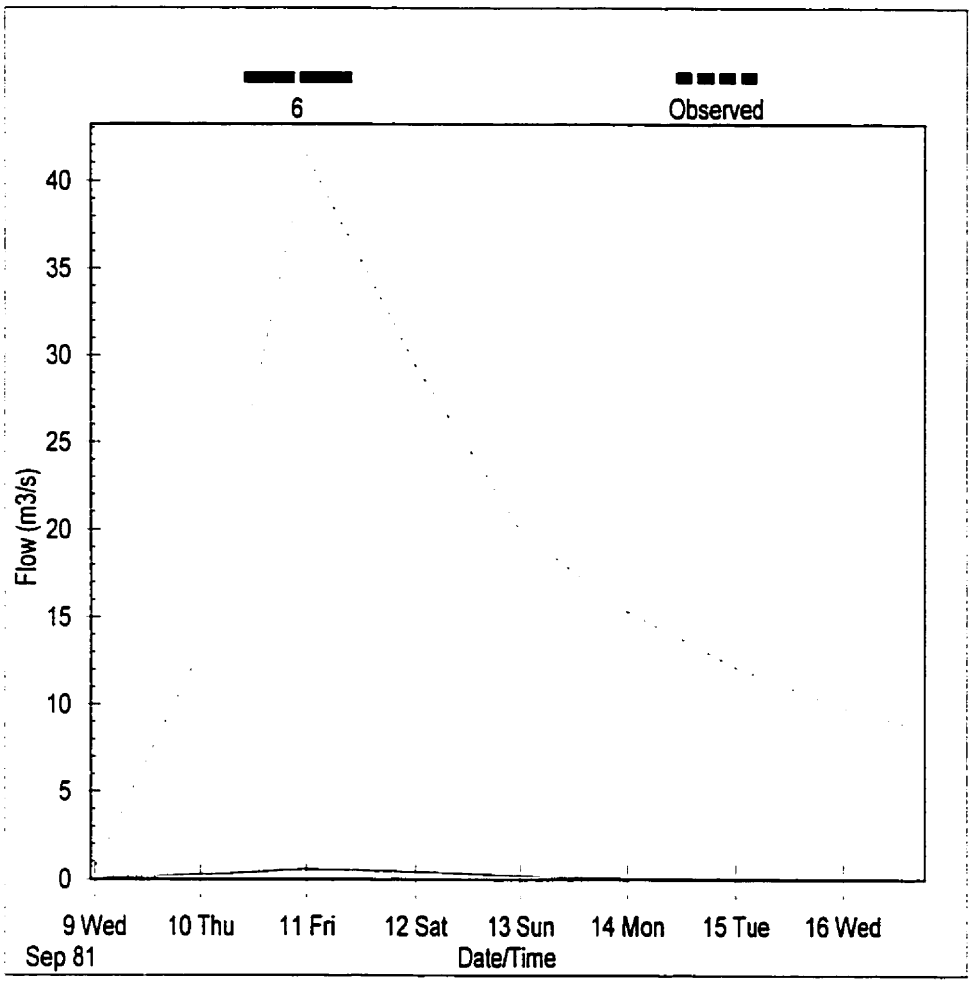

Figure 5.4 Storm 2, computed and observed hydrographs with initial input values

The standard error of estimate (*SEE*) was used to quantify the difference between observed and computed values for all the storm events. The *SEE* value indicates the overall magnitude of the error by squaring the difference between the observed (Qo) and computed (Qc) streamflow:

$$SEE = \sqrt{\frac{\sum_{i=1}^{n} (Qoi - Qci)^2}{n-2}} \qquad \text{Eq. 5.2}$$

A *SEE* value of zero indicates that the computed streamflow and the observed streamflow are in prefect agreement. The *SEE* value for the initial run was $2.87 \times 10^7 m^3$. In an effort to reduce the underprediction of the computed streamflow volume and lower the *SEE*, the model's parameters needed to be calibrated and sensitivity analysis undertaken.

5.3 Sensitivity Analysis and Calibration

Calibration is the manipulation of parameter values to improve model output until computed values approximate measured values (Oreskes et al. 1994). Based on the results of the initial modelling run, parameters that would increase the streamflow volume needed to be identified and adjusted. Sensitivity analysis was used to identify which parameters were most sensitive to change. Sensitivity analysis involves altering the input value of a parameter and assessing the resultant change in model output (Melching et al. 1990). A significant change in output values signifies that the model is sensitive to the

tested parameter. PCSWMM has a sensitivity analysis module and all channel and catchment parameters were tested by increasing and decreasing their values by 100%, 75%, 50% and 25%. Channel parameters had little effect on the streamflow volume and the most sensitive catchment parameter was percent of the subcatchment area that was impervious and directly connected to the channel (Figure 5.5).

The model was run a second time with the percent impervious parameter increased by 100% for each area and all other parameters held constant. In the initial run the parameter values for the percent impervious directly connected ranged from 0% to 1%, therefore the increased values were 1% to 2%. The resultant computed streamflow volume output resulted in a slightly lower *SEE* value (Table 5.3) compared with the initial run and underestimation of the observed volume was reduced to -70% to -98% (Table 5.3). Figure 5.6 shows the computed and observed volumes are closer to the line of agreement on this run. Figure 5.7 plots both the computed and observed hydrographs and shows that improvement over the first run is slight.

Several additional model iterations were done with the percent impervious directly connected increased by 100%. The resultant *SEE* value was lowered each time (Table 5.4) and the lowest *SEE* value occurs when the percent impervious directly connected is increased to values of 32% to 64%.
The computed volume ranges from underestimating the observed flow by -50% and overestimating it by 416% (Table 5.5). Eight of the twelve storms events have a computed output between +/- 50% and the remaining four storms are

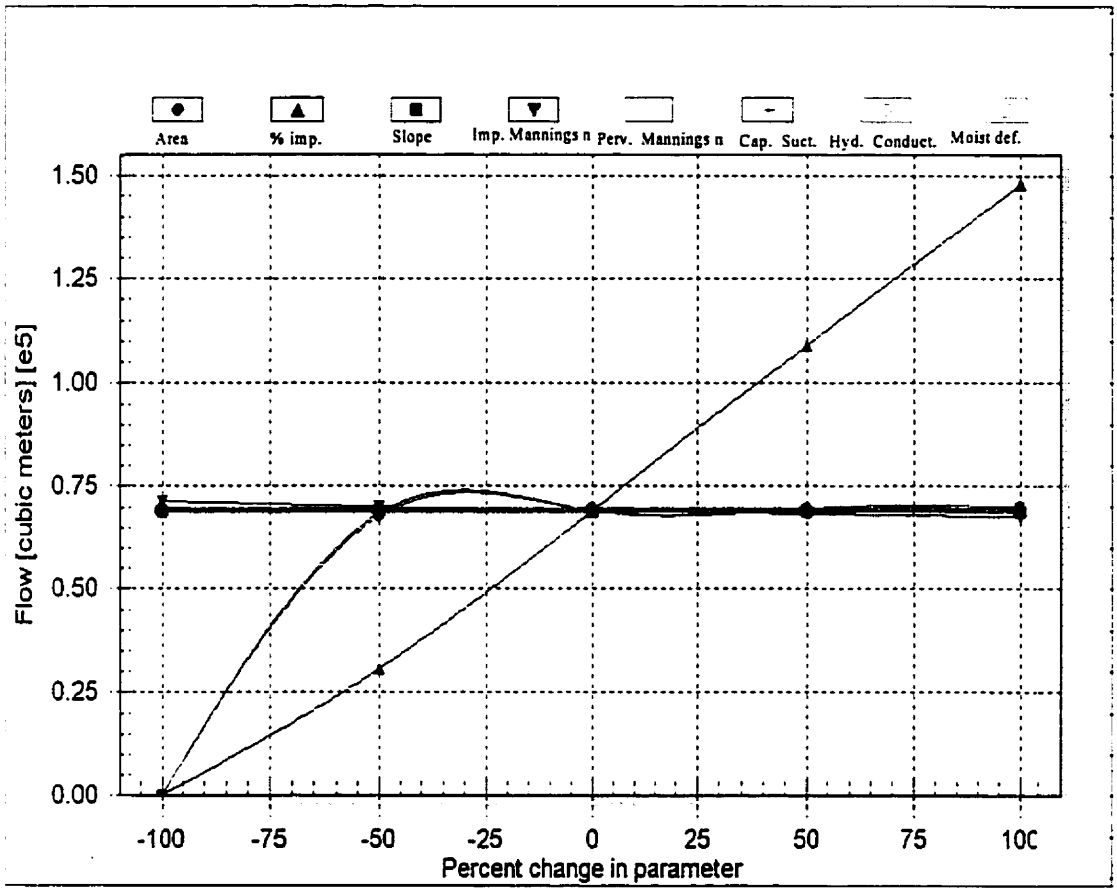

Figure 5.5 Non-linear sensitivity analysis for Storm 8

Table 5.3 Observed Streamflow Volume and Modified Computed Volume

Storm number	Computed (1×10^5 m^3)	Observed (1×10^5 m^3)	Percent difference
1	8.41	22.0	-62
2	8.00	70.9	-89
3	1.97	6.48	-70
4	3.54	3.74	-5
5	6.03	11.8	-49
6	4.33	8.71	-50
7	38.4	870	-96
8	1.34	1.59	-15
9	19.6	152	-87
10	2.85	11.2	-75
11	2.84	10.7	-73
12	2.06	21.1	-90
13	1.85	26.2	-93

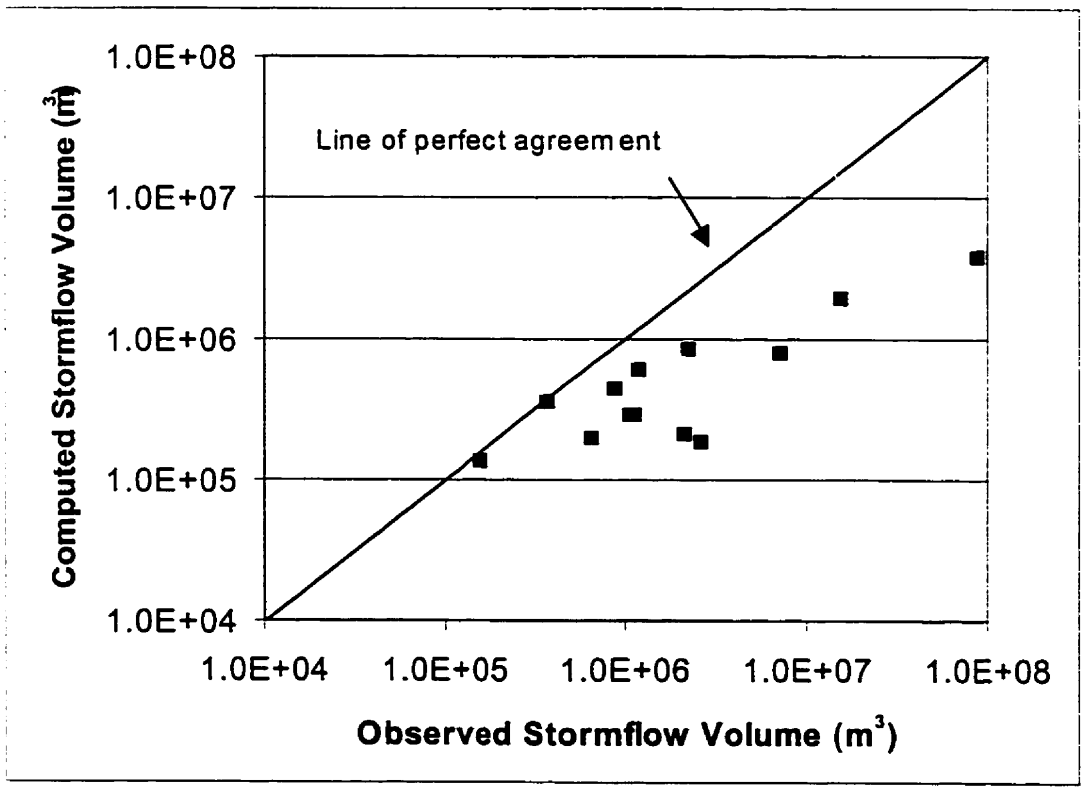

Figure 5.6 Stormflow runoff with percent impervious increased by 100%

overestimated by 209% to 416%. Figure 5.8 shows the improvement in the volume of computed and observed hydrograph. Figure 5.9 illustrates the improvement in the distribution of points about the line of perfect agreement compared with the point distribution from the initial run. Figure 5.10 shows all the model runs and illustrates the sequential improvement in model performance with an increase in percent imperviousness.

With the percent impervious directly connected at values of 32% to 64% sensitivity analysis shows that the width of the subcatchment has become the most sensitive parameter. The subcatchment width along with the slope and roughness parameters have been described as calibration parameters in SWMM. For overland flow calculations the subcatchment width, slope and roughness are all combined into one value(James et. al 1999) and generally slope and roughness are held constant during calibration. Further attempts at calibrating the model by modifying the subcatchment width parameter did not improve the output values and the *SEE* values increased indicating less overall agreement between computed and observed volumes (Table 5.6). The hydrographs produced by modifying the subcatchment width retained the same shapes they had when the percent impervious parameters were set at 32% to 64%. Therefore, although overall computed stormflow volume still varies greatly from the observed volume and the *SEE* value is far from zero, modelling was discontinued.

Correlation analysis showed that number of raingauges and number of days of rainfall have no significant influence on observed and computed flow, but

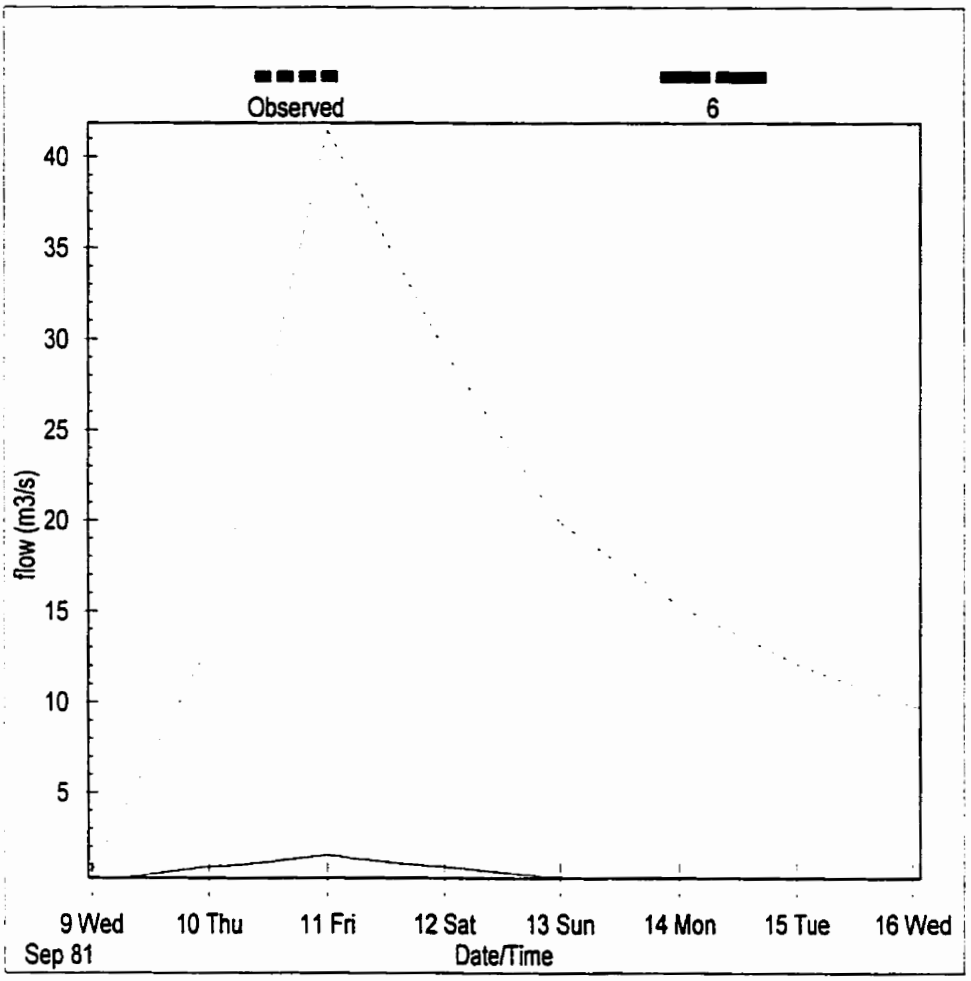

Figure 5.7 Storm 2, computed and observed hydrographs with 1-2% impervious

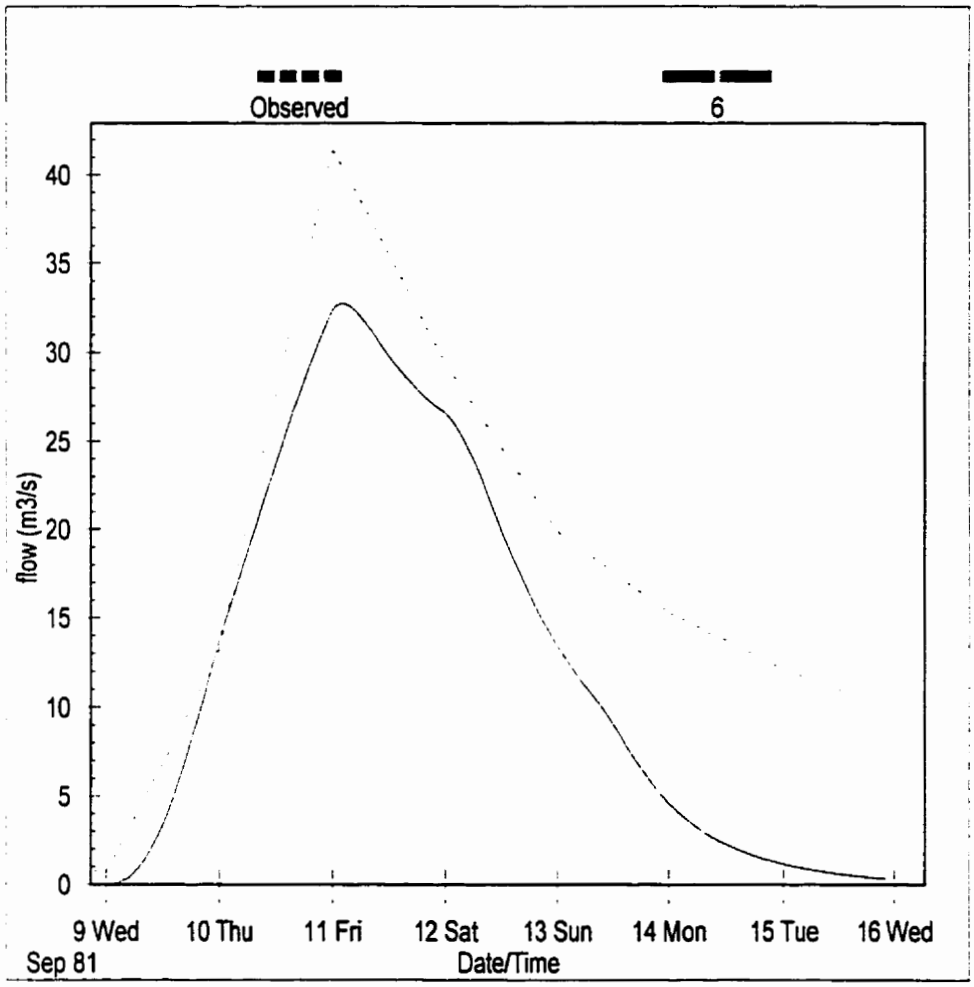

Figure 5.8 Storm 2, computed and observed hydrograph with 32-64% impervious

Table 5.4 The *SEE* Between Observed and Computed Stormflow Volume with Increased % Impervious Directly Connected

% impervious directly connected	Standard Error Estimate (SEE) (m^3)
0-1	2.78×10^7
1-2	2.74×10^7
2-4	2.68×10^7
4-8	2.56×10^7
8-16	2.34×10^7
16-32	2.00×10^7
32-64	1.38×10^7

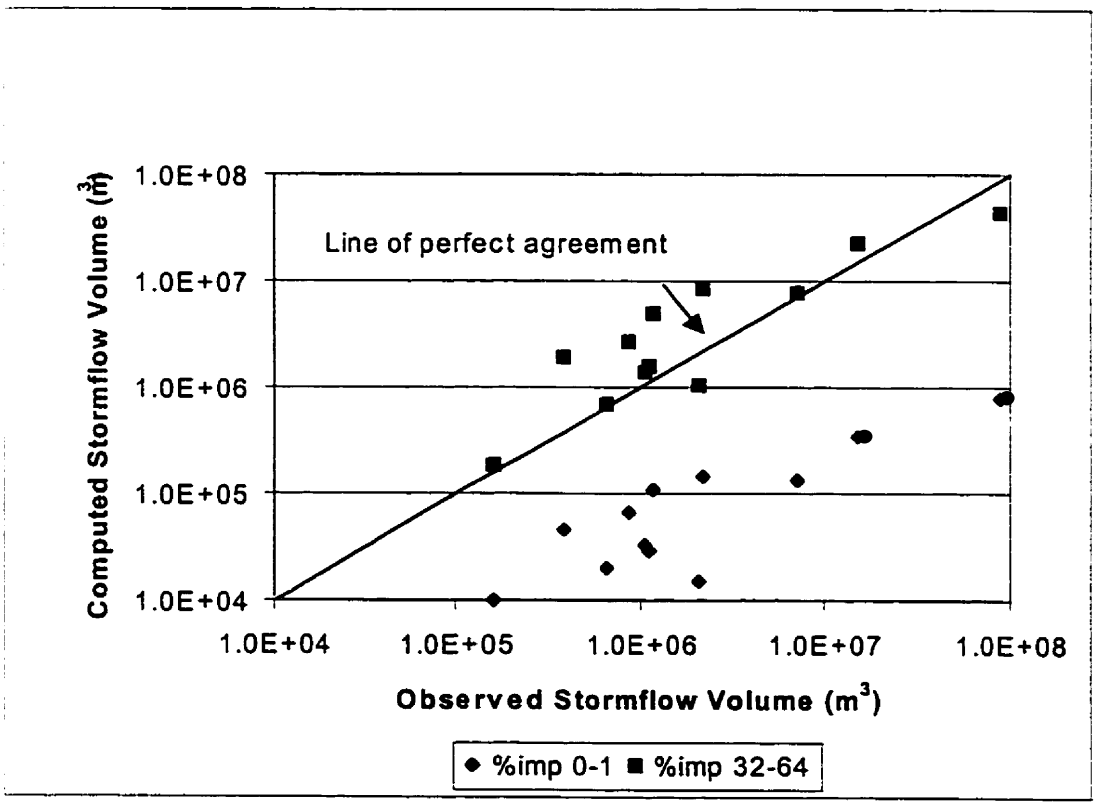

Figure 5.9 Comparison of stormflow runoff with % impervious values increased

Table 5.5 Observed Streamflow Volume and Calibrated Computed Volume

Storm number	Computed (1×10^5 m^3)	Observed (1×10^5 m^3)	Percent difference
1	86.1	22.0	291
2	77.8	70.9	10
3	6.89	6.48	6
4	19.3	3.74	416
5	49.3	11.8	318
6	26.9	8.71	209
7	432.0	870.0	-50
8	1.86	1.59	17
9	223.0	152.0	47
10	16.0	11.2	43
11	13.7	10.7	28
12	10.5	21.1	-50

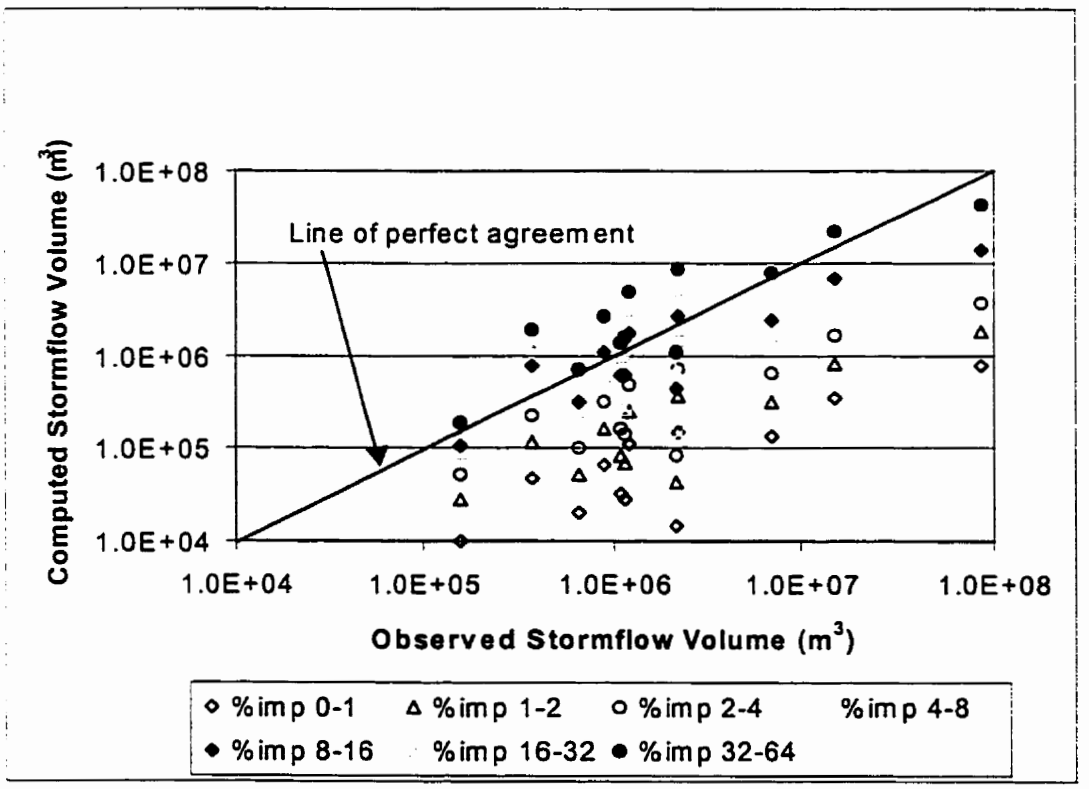

Figure 5.10 Stormflow volume with sequentially increased values of % impervious directly connected

total rainfall does (Figure 5.11 and Table 5.7). The high correlation between rainfall and stormflow for both the computed and observed volume was an expected trend, indicating that increased rainfall depth is associated with increased stormflow. The observed runoff depth is calculated by dividing the stormflow volume by the area of the catchment (Table 5.8). To determine whether the relationship between runoff depth and rainfall is reasonable for South Africa both the computed and observed ratio of runoff to rainfall was calculated for each storm event. The runoff/rainfall ratio values range from 0.03 to 0.38 for the SWMM runoff and observed ratio values range from 0.02 to 0.77. Generally lower rainfall depth is associated with lower ratio values and higher ratio values are associated with higher rainfall depth for both the observed runoff and that generated by SWMM. Therefore, in SWMM 3% to 38% of the rainfall became runoff and 2% to 77% of the rainfall in the Mfuli catchment became runoff. The average annual runoff for South Africa is 10% (Aquastat 1995). Given that an annual value will be less than values based on individual storms and that this study encompasses one subwatershed not the whole country the runoff / rainfall ratios are reasonable.

The relationships between the computed and observed storm volumes required further investigation. There appears to be no relationship between the date of the storm occurrence and the relationship between observed and computed flow. The storms with the lowest rainfall and those with the highest rainfall are computed within the +/- 50% range of measured versus computed stormflow volume. Among the storm events that fall into the mid range

Table 5.6 **The *SEE* Between Observed and Computed Stormflow Volume with Changes in the Width Parameter**

Width Parameter	Standard Error Estimate (SEE) (m^3)
initial width values	1.38×10^7
increased by 25%	1.39×10^7
increased by 50%	1.39×10^7
decreased by 25%	1.41×10^7
decreased by 50%	1.46×10^7

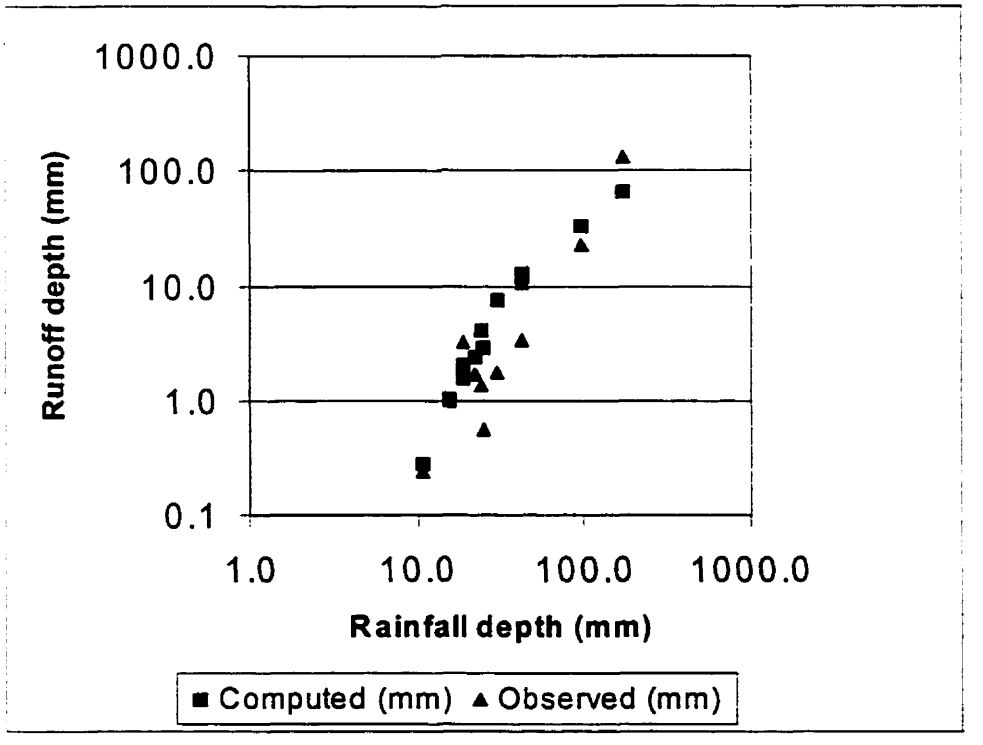

Figure 5.11 Total rainfall depth versus computed and observed runoff depth

Table 5.7 Correlation Coefficients

Stormflow volume	Days of rain	Number of gauges	total rainfall depth
Computed	0.17	0.30	0.99
Observed	0.08	0.14	0.93

Table 5.8 Rainfall Depth with Calibrated SWMM Runoff and Observed Runoff Depths

Storm Number	Rainfall (mm)	SWMM Runoff (mm)	SWMM Runoff / Rainfall	Observed Runoff(mm)	Observed Runoff / rainfall
1	43	13	0.31	3	0.08
2	42	12	0.28	11	0.25
3	15	1	0.07	1	0.06
4	25	3	0.12	1	0.02
5	30	7	0.25	2	0.06
6	24	4	0.17	1	0.05
7	172	65	0.38	132	0.77
8	11	0.3	0.03	0.2	0.02
9	98	34	0.35	23	0.24
10	22	2	0.11	2	0.08
11	19	2	0.11	2	0.09
12	19	2	0.08	3	0.17

of rainfall the four storm events greatly overestimated by the model (storms 1, 4, 5, 6) are found along with other storms falling within the +/- 50% range. In an effort to understand these phenomena, particular attention was paid to storms that had similar total depth of rainfall. Storm 1 has a total rainfall depth (43 mm) similar to that of Storm 2 (42 mm). However, the observed stormflow volume is only 2.20 $x10^6$ m^3 for Storm 1 and is much higher for storm 2 at 7.09 $x10^6$ m^3. Storms 4, 5, and 6 have similar but slightly higher than the rainfall of storms 10, 11, 12, however their observed stormflow is generally lower.

The computed hydrographs for Storms 1, 2, 3, 10 and 11 are similar in shape to the observed hydrographs. The computed hydrographs for the storms with the highest rainfall (Storms 7 and 9) are characterised with rough rising and recession limbs and are drawn out. The large quantity of runoff generated by these storms would exceed the capacity of the channel and the excess water would be held in storage to be released when channel capacity would allow, explaining for the hydrographs' unusual shape. Only Storms 1 and 2 have concurrent peak discharge for both their computed and observed hydrographs, the computed hydrograph peaks early for Storms 4, 5, 7, and 10 and Storms 3, 6, 8, 9, 11 and 12 peak late. The rising limbs for Storms 3, 10, 11 and 12 are delayed and for Storms 6, 7, 8, and 9 they are early. The computed hydrographs for Storms 1, 2, 3, 4, and 5 are similar in shape to the associated observed hydrographs.

Chapter 6: Discussion

6.1 Calibrated SWMM

The best agreement between observed and SWMM computed stormflow volume occurred when the parameters for the percent of the catchment that was impervious and directly connected to the channel were high. Originally the Runoff module treated overland flow as the only component of stormflow and infiltrated water was lost from the system (James et al. 1999). A groundwater subroutine was later added to the Runoff module so that subsurface flow could be captured, which was particularly useful in underdeveloped areas (James et al. 1999). However, this subroutine was not applied in this study because sufficient data for the groundwater parameters were lacking. Without the groundwater subroutine, modelling the Mfuli catchment with such high values of impervious areas means that less water was lost from the system and more was forced into overland flow. In a rural area it is expected that areas of infiltration would be high and the percent of impervious area would be low compared with those of an urban area. Therefore, adjusting the percent impervious parameters to such high values could be considered 'curve-fitting' and the physical basis for these parameters has been lost. However, there may be a physical explanation for the apparently high impervious values in this region.

Most of the Mfuli catchment falls into the Fa and Fb land type (Figure 6.1 and Table 6.1). This land type is characterised as a young landscape with Mispach and Glenrosa soils derived from rock weathering (Land type Survey Staff 1988). Both Glenrosa and Mispach soils are described as having a thin soil layer, with depth of approximately 15 to 50 cm, overlying bedrock (South African Sugar Association 1984). Rainfall in these areas would quickly saturate the thin soil layer resulting in overland flow or rapid interflow draining into the channel. These thin soils, with bedrock close to the surface, would limit infiltration and act as an impervious layer in a similar manner to the percent impervious directly connected. The Mfuli region would therefore require higher values for the percent impervious directly connected in the SWMM model than one would expect for a rural region.

The overestimations of SWMM stormflow volume for storms 1, 4, 5, and 6 could be attributed to unobserved withdrawals from the Mhlatuze River system. When frontal storms were chosen as the events to model in this study, the assumption was made that farmers in the Nkwalani Valley would not likely pump water from the Mhlatuze during rain events for irrigation. However, if farmers were pumping water during the modelled events to replenish their farm dams for future use, withdrawals of this kind from the Mhlatuze system are not accounted for. South African water laws have historically favoured the rights of the farmers and at the time of this study there were no restrictions on the amount of water farmers along the river could remove. Water pumped from the system between the Goedertrow dam and the River's Bend weir could explain why there was a

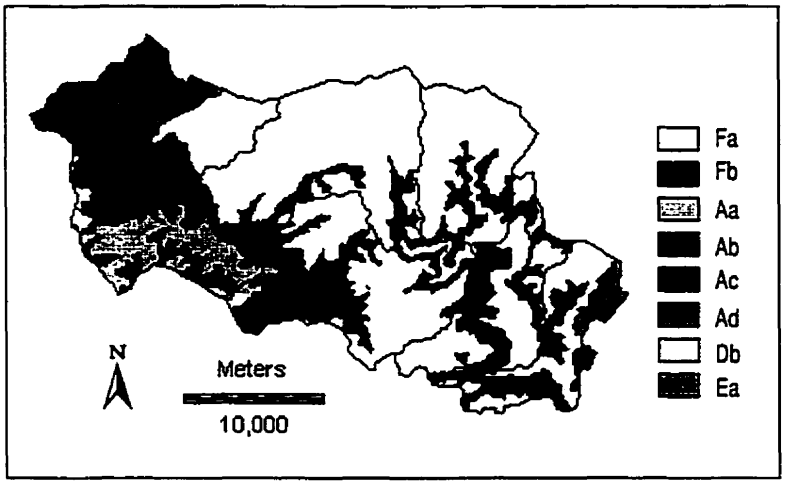

Figure 6.1 Land types found in Mfuli Basin (Source: Land Types of the Map 2830 Richards Bay)

Table 6.1 Description of Soils in Land Type Classes

Land Type	General soil pattern	Soil forms
Aa - Ad	red or yellow apedal soils, freely drained, without water tables	Inanda, Kranskop, Magwa, Hutton, Griffin, Clovelly
Db	after subtracting rocks, stones and boulders, duplex soils with non-red B horizons occupy more than half the landcover	Escourt, Sterkspruit, Swartland, Valsrivier, Kroonstad
Ea	vertic, melanic, dark and /or red soils, with high base status	Shortlands, Glendale
Fa - Fb	pedologically young landscapes, orthic topsoils	Glenrosa, Mispach

Source: Land Types of the Map 2830 Richards Bay

lower volume of stormflow observed at the weir than the amount computed by SWMM.

6.2 Uncertainty and Error Analysis

Uncertainty analysis is a method of examining hydrologic model results by highlighting and ranking sources of error (James 1994). Error in this context refers to the difference between the observed and the computed streamflow volume. The sources of error have been adapted from those outlined by James (1994) and are divided into three categories based on association with the model, the data or the user. Sources of error associated with the model include:

1. mistakes in the numerical accuracy of the program code;
2. poor formulation of the relationships between hydrologic processes in the code; and
3. the number and resolution of the hydrologic processes represented.

Sources of error associated with the data include:

1. random or systematic malfunctions of field instruments;
2. sampling error based on the location, timing and resolution of observations; and
3. secondary source data availability and accuracy.

Sources of error associated with the model user are generally related to the estimation of parameter values and assumptions made during the modelling process and data analysis interpretations. These categories are not mutually exclusive and in this study the limitations of the available data likely propagated user error in the estimation of model input and parameter values.

Source error originating within the models code and program structure is beyond the scope of this study and the focus will be on user and data source error. However, some observations made during the application of the HYMAS model deserve mention. HYMAS contained either numerical errors or poor arrangement of the internal relationships between the hydrologic processes being modelled. This was reflected in the difficulties in keeping the model running. Another potential source of error caused by the structure of the HYMAS model is that it requires numerous input parameters and the user has no control over the number and type of processes being modelled. This poses problems in data poor regions such as the Mfuli basin. For example, groundwater parameters must be specified for the HYMAS model to run, however, the groundwater data available for the Mfuli basin was insufficient to estimate the required parameters adequately. Therefore, values had to be estimated with no physical basis. By contrast, the Runoff module in SWMM allows the user more flexibility in the processes being modelled and the groundwater subroutine was not applied.

Sources of error associated with the data were common to both the SWMM and the HYMAS modelling applications. First, there were the limitations in primary data collection. The Mfuli Basin has few roads and at the time of this study travelling on foot in Zululand was unsafe. Therefore, cross-sectional surveys and channel observations were limited to places close to where roads cross the Mfuli River. The roads in this region tend to follow the high ground delineating the subcatchment boundaries, so the cross-sectional surveys are located close to the subcatchment boundaries. The road does not cross the Mfuli

river in subcatchment 5 so there is no cross-sectional profile for the channel segment in this area. Channel parameters for this segment of the river had to be estimated based on the surrounding segments. Similarly GPS co-ordinates for ground-truthing and observations of soil profiles were limited to areas close to the roads.

The rest of the data collected for this study consisted of secondary data and there is always an unknown level of error associated with any secondary data set. This study utilizes several types of secondary data sets which are subject to instrument malfunctions and data entry errors. For example, there are numerous gaps in the raingauge and weir streamflow data sets where either the gauge equipment malfunctioned or incorrect values have been removed. Although efforts are made by the suppliers to ensure that these data are correct there is still a possibility of random erroneous values. Another source of error associated with the data involves sampling error. The sparseness of the raingauge and weir coverage within the Mfuli basin represents this type of error. With so few raingauges in this area a method had to be adopted that would distribute the rainfall measured at gauges predominately outside the catchment over the catchment's area. Using spatial averaging methods, such as inverse distance weighing, to distribute rainfall introduces error because the rainfall assigned to the catchment will never be as low or as high as the rainfall measured at the gauges. Another limitation that had to be overcome during the application of SWMM was that rainfall in this area is measured as daily depths. SWMM requires a shorter time step for rainfall input, and daily depths had to be

converted to hourly depths.

Without a weir to directly measure the streamflow of the Mfuli River error is introduced when an indirect method to determine the river's stormflow had to be devised. The location of the nearest weir (River's Bend) is downstream of the confluence of the Mhlatuze and Mfuli systems. The assumption that the Mhlatuze's contribution to the combined stormflow measured at the weir could be separated out by subtracting the Goerdertrow dam's outflow from the River's Bend weir may underestimate the contribution of the Nkwalani Valley to the Mhlatuze's stormflow. Another source of error introduced by this method of deriving the Mfuli's flow at the Rivers Bend weir is the possibility of unaccounted for withdrawals from the Mhlatuze River by the farmers in the Nkwalani Valley. Estimating stormflow using hydrograph separation techniques is somewhat subjective and also introduces the possibility of error.

Source error associated with the user focuses primarily on assumptions and parameter estimation. Two major assumptions have already been discussed in the context of coping with raingauges and weir deficiencies. A significant source of possible error regarding the 'observed' stormflow at the River's Bend weir involves baseflow separation of the hydrograph. The type of baseflow separation method chosen has a great impact on the estimated stormflow volume. For example the constant-discharge method (McCuen 1989), where the line separating baseflow from stormflow starts at the lowest discharge rate at the beginning of the rising limb and extends at a constant discharge rate until it intersects the hydrograph's recession limb, would have resulted in higher

stormflow volume than the concave baseflow separation method used in this study. The concave baseflow separation method requires that an inflection point on the recession limb be chosen, a somewhat subjective practice that greatly affects the amount of baseflow separated from the hydrograph. Regardless of the separation technique chosen daily measurements of streamflow recorded at the weir restrict the hydrograph separation time steps to daily increments. With such large time steps separated stormflow may include slower moving groundwater or input from convective storms not captured by the sparse raingauge coverage.

Other sources of possible error involve the estimation of parameter values. The cross referencing between field photographs, the Land Type Map, and the Sugar Association's identification of soils book to classify soils is prone to error. Field observations were limited to areas close to the roads, thereby excluding most of the Mfuli area. The questionable accuracy of the soils data for this area will effect the infiltration parameters of the Green-Ampt equation. Another assumption made during this study was that the Mfuli system completely drys out between storm events. Finally, the original values assigned for the percent impervious directly connected parameters based on bare ground along the channel identified in the in the classified satellite image were inconsistent with model results.

Errors propagated by the natural variability of the hydrologic system effect all aspects of the modelling process. In an effort to address the heterogeneity of the Mfuli system the basin was subdivided into six fairly homogenous

subcatchments. However, generalizations still had to be made at this level of discretization and the natural variability of the system was not totally captured by a model.

6.3 Ranking the Sources of Error

Part of uncertainty analysis is to rank the sources of error (James 1994). The most important limiting factor in modelling the Mfuli system is the lack of data. The assumptions made to cope with the deficient raingauge and weir data have a great impact on the modelling results because rainfall drives the hydrologic system and the models and streamflow is used to assess the models' performance. The lack of groundwater data would have been a problem if the HYMAS model had run, since the parameters for the groundwater components would have had no physical basis. The calibration of the HYMAS model would have proven very difficult and the level of confidence in so many parameters being estimated and calibrated correctly would have been low. The lack of groundwater data meant that subsurface flow was not modelled in SWMM and caused the estimation of the percent impervious directly connected parameters to become very important. Using the satellite image to estimate this parameter appears to have been unsuccessful because the calibration of the model showed that performance was greatly improved when this parameter's values much higher than those initially assigned. The Land type map proved more appropriate for estimation of the percent impervious area than the satellite image.

Hydrologic model structure is the second most important source of error. HYMAS was originally chosen because it was developed in South Africa for southern African conditions. However, the structure of the model forced parameter estimations without physical basis and the model proved unstable and impossible to run. SWMM was developed for urban areas although it had been used successfully in rural areas (James et al. 1999). Given the data limitations of this region, a model that can be reduced to a simplified structure is needed and SWMM meets that criteria. However, with only twelve suitable events to test the model's capability in this region it is difficult to assess the performance of SWMM. SWMM did yield results that generally captured stormflow volume to within +/- 50% of that estimated at the weir and with so many data limitations on modelling this area these results are likely respectable.

Chapter 7: Summary and Concluding Statement

South Africa faces a serious challenge because the availability of water in the country remains fixed, yet water demands are steadily increasing as the population expands and standards of living improve (Biswas 1990). Rainfall in South Africa is generally low and is prone to extreme conditions such as hurricanes and drought. Water resource management is needed to ensure that an adequate water supply is available, especially during times of drought. Hydrologic models can be used to provide an estimate of present and future resource supply (Jensen and Mantoglou 1992) and serve as a basis for decision making (Bergström 1991). Using classical mathematic descriptions, deterministic hydrologic models depict the cause and effect relationships among processes occurring within a catchment (Haggett and Chorley 1967, Fleming 1979, Ward and Elliot 1995). However, even the most rigorous models describing catchment response are crude representations of reality (Grayson et al. 1996). The purpose of this research is to hydrologically model the Mfuli subcatchment of the Mhlatuze River Basin in KwaZulu-Natal.

The HYMAS (Hydrological Model Application System) catchment model (Hughes and Sami 1994) was initially chosen for this study because it was developed in South Africa for southern African conditions. HYMAS is a new and developing system that is not 'user friendly' and the application of the HYMAS VTI (Variable Time Interval) model in the Mfuli basin was problematic. The model frequently would not run and it doesn't offer any output to detect the

source of the problem. Parameter estimation was also difficult because of poor parameter explanation and a lack of sufficient source data to meet the many parameter requirements of the model. The internal code of the model is unstable and the computer would freeze at times and had to be rebooted. Technical support for this program was also insufficient and questions to the developer went unanswered. Eventually the model would not run at all and so was abandoned.

When the HYMAS package became unusable, a model was required that offered technical support, was discussed in the literature, had been used successfully by people other than the model's developers and was able to use the data collected for the HYMAS project. The Storm Water Management Model (SWMM) met all these requirements and the runoff module offered in SWMM, was selected to replace the VTI model in HYMAS.

The availability of rainfall and discharge data in the Mfuli region determined the years that could be modelled and the type of modelling which could be done. Sparse raingauge coverage meant that convective storms could not be included in modelling and only frontal storms could be used. It was assumed that a frontal event had occurred, if precipitation had been recorded at most raingauge stations. Event-based modelling was done for these selected storms. Between September 1980 and March 1987 twelve frontal rainfall events were identified and the inverse distance weighting method (Lynch and Schulze 1995) was used to distribute rainfall to six Mfuli subcatchments. The discretization of these subcatchments was based on vegetation, geology,

settlement and subwatersheds defined by tributary drainage. There are no weirs measuring streamflow in the Mfuli catchment. The Goedertrow dam controls the flow into the Mhlatuze River and a weir measures streamflow below the dam. The 'Rivers Bend' weir downstream of the confluence of the Mhlatuze and the Mfuli measures the combined streamflow of the two rivers. Flow from the Mfuli catchment during frontal storms was determined by subtracting the Goedertrow weir discharge from the Rivers Bend flows. The Mfuli hydrograph was then divided into storm runoff and baseflow using the concave baseflow separation method outlined by McCuen (1989). The area under the curve represents storm runoff volume and can be compared to stormflow computed by the SWMM model.

The SWMM runoff module was run for each of the twelve storm events by altering only the rainfall input and maintaining all evaporation values and channel and catchment parameters. The computed volume underestimated the observed volume by -88% to -99% and the Standard Error of the Estimate (*SEE*) value was 2.87 x $10^7 m^3$. Sensitivity analysis showed that the percent of the catchment impervious and directly connected to the channel was the most sensitive parameter. This parameter was initially set at 0% to 1% but was gradually increased to values of 32% to 64% so that the *SEE* value was lowered to 1.38 x $10^7 m^3$ and computed flows were closer to measured. Most of the Mfuli catchment is composed of thin soil overlying bedrock which limits infiltration and acts as an impervious layer in a similar manner to the percent impervious directly connected. The Mfuli region would therefore require higher values for the percent

impervious directly connected for the SWMM model than one would expect for a rural region.

Eight of the twelve storms events, consisting of the highest and lowest rainfalls have a modelled output between +/- 50% of the measured stormflow and the remaining four storms are overestimated by 209% to 416% by SWMM. A possible explanation for the overestimation of SWMM stormflow volume for these storms is unobserved withdrawals from the Mhlatuze River system by the farmers of the Nkwalani Valley. Water pumped from the river between the Goedertrow dam and the River's Bend weir would result in a lower volume of stormflow observed at the weir and apparent 'overprediction' by SWMM. Another possibility is that the sparse coverage of rainguages in this area resulted in unrepresentative rainfall input for these storms.

Uncertainty analysis identifies and ranks the sources of model error, which is the difference between the computed response of the model and observed data (James 1994). The primary source of model error in the Mfuli system is the lack of data and assumptions made to cope with deficient raingauge and weir data have a great impact on the modelling results. Given the data limitations of this region, a model that can be reduced to a simplified structure is needed and SWMM meets that criteria.

The hydrologic extremes of droughts and floods along with the semi-arid conditions of the South Africa pose difficulties for water management planners. The geologic formations underlying South Africa store insufficient groundwater to stabilise river base flow (Conley and Midgley 1988) so surface runoff drives

South Africa's river systems. Rainfall-runoff hydrologic models can be used to assess and compute water availability although this study has shown that the Mfuli region requires more raingauge and streamflow data for reliable model calculation and assessment. Given the limited accessibility and secondary data available for this region a simple hydrologic model should be used. More complex models are inappropriate because many parameters would have to be assigned without physical basis. HYMAS was designed for application in Southern Africa but it has too many parameters that require data that are unavailable. SWMM has the capability of being simplified is more 'user friendly' and is well documented. The results produced by the runoff module of SWMM are reasonable given the limited data in the region.

References

Abbott, M.B., J.C. Bathurst, J.A. Cunge, P.E. O'Connell, and J. Rasmussen 1986. An Introduction to the European Hydrological System-Systeme Hydrologique Europeen: SHE, 1, History and philosophy of a physically-based, distributed modelling system. Journal of Hydrology **87**: 45-59.

Aquastat 1995. South Africa. URL: http://www.fao.org/waicent/faoinfo/agricult/agl/aglw/aquastat/safrica.htm

Beven, K.L. 1989. Changing ideas in hydrology - The case of physically-based models. Journal of Hydrology **105**: 157-172.

Beven, K.L. and E.F. Wood 1983. Catchment geomorphology and the dynamics of runoff contributing areas. Journal of Hydrology **65**: 139-158.

Bergström, S. 1991. Principles and confidence in hydrological modelling. Nordic Hydrology **22**: 123-136.

Biswas, A.K. 1990. Objectives and concepts of Environmentally-sound Water Management. *In* Environmentally Sound Water Management. *Edited by* N.C. Thanh and A.K. Biswas, pp 30-58. Oxford University Press, Oxford, UK.

Campbell, J.B. 1996. Introduction to Remote Sensing, Second Edition. The Guilford Press, New York, USA.

Conley, A.H. and D.C. Midgley 1988. National water management in the Republic of South Africa- towards a consultative partnership with diverse users in a semi-arid country. Journal of Hydrology **100**: 473-487.

Dingman, S.L. 1994. Physical Hydrology. Prentice Hall, Inc., Toronto, Can.

Drayton, R.S., B.M. Wilde and J.H.K. Harris 1992. Geographical information system approach to distributed modelling. Hydrological Processes **6**: 361-368.

Fleming, G. 1979. Deterministic models in hydrology. FAO Irrigation and Drainage Paper 32, Food and Agriculture Organization of the United Nations, Rome.

Grayson, R.B., I.D. Moore and T.A. McMahon 1992. Physically based hydrologic modelling 2. Is the concept realistic? Water Resources Research **26**: 2659-2666.

Haggett, P. and R.J. Chorley 1967. Models, paradigms and the new geography. *In* R.J. Chorley and P. Haggett, *editors,* Models in Geography, Methun & Co., London, pp. 19-39.

Hughes, D.A. 1989. Estimation of the parameters of an isolated event conceptual model from physical catchment characteristics. Hydrologic Sciences Journal **34**: 539-557.

Hughes, D.A. 1994. HYMAS: A hydrological modelling Application System, Guide to the system and user manual. Institute for Water Research, Rhodes University, Grahamstown, R.S.A.

Hughes, D.A. and K. Sami 1994. A semi-distributed, variable time interval model of catchment hydrology - structure and parameter estimation procedures. Journal of Hydrology **155**: 265-291.

James, W. 1994. Rules for Responsible Modelling. Computational Hydraulics International, Guelph, Can.

James, W., W. Huber, R. Dickinson, and W.R.C. James 1999. Water Systems Models HYDROLOGY. Users Guide to SWMM4 RUNOFF and Supporting Modules. Computational Hydraulics International, Guelph, Can.

Jensen, K.H. and A. Mantoglou 1992. Future of distributed modelling. Hydrological Processes **6**: 255-264.

Klemes, V. 1986. Operational testing of hydrological simulation models. Hydrological Sciences Journal, **31**: 13-23.

Land Type Survey Staff 1988. Land Types of the Map 2830 Richards Bay. Memoirs on the Agricultural Natural Resources of South Africa No. 11. RSA.

Lillesand, T.M. and R.W. Kiefer 1994. Remote Sensing and Image Interpretation, third edition. John Wiley and Sons, Inc. Toronto, Can.

Lu, M., T. Koike and N. Hayakawa 1996. A distributed hydrological modelling system linking GIS and hydrological models. *In* K. Kovar and H.P. Nachtnebel, *editors*, Application of Geomorphic Information Systems in Hydrology and Water Resources Management. Proceedings of HydroGIS'96 Conference, Vienna. IAHS Publication, 235. pp. 141-149.

Lynch, S.D. and R.E. Schulze 1995. Techniques for estimating areal daily rainfall. Proceedings of Seventh South African Hydrological Sciences Symposium, Grahamstown, RSA.

McDonnell, R.A. 1996. Including the spatial dimension: using geographical information systems in hydrology. Progress in Physical Geography **20**: 159-177.

McCuen, R.H. 1989. Hydrologic Analysis and Design. Prentice- Hall, New Jersey, U.S.A.

Melching, C.S., B.C. Yen and H.G. Wenzel Jr. 1990. A reliability estimation in modelling watershed runoff with uncertainties. Water Resources Research **26**: 2275-2276.

Michaud, J. and S. Sorooshian 1994. Comparison of simple versus complex distributed runoff model on a midsized semiarid watershed. Water Resources Research **30**: 593-605.

Midgley D. C., W.V. Pitman and B.J. Middleton 1994. Surface Water Resources of South Africa 1990, Volume VI, First Edition, Water Research Commission Report No 298/6.1/94, WR90 (1994).

More, R.J. 1967. Hydrologic models and geography. *In* R.J. Chorley and P. Haggett, *editors,* Models in Geography, Methun & Co., London, pp. 145-179.

Mroczkowski, M., G.P. Raper and G. Kuczera 1997. The quest for more powerful validation of conceptual catchment models. Water Resources Research **33**: 2325-2335.

Nicholson, S.E. 1996. Environmental Change Within the Historical Period. *In* The Physical Geography of Africa. *Edited by* W.M. Adams, A.S. Goudie and A.R. Orme, pp 60-88. Oxford University Press Inc. New York, N.Y. USA.

O'Loughlin, E.M. 1981. Saturation regions in catchments and their relations to soil and topographic properties. Journal of Hydrology **53**: 229-246.

Oreskes, N., K. Shader-Frechette, B. Kenneth 1994. Verification, validation, and confirmation of numerical models in the earth sciences. Science **263**: 641-646.

Refsgaard, J.C. 1997. Parameterisation, calibration and validation of distributed hydrological models. Journal of Hydrology **198**: 69-97.

Refsgaard, J.C. and J. Knudsen 1996. Operational validation and intercomparison of different hydrologic models. Water Resources Research **32**: 2189-2202.

Seyfried, M.S. and B.P. Wilcox 1995. Scale and the nature of spatial variability: field examples having implications for hydrologic modelling. Water Resources Research **31**: 173-184.

Small, R.J. 1989. Geomorphology and Hydrology. Longman Group UK Limited, Essex, UK.

South African Sugar Association 1984. Identification of the Soils of the Sugar Industry. Bulletin No. 19 (revised). South African Sugar Assoication Experiment Station, Natal 4300, RSA.

Ward, A.D. and W.J. Elliot 1995. Environmental Hydrology. CRC Press LLC, Florida, USA.

'White Paper' on Water Supply and Sanitation Policy 1995. The Department of Water Affairs and Forestry, Pretoria, RSA.

Wolock, D.M. and G.J. McCabe Jr. 1995. Comparison of single and multiple flow direction algorithms for computing topographic parameters in TOPMODEL. Water Resources Research **31**: 1315-1324.

Young, P., S. Parkinson and M. Lees 1996. Simplicity out of complexity in environmental modelling: Occam's razor revisited. Journal of Applied Statistics **23**: 165-210.

Appendix A: Channel and Subcatchment Input Values

Subcatchment one, containing the headwaters of the Mfuli river, was modelled without a channel. Therefore, the Mfuli river was divided into five channel segments. All five segments were modelled with a parabolic shape. Table A.1 lists all the input parameters allocated for each channel segment.

Table A.1 SWMM Channel Input

Subcatchment number	2	3	4	5	6
Channel segment number	1	2	3	4	5
length (m)	25377	17016	755	18019	6451
width (m)	8	41	75	41	57
slope	0.011	0.006	0.026	0.004	0.003
Mannings n	0.05	0.05	0.045	0.03	0.03
full depth (m)	0.63	1.20	1.25	1.20	2.96
initial depth (m)	0.004	0.004	0.004	0.004	0.004

For each subcatchment descriptive characteristics were assigned. The initial input values used for each subcatchment are listed in Table A.2. After calibration all channel input values remained the same. With the exception of the percent of the catchment impervious and directly connected, all catchment values remained the same (Table A.3).

Table A.2 Initial Subcatchment Input Values

Subcatchment number	1	2	3	4	5	6
width (m)	14886	12608	10664	6281	8843	6214
area (ha)	11890	19996	12997	8033	7168	6200
slope	0.029	0.022	0.034	0.035	0.041	0.022
% impervious	1.0	1.0	1.0	0.0	0.0	1.0
impervious n	0.24	0.24	0.24	0.24	0.24	0.24
pervious n	0.4	0.4	0.13	0.13	0.13	0.13
average capillary suction (mm)	225	200	162	162	262	200
hydraulic conductivity (mm/hr)	8.3	12.5	6.5	6.5	8.3	6.5
moisture deficit	0.26	0.33	0.30	0.30	0.29	0.33

Table A.3 Final Subcatchment Input Values

Subcatchment number	1	2	3	4	5	6
width (m)	14886	12608	10664	6281	8843	6214
area (ha)	11890	19996	12997	8033	7168	6200
slope	0.029	0.022	0.034	0.035	0.041	0.022
% impervious	64.0	64.0	64.0	32.0	32.0	64.0
impervious n	0.24	0.24	0.24	0.24	0.24	0.24
pervious n	0.4	0.4	0.13	0.13	0.13	0.13
average capillary suction (mm)	225	200	162	162	262	200
hydraulic conductivity (mm/hr)	8.3	12.5	6.5	6.5	8.3	6.5
moisture deficit	0.26	0.33	0.30	0.30	0.29	0.33

Appendix B: Storm Event Hyetographs

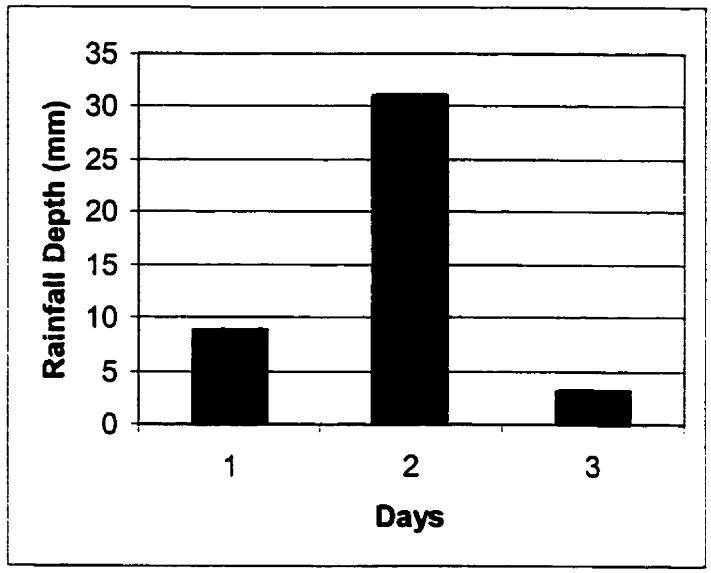

Figure B.1 **Storm 1**

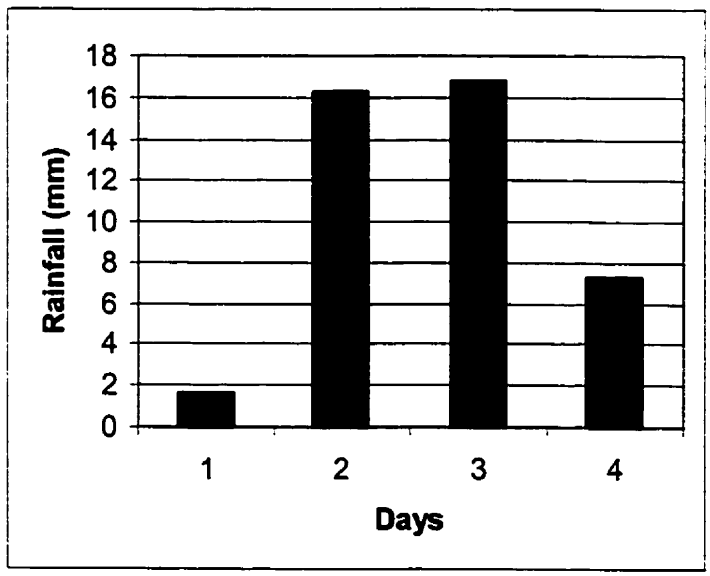

Figure B.2 **Storm 2**

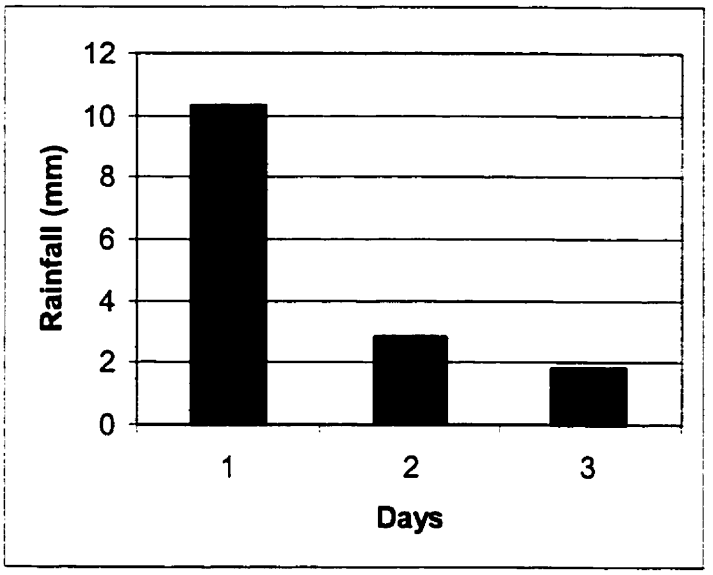

Figure B.3 Storm 3

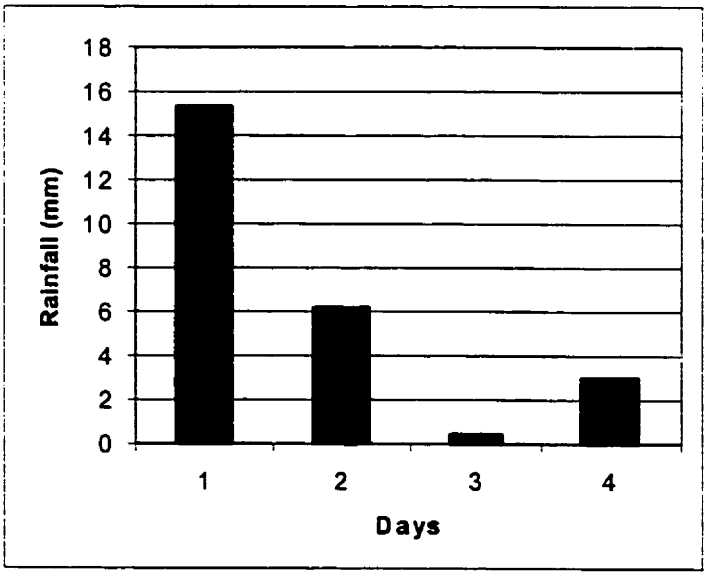

Figure B.4 Storm 4

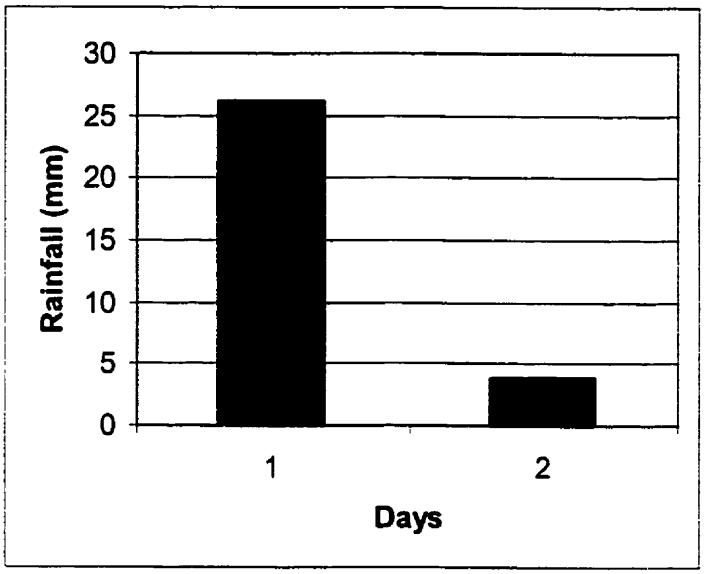

Figure B.5 Storm 5

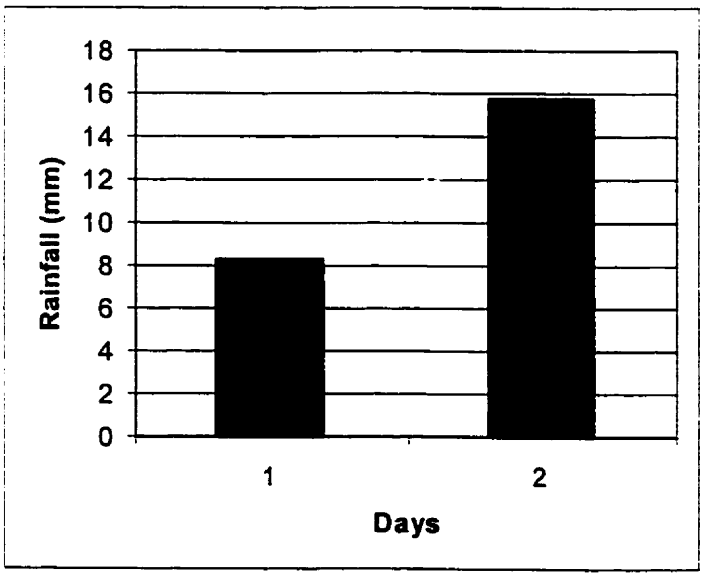

Figure B.6 Storm 6

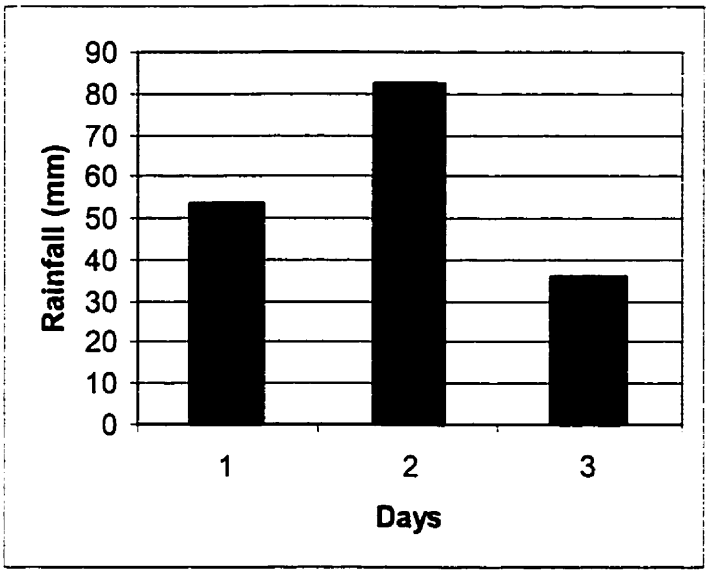

Figure B.7 Storm 7

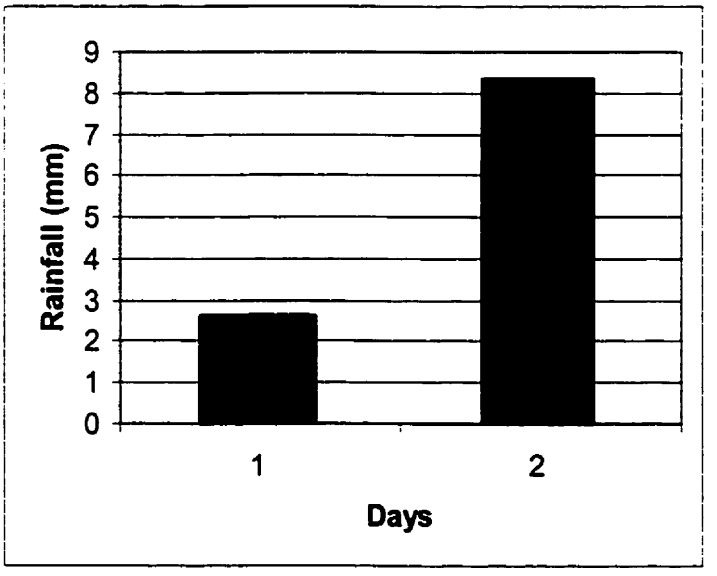

Figure B.8 Storm 8

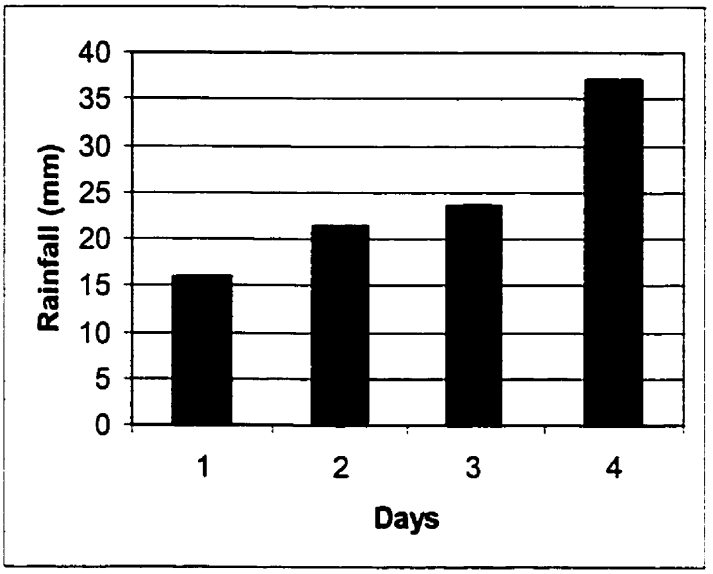

Figure B.9 Storm 9

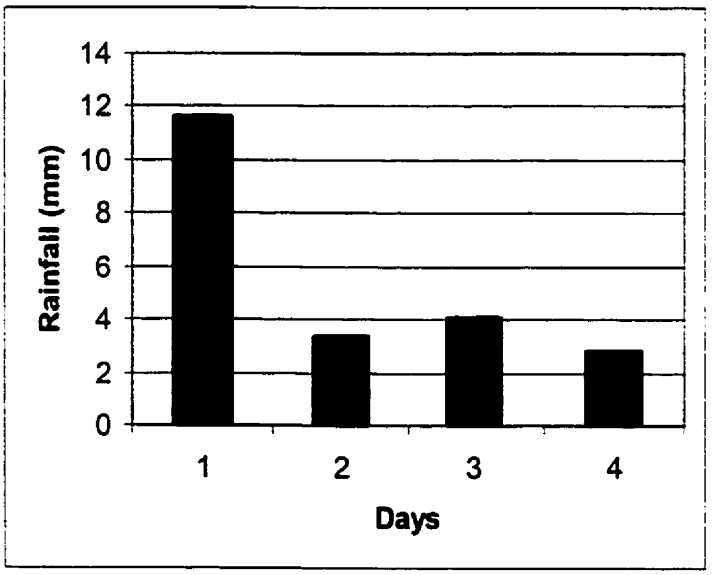

Figure B.10 Storm 10

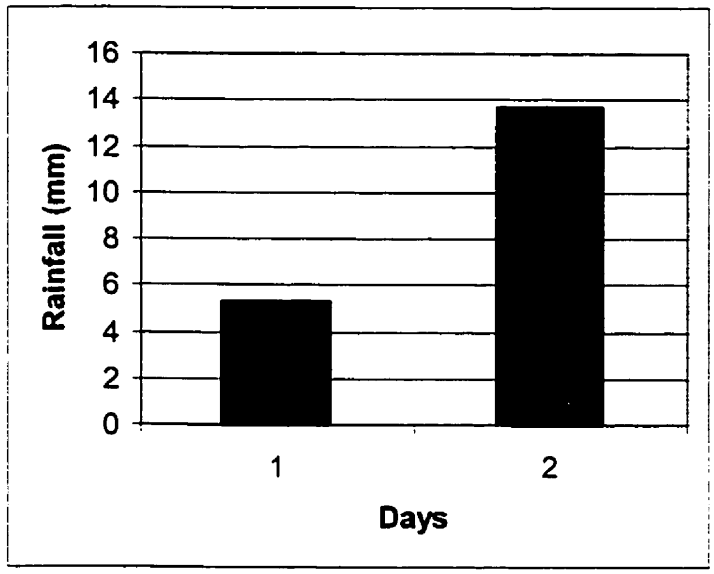

Figure B.11 Storm 11

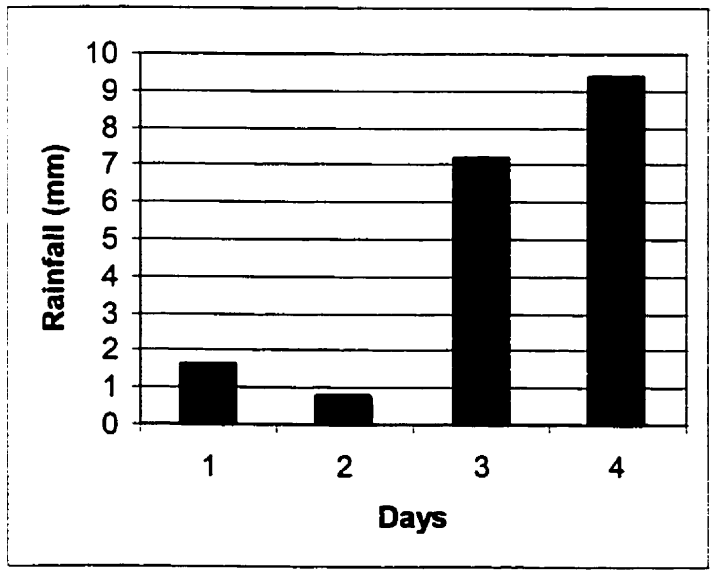

Figure B.12 Storm 12

Appendix C: Hydrographs of Computed and Observed Stormflow

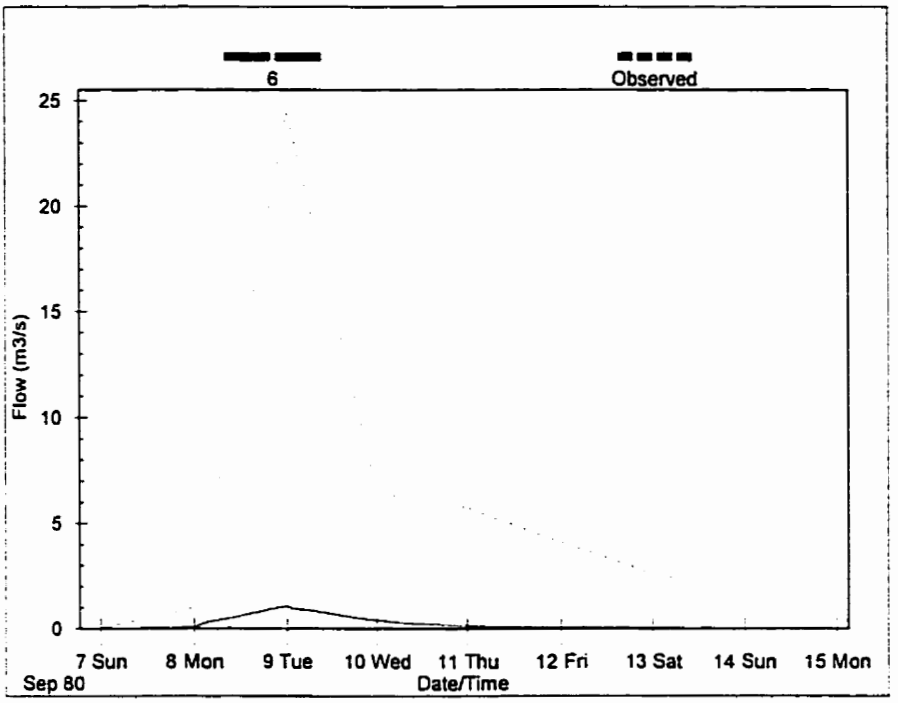

Figure C.1 Storm 1, with 0-1% impervious

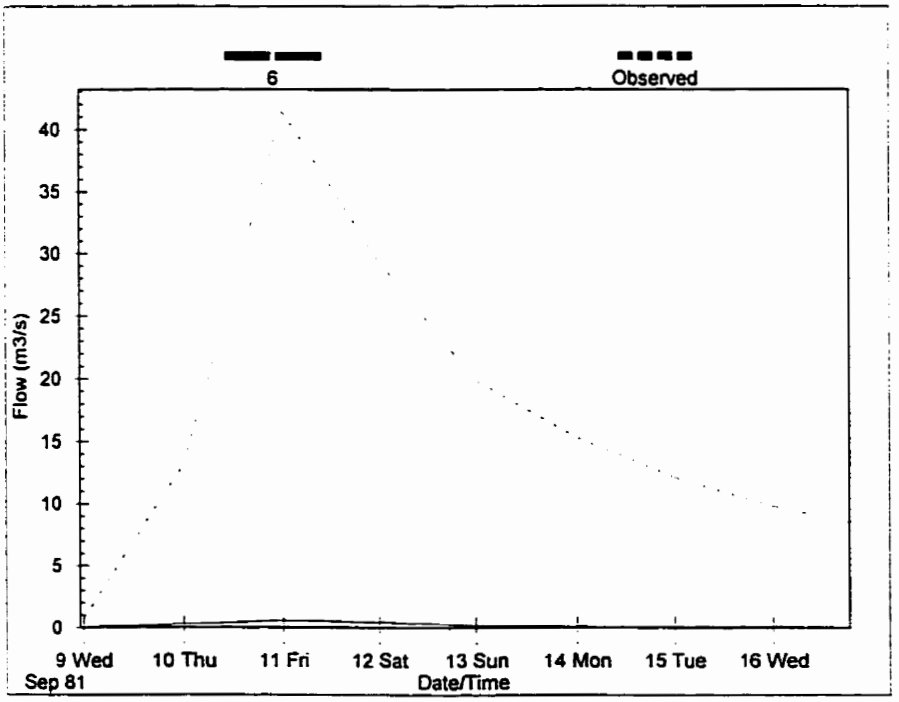

Figure C.2 Storm 2, with 0-1% impervious

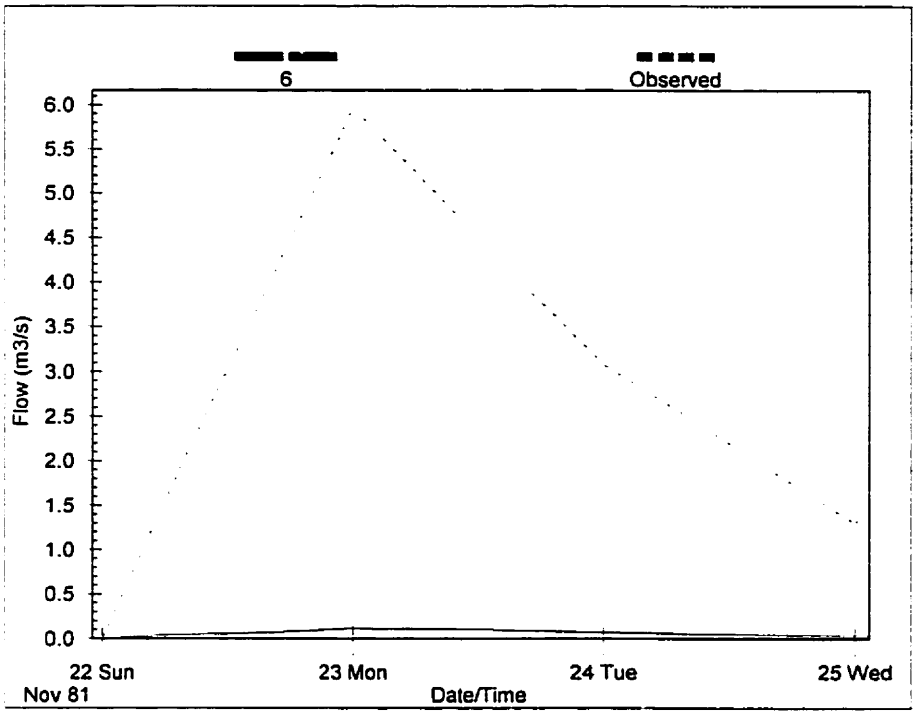

Figure C.3 Storm 3, with 0-1% impervious

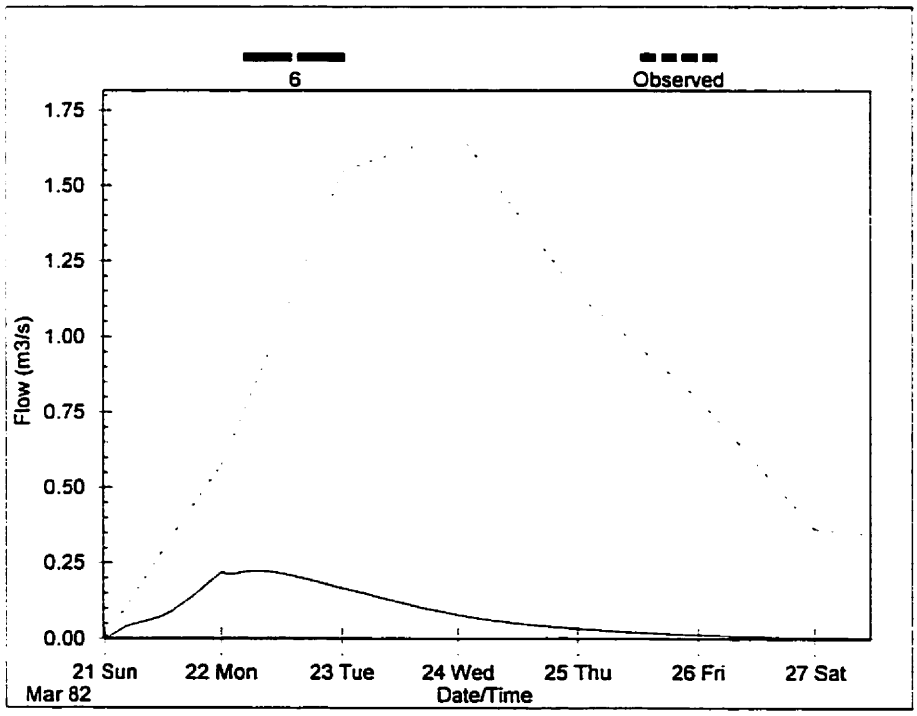

Figure C.5 Storm 4, with 0-1% impervious

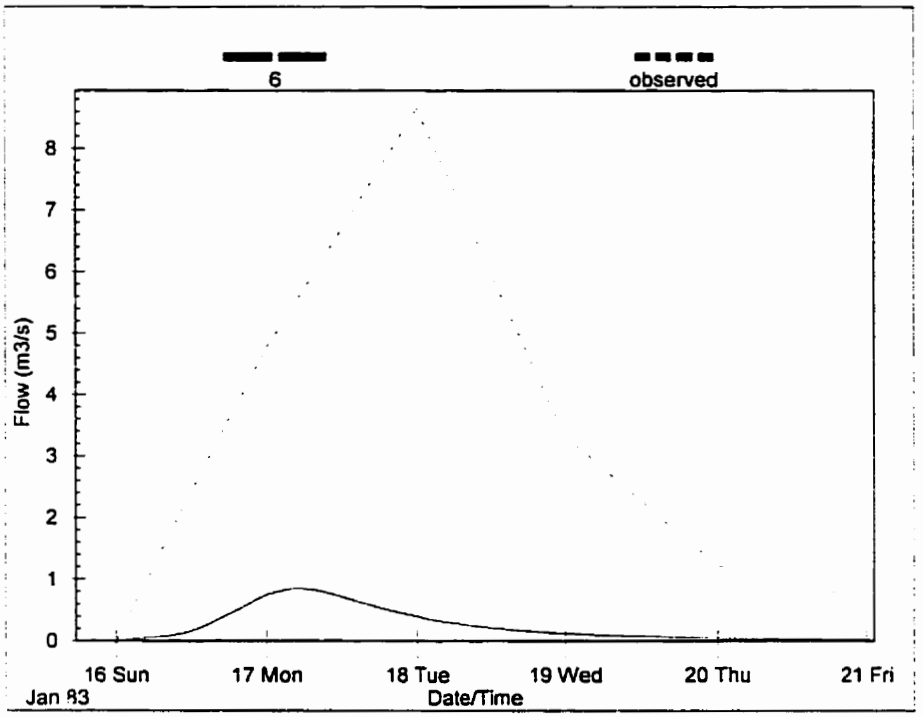

Figure C.5 Storm 5, with 0-1% impervious

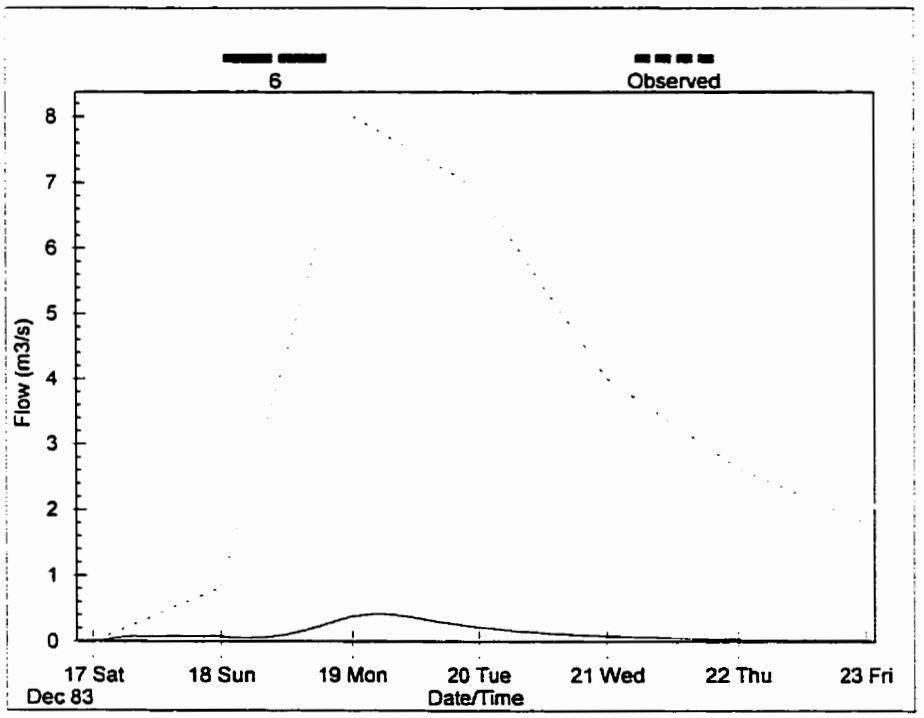

Figure C.7 Storm 6, with 0-1% impervious

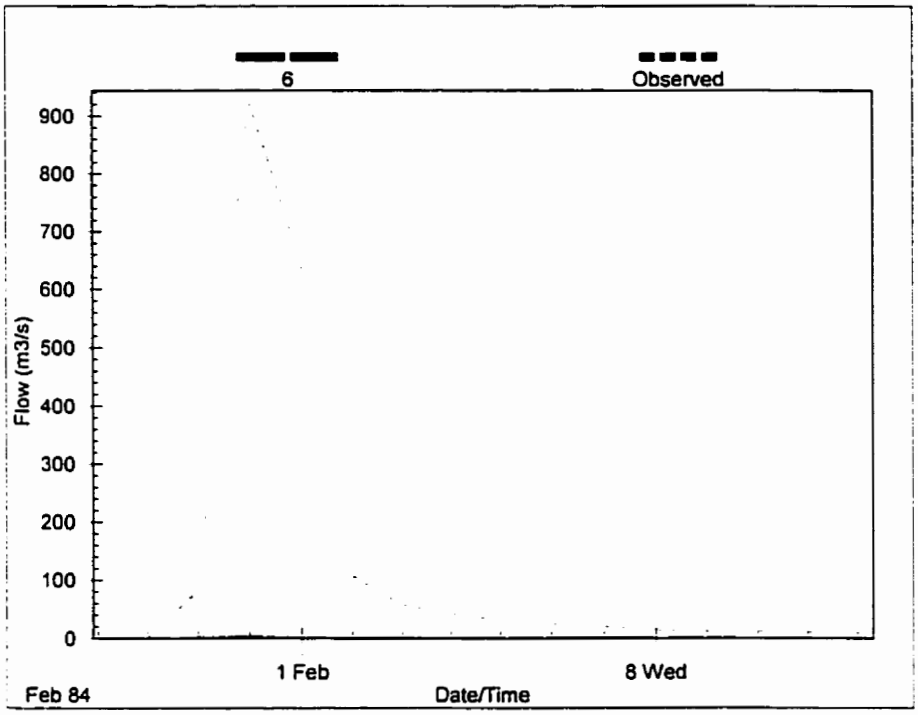

Figure C.7 Storm 7, with 0-1% impervious

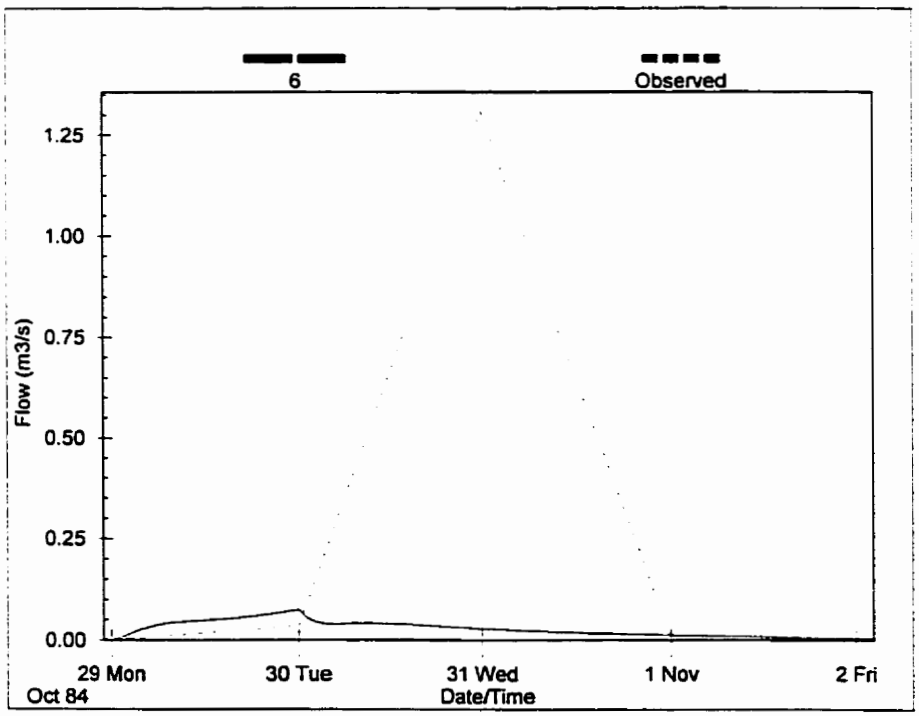

Figure C.8 Storm 8, with 0-1% impervious

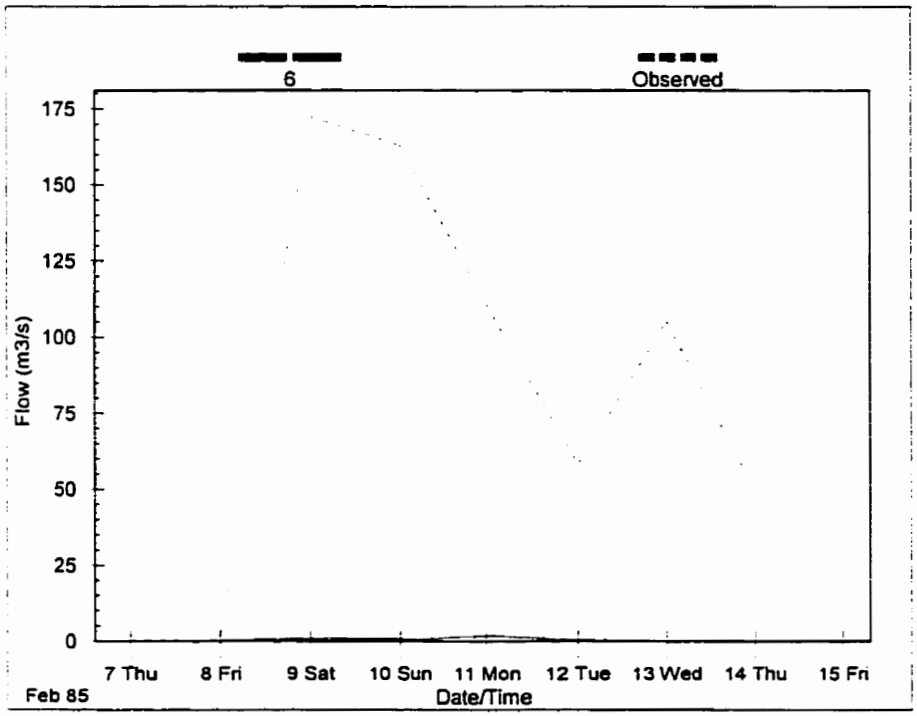

Figure C.9 Storm 9, with 0-1% impervious

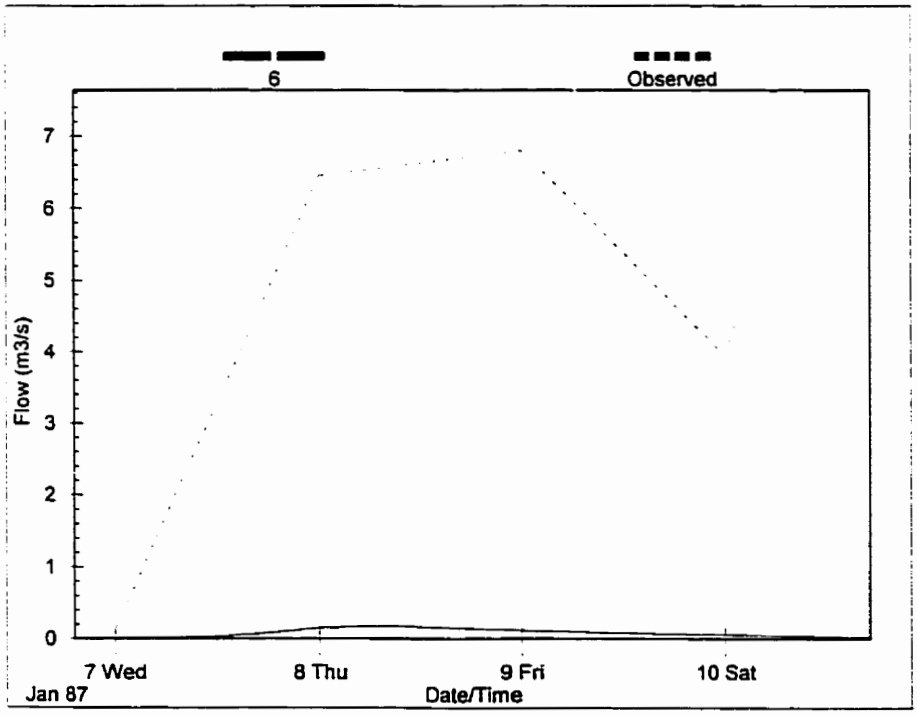

Figure C.10 Storm 10, with 0-1% impervious

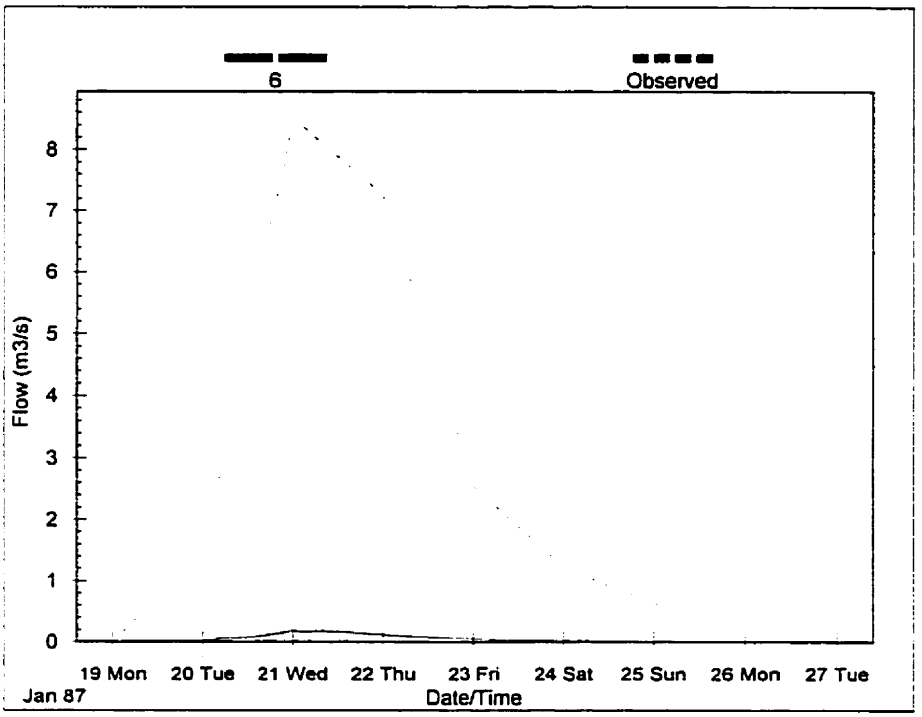

Figure C.11 Storm 11, with 0-1% impervious

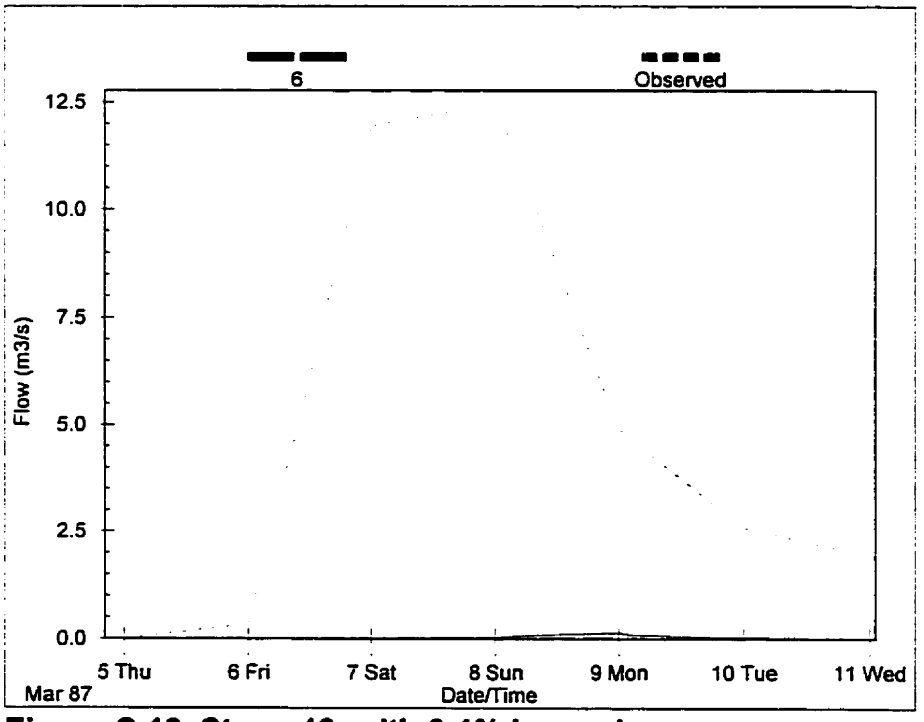

Figure C.12 Storm 12, with 0-1% impervious

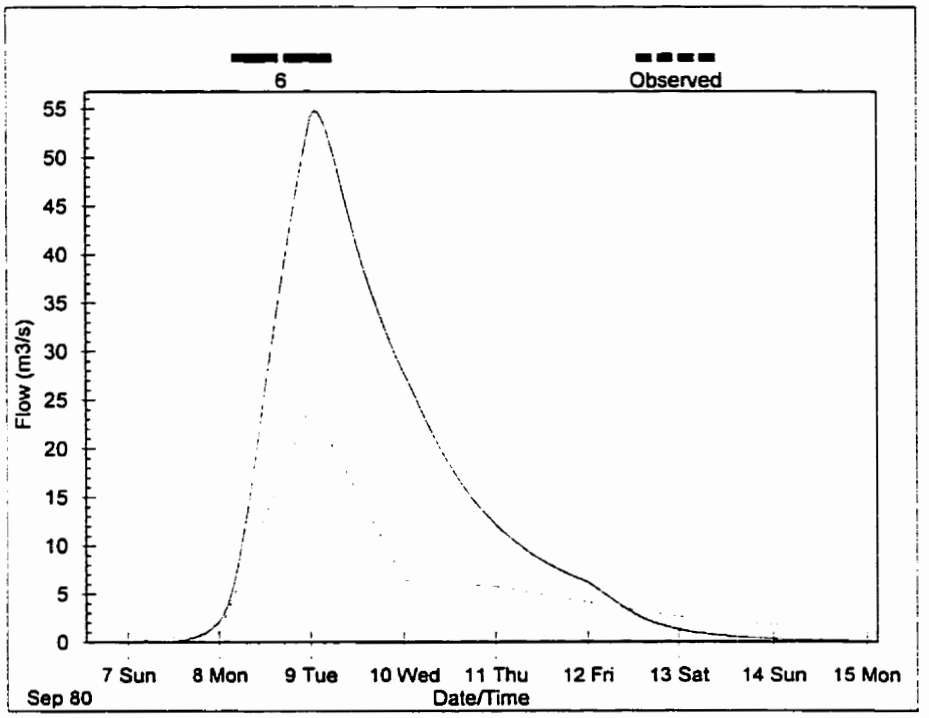

Figure C.13 Storm 1, with 32-64 % impervious

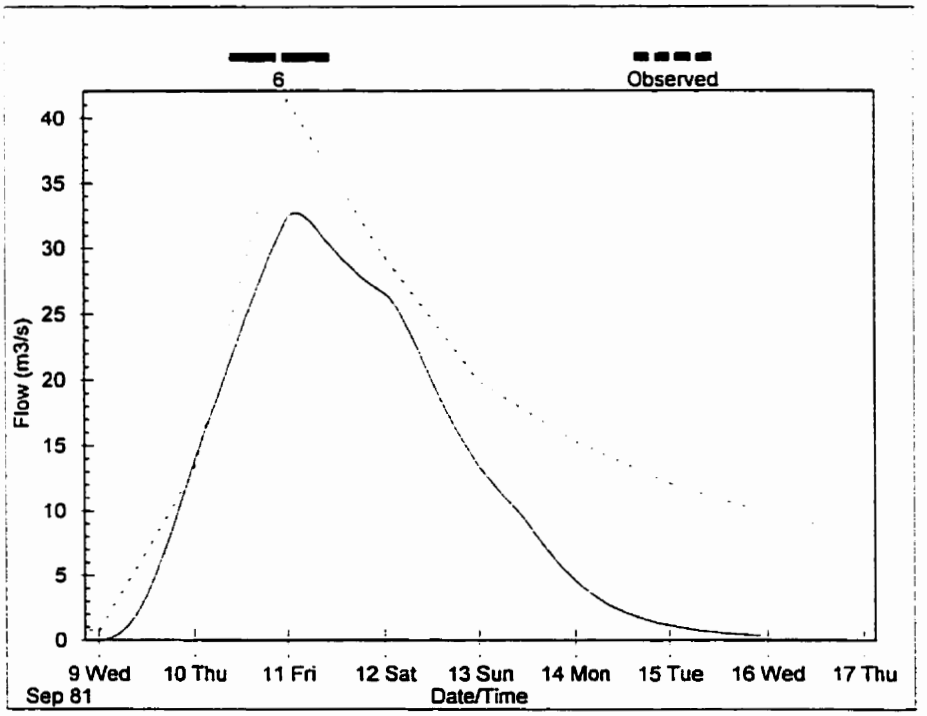

Figure C.14 Storm 2, with 32-64% impervious

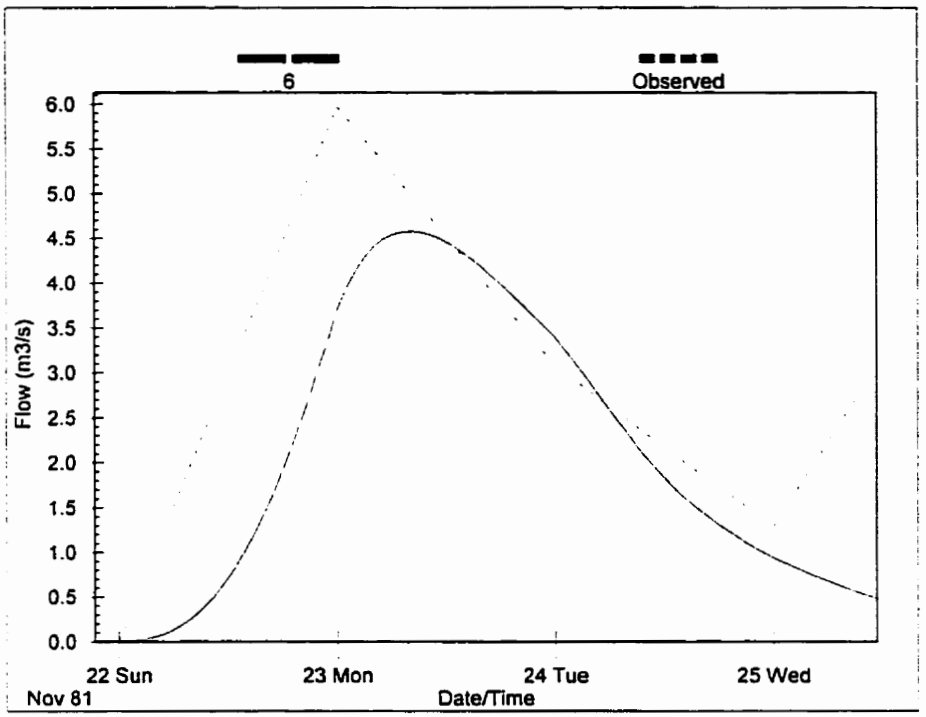

Figure C.15 Storm 3, with 32-34% impervious

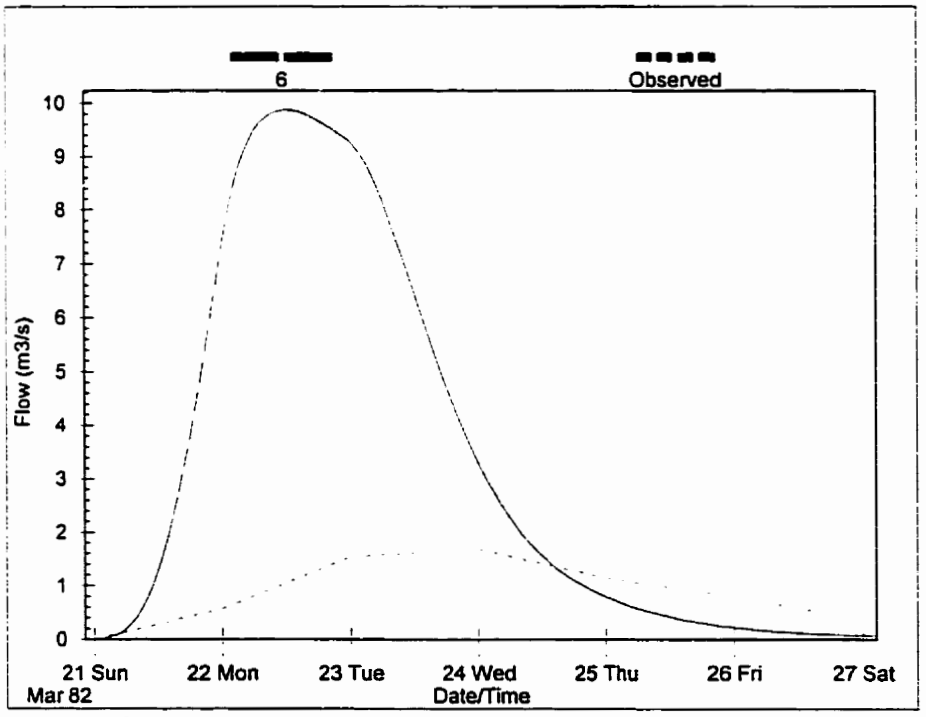

Figure C.16 Storm 4, with 32-64% impervious

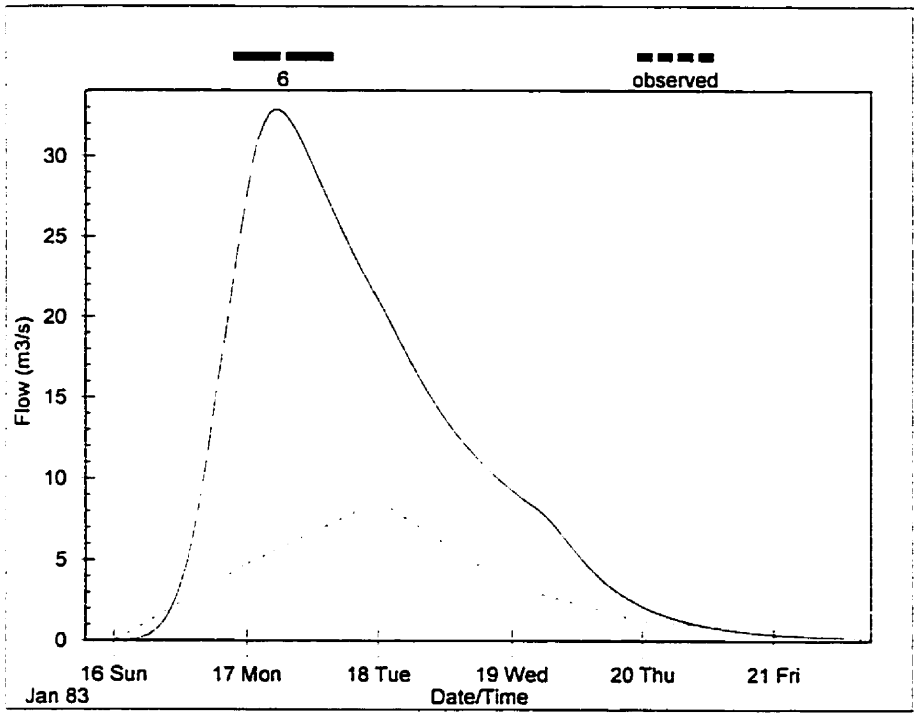

Figure C.17 Storm 5, with 32-64% impervious

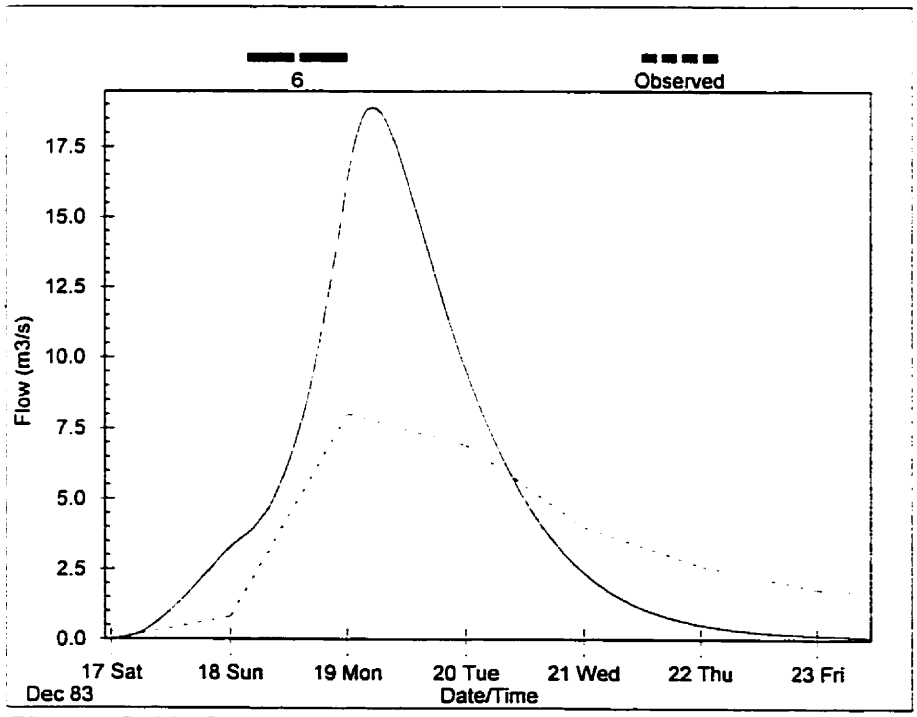

Figure C.18 Storm 6, with 32-64% impervious

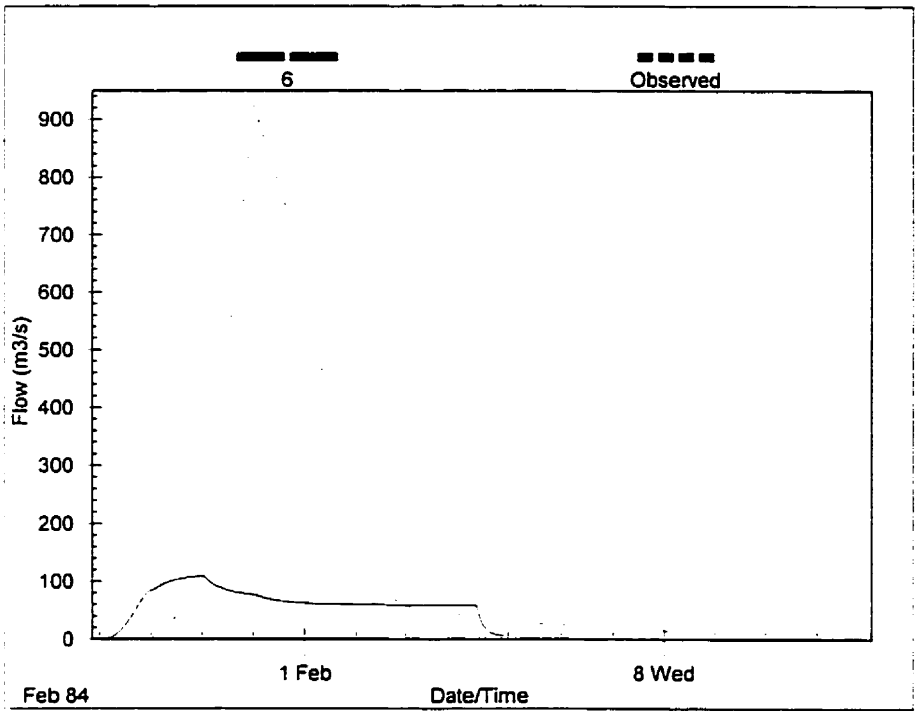

Figure C.19 Storm 7, with 32-64% impervious

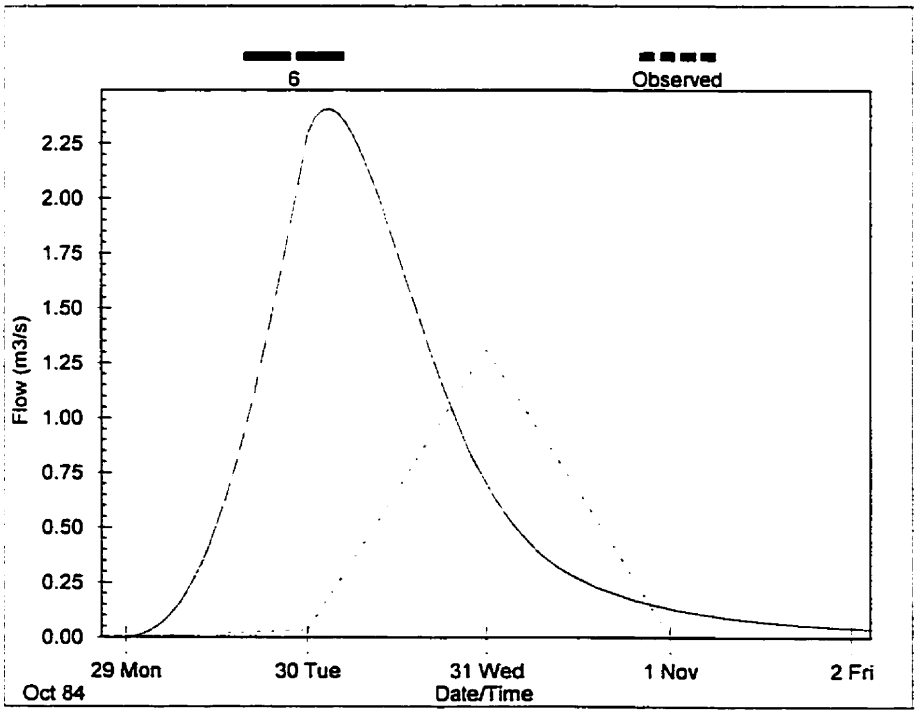

Figure C.20 Storm 8, with 32-64% impervious

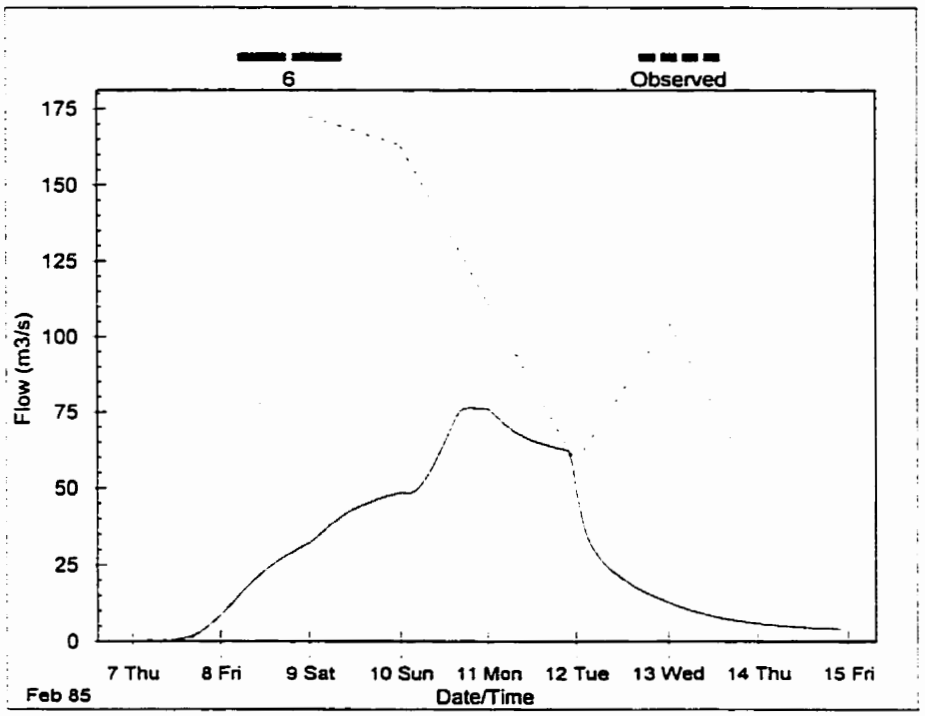

Figure C.21 Storm 9, with 32-64% impervious

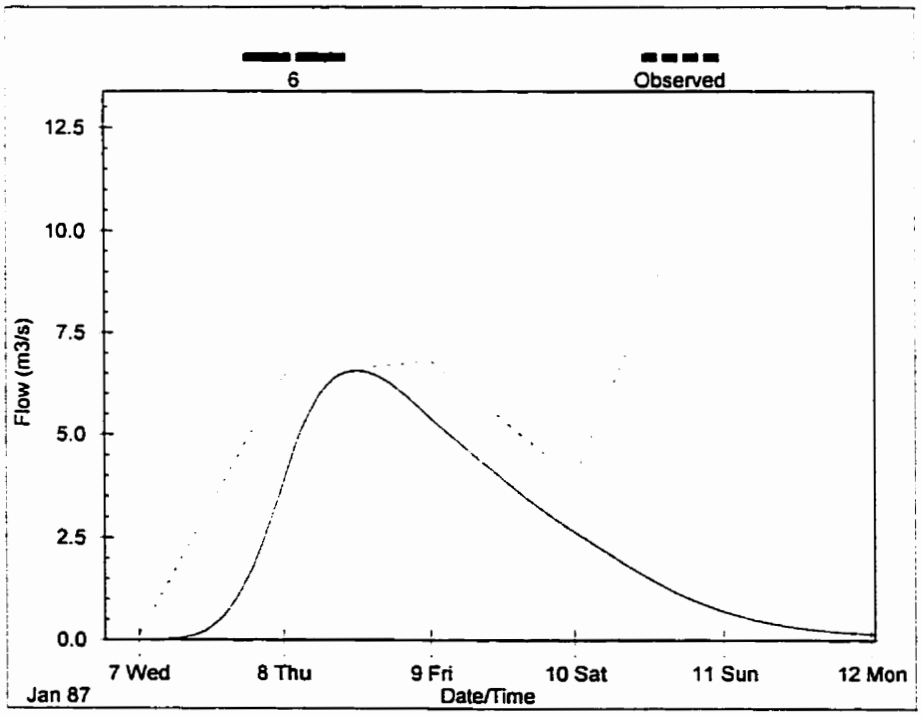

Figure C.22 Storm 10, with 32-64% impervious

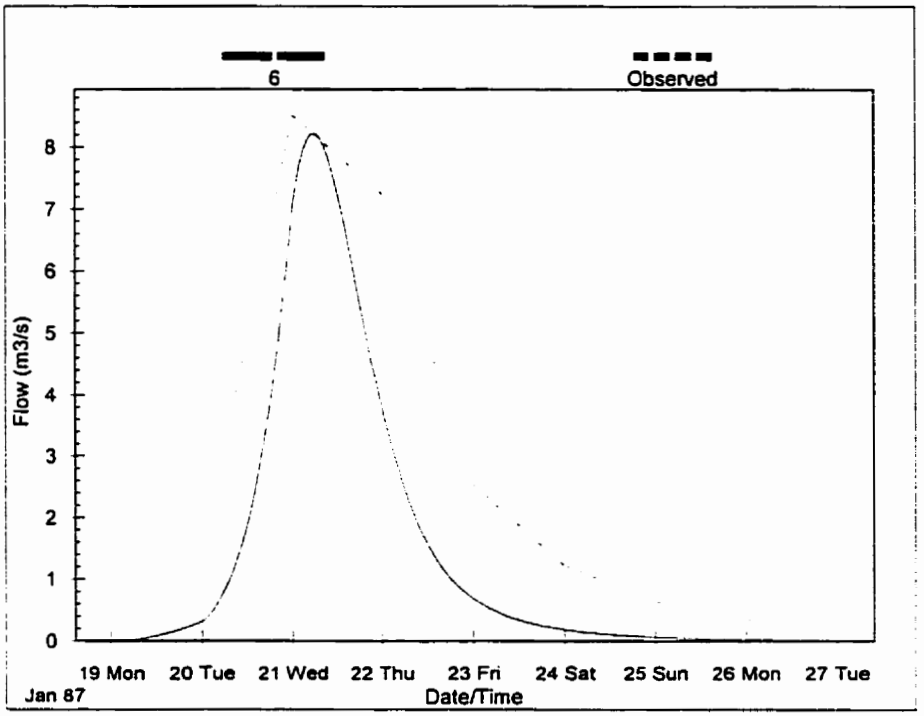

Figure C.23 Storm 11, with 32-64% impervious

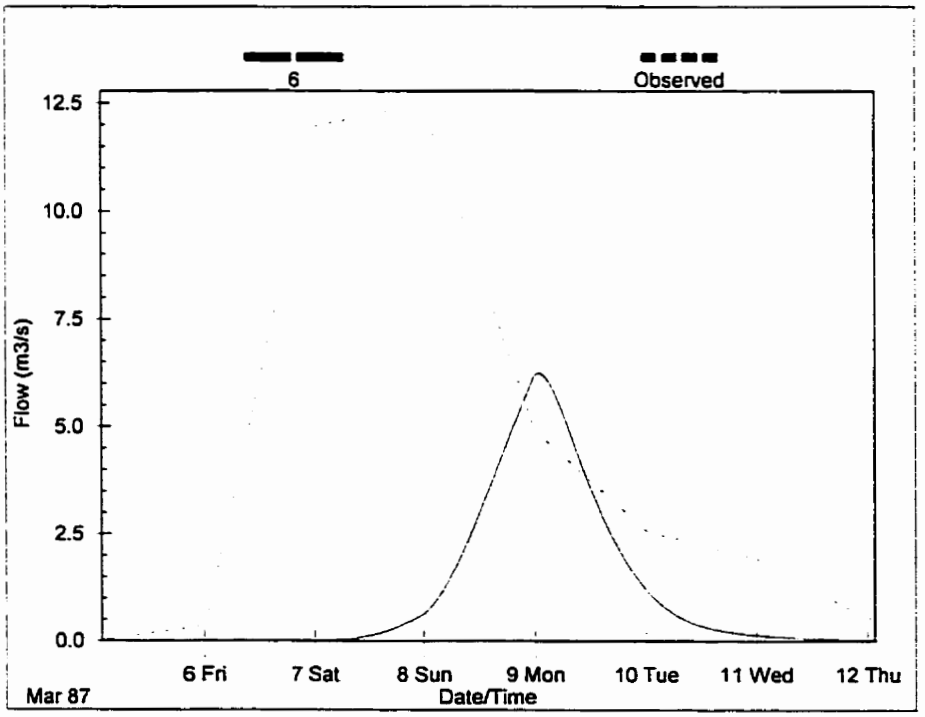

Figure C.24 Storm 12, with 32-64% impervious

Appendix D: Hydrograph Separation of Weir Discharge

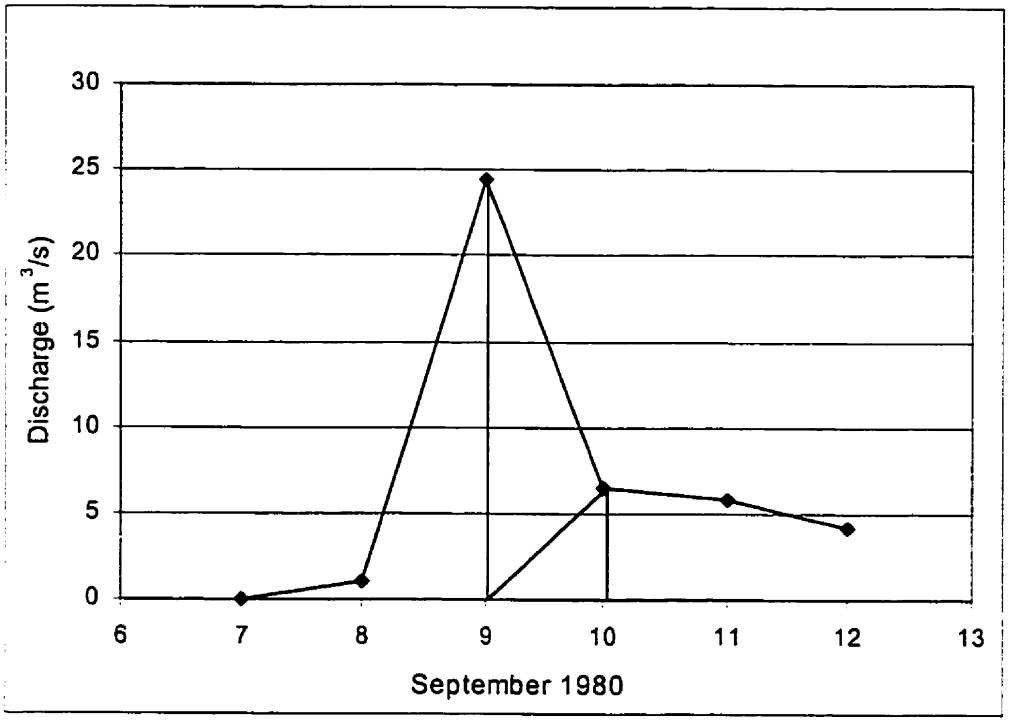

Figure D.1 **Storm 1**

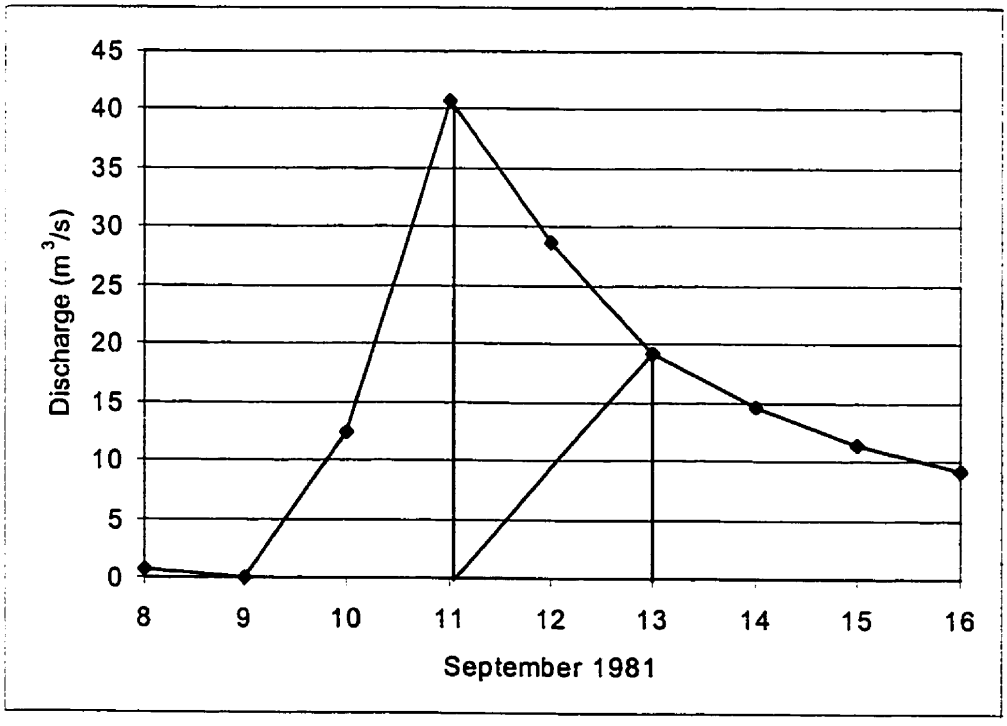

Figure D.2 **Storm 2**

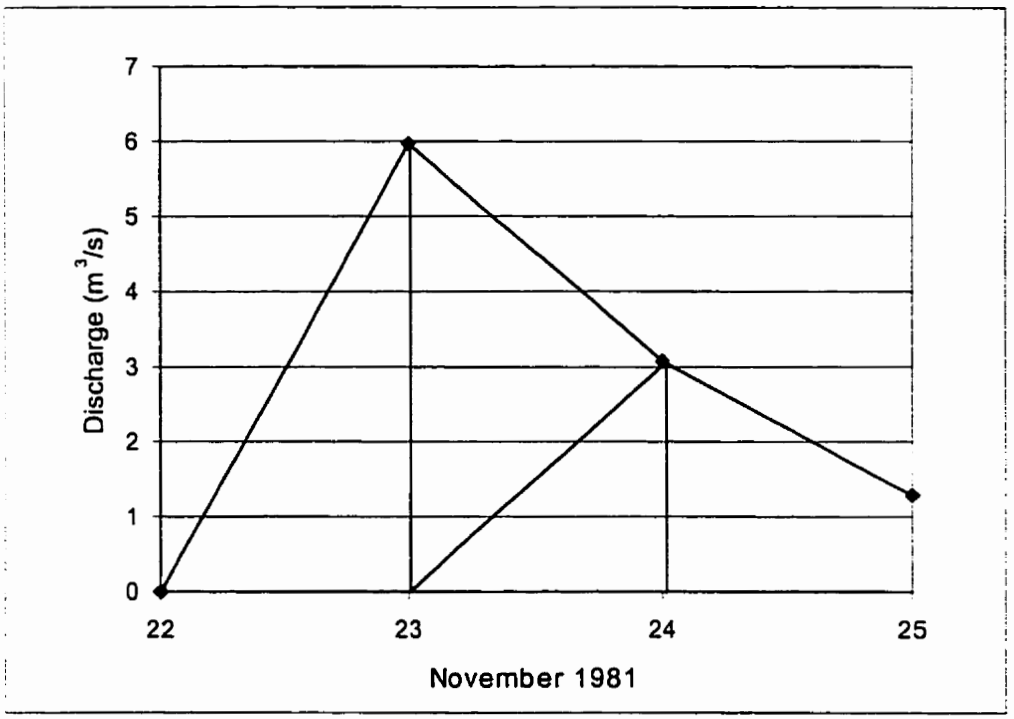

Figure D.3 **Storm 3**

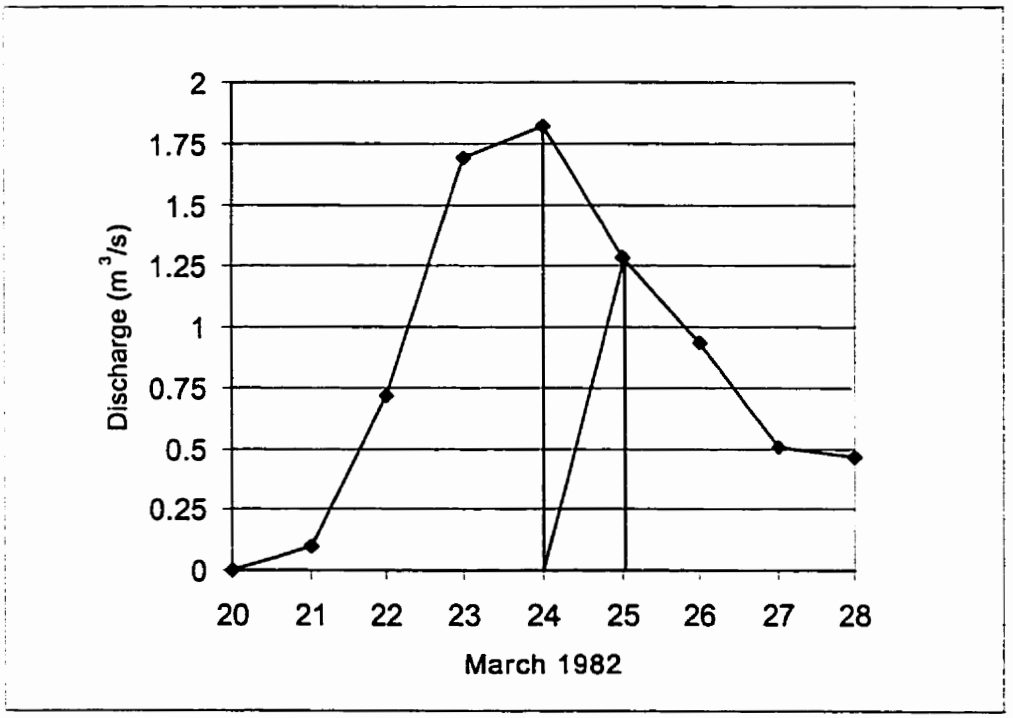

Figure D.4 **Storm 4**

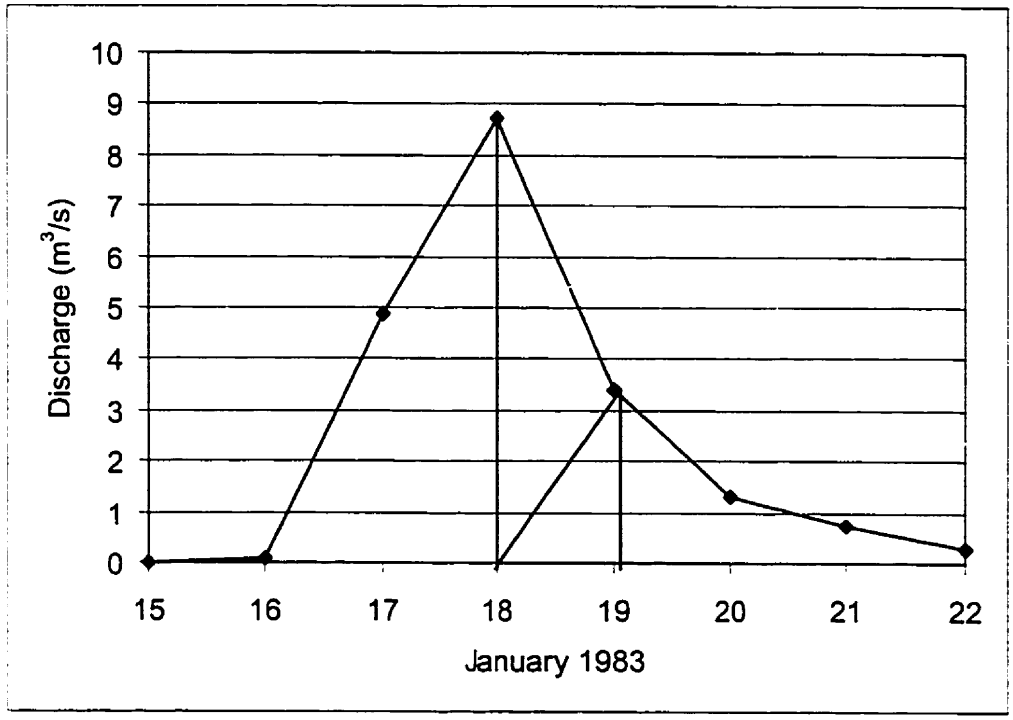

Figure D.5 **Storm 5**

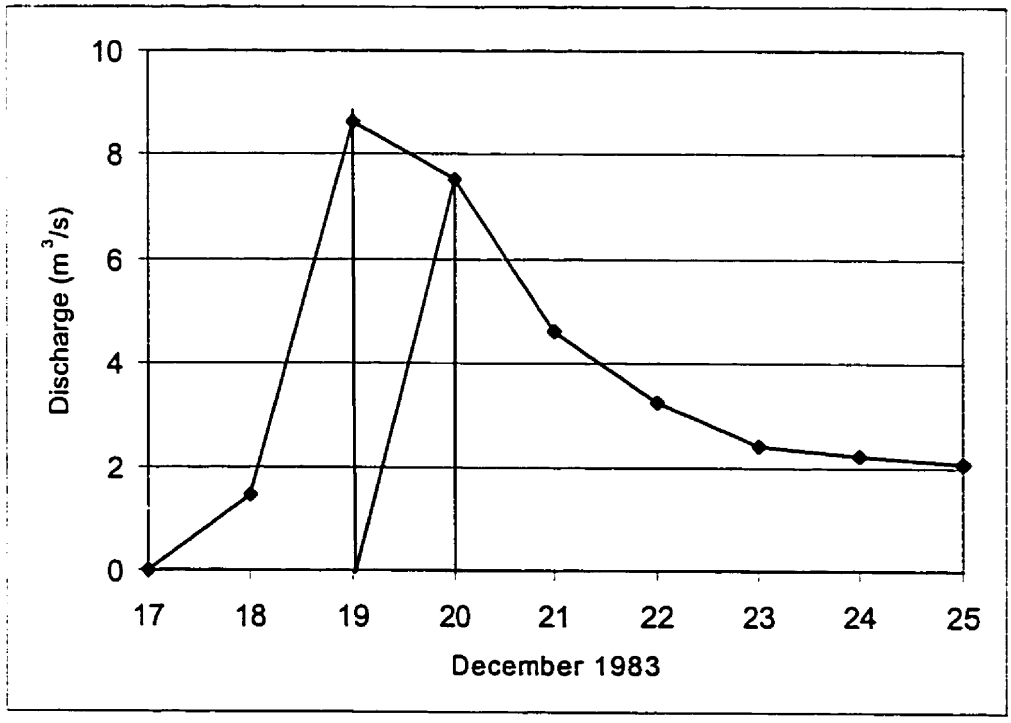

Figure D.6 **Storm 6**

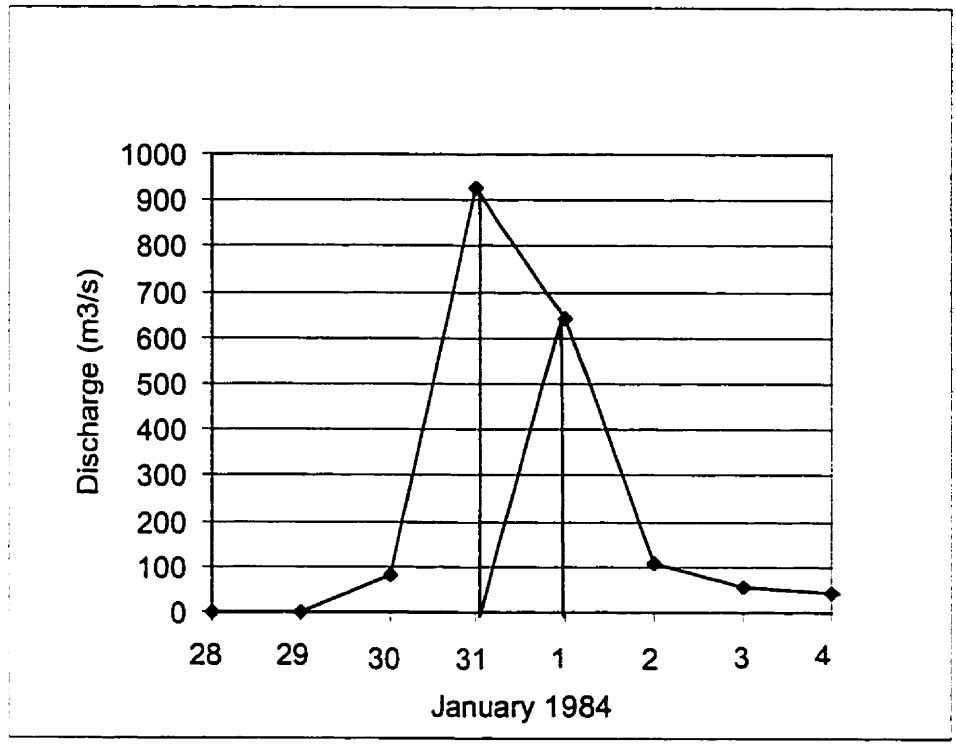

Figure D.7 **Storm 7**

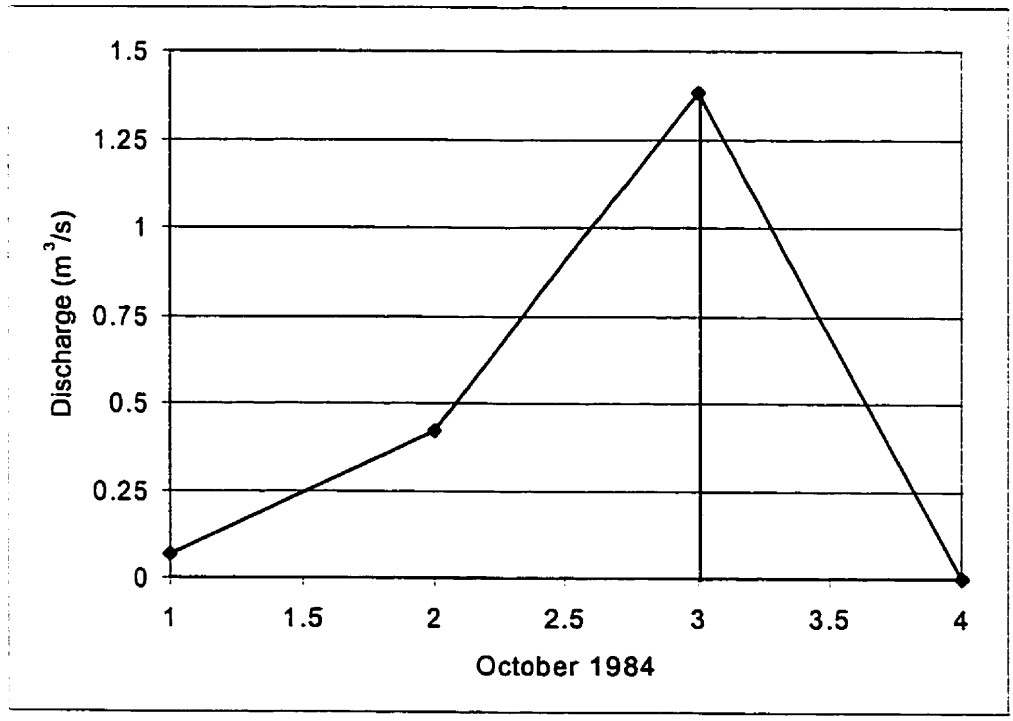

Figure D.8 **Storm 8**

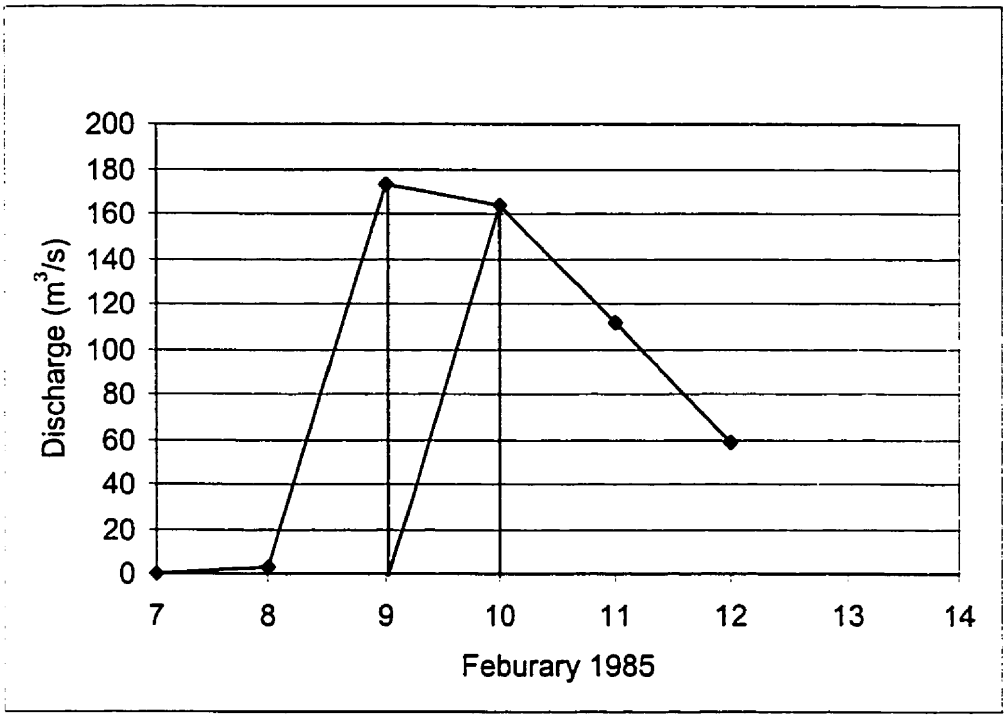

Figure D.9 **Storm 9**

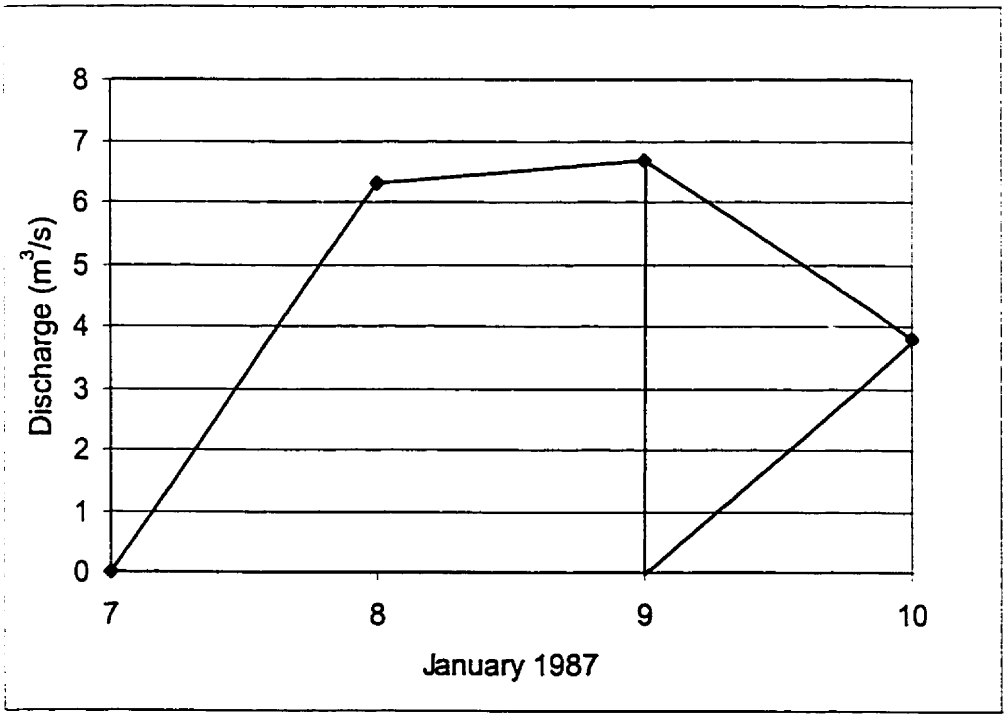

Figure D.10 **Storm 10**

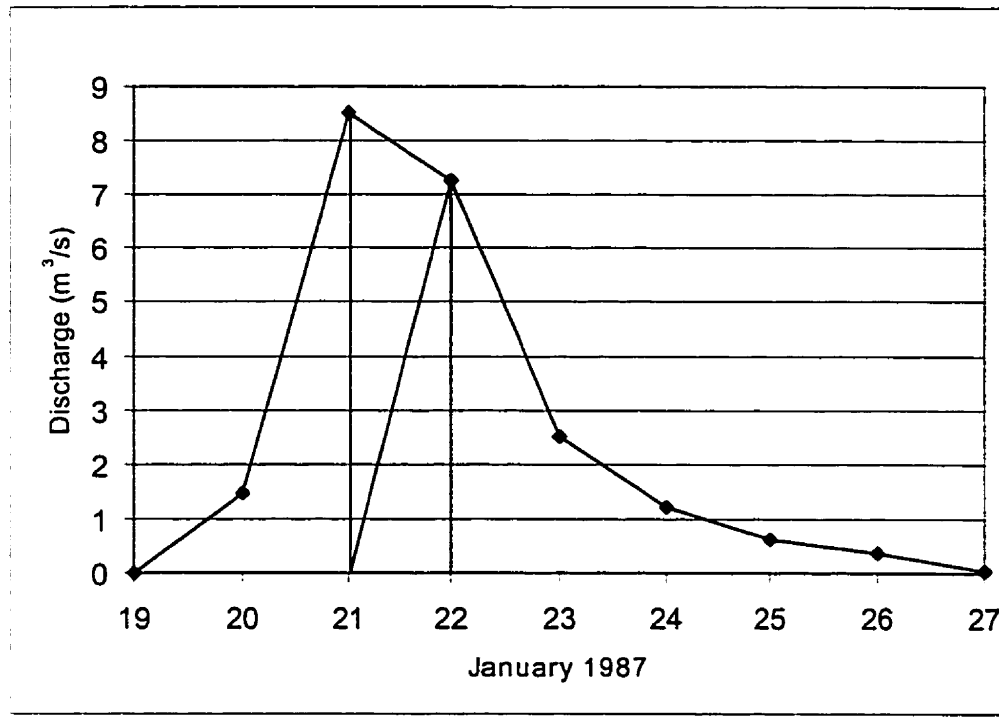

Figure D.11 **Storm 11**

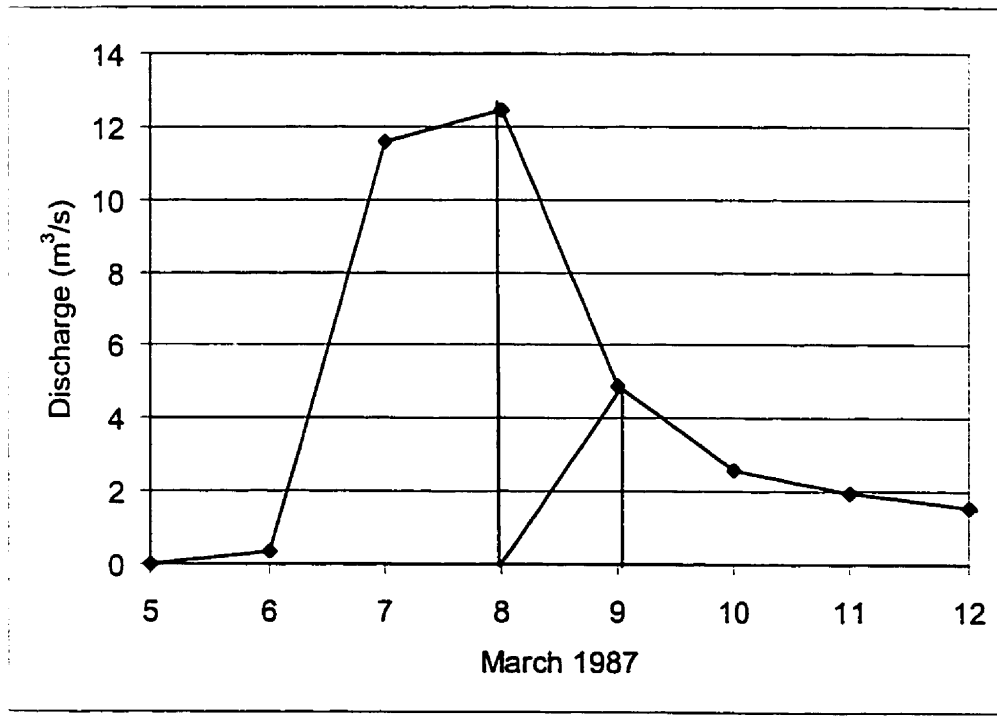

Figure D.12 **Storm 12**