Hydrological Modelling of Sergoit Basin for the Estimation of Catchment Yield: A Comparative Study of MIKE 11-NAM and SWAT Models.

By

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NOVEMBER, 2015

DECLARATION

DECLARATION BY THE CANDIDATE

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To my Dear Mother Roseline,Sister Elizabeth, Nephew Joe, friends and teachers, without whose love and support the completion of this work would not have been possible.

ABSTRACT

Hydrological models provide a way to conceptualize and investigate the relationships between climatic variables and management practices with water resources. The decision on which modelling approach to employ poses a challenge to water resource managers and researchers. Due to their different structures and varying data requirements, models should be tested prior to application. The challenge of lack of current data that hinders quantification of a catchment's water yield. The objective of this research was to set up, calibrate and validate the lumped conceptual model (MIKE 11-NAM)and the semi-distributed physically based model (SWAT), evaluate both models using statistical and graphical techniques and thereafter apply the models to estimate the current catchment yield of the Sergoit basin and compare the results. Meteorological data was sourced from the Kenya Meteorological Department. Both models were setup, calibrated and validated.Data for the periods 1975 to 1977 and 1982 to 1984 was used for calibration and validation of the NAM model, while 1975 to 1979 and 1981 to 1984 data inclusive of a one year warmup period was used for calibration and validation of the SWAT model respectively. Goodness of fit statistics and graphical methods were used to evaluate model performance. The models were then used to estimate thecatchment yield for the period 2005 to 2009. The overall results from the goodness-of-fit statistics shows differences in performance and overall behaviour of the two models. NAM performed better than SWAT during the calibration period with an NSE, R^2, IA, and PBIAS of 0.81, 0.81, 0.94 and 1.80% and 0.69, 0.70, 0.90, and 15.11% respectively. The validation period marked a slight performance drop with NAM and SWAT attaining an NSE, R^2, IA, and PBIAS of 0.78, 0.80, 0.95 and 0.65% and 0.65, 0.65, 0.89 and -11.82% respectively. There is a general tendency to underestimate the peak values in both models. On the basis of extreme value analysis, the NAM model performed better than the SWAT model. The general underestimation increases for larger values, indicating poor extrapolation capabilities. The semi-distributed nature of the SWAT model and the large number of model parameters makes it difficult to calibrate and is vulnerable to the quality of data, whereas the lumped nature of the NAM model and low number of model parameters makes it easier to calibrate and gives a better overall performance as most values are averaged throughout the basin. The NAM model estimates the mean annual basin yield for the period 2005 to 2009 at 94.8 MCM/year while the SWAT model gives a lower estimate of 69.6 MCM/year. The study recommends the installation of well distributed weather stations within the Sergoit Basin to improve on the representativeness and the data captured and further study is recommended to incorporate effects of land use and climate change as these have an impact on the catchment's water yield.

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LIST OF ABBREVIATIONS

APR	Areal Precipitation Ratio
CAAC’s	Catchment Area Advisory Committees
CGIAR-CSI	Consortium for Spatial Information.
CIDP	County Integrated Development Plan
DEM	Digital Elevation Model
FAO	Food and Agriculture Organization
GIS	Geographical Information Systems
GWP	Global Water Partnership
IA	Index of agreement
IDW	Inverse Distance Weighting
ILRI	International Livestock Research Institute
IWRM	Integrated Water Resources Management
JICA	Japanese International Cooperation Agency
KMD	Kenya Meteorological Department
KSS	Kenya Soil Survey
LH-OAT	Latin Hypercube-One at a Time
MAE	Mean absolute error
MDG’s	Millennium Development Goals
MSE	Mean square error
NAM	Nedbør-Afstrømnings-Model. (Precipitation-Runoff-Model.)
NOAA	National Oceanic and Atmospheric Administration
NSE	Nash-Sutcliffe Efficiency
OAT	One-At-a-Time
PBIAS	Percent bias
RGS	River gauging station
RMSE	Root mean square error
SWAT	Soil and Water Assessment Tool
USDA	United States Department of Agriculture
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environmental Program
WRMA	Water Resources Management Authority

LIST OF APPENDICES

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First and foremost I thank the Almighty God for the gift of life and the chance to pursue my dreams. My heartfelt gratitude goes to my supervisors Dr. Joel Kibiiy, Prof. Ochieng and Prof. Willems for their considered advice, support and guidance throughout this study. Special thanks is owed to thestaff and faculty of the Department of Civil and Structural Engineering of Moi University and the MUK-VLIR_UOS project for financial support to undertake my studies. To Prof. Sitters for his kind and prompt assistance, my class mates and colleagues for their support I am very appreciative.

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I take this opportunity to acknowledge all of your contributions to the completion of this work and declare my sincere appreciation for your assistance and encouragement without which it would have been impossible to reach this far.

Sergoit means "Good luck ahead" in Kalenjin.

CHAPTER 1: INTRODUCTION

1.1 Introduction

This chapter gives a general introduction to this study, the hydrological modelling of the Sergoit catchment. The importance and need for the effective management of water resources in global and local contexts is expounded. This is followed by an introduction into hydrological modelling and modelling approaches and the challenges of data scarcity. The scope and the definition of the problem are given as well as the objectives of the study. The characteristics of study area are given followed by the general outline of this research.

1.1.1 The need for water resource management

Water is indispensable for the propagation of all life forms and indeed all human activity. The United Nations Committee on Economic, Social and Cultural Rights in 2003declared the access to safe freshwatera basic universal human right(Kundzewicz et al., 2007). There is increasing demand on the available water resources due to but not limited to the following reasons as stated in the United Nations Water periodic report of 2012.

1. The increasing water resource demand has been driven mainly by global demographics;our global population stands at about 7 billion from the previous population of 5.3 billion in 1992.
2. The increased rural to urban migration of populations, and the displacement of populations occasioned by social and political conflict.
3. An increase in wealth in the fast developing economies has led to increased water use demand that have had an adverse impact on the use and management of water resources.

4. Additionally, climate change, pollution, economic turmoil, increased demand for food, energy and increased industrial development.

These issues have raised competition between water uses resulting in complicated allocation decisions which further compound the challenges of managing water resources (UNEP, 2012).

In a global sense these issues form a back drop that necessitates the growing need to assess, quantify and manage water resources effectively. The need to manage water resources emanates from endemic systematic failures in the management of water resources over the past years. What has exacerbated the rapidly accelerating pressures felt today on the freshwater resources arising from these increasing demands,are failures by local management that may lack capacity or may not be well equipped to handle the challenges and adapt or adequately respond to them (UNEP, 2012).

A river-basin is a natural system that is made up of a number of components.These include: water sources (inputs),demands(water use), in-stream and off-stream components, and other intermediates such as treatment and recycling.

It is thus appropriate to handle the question of water resource management as a single system in an integrated way. Global Water Partnership (GWP, 2000) defines Integrated Water Resources Management (IWRM) as a “process which promotes the coordinated development and management of water, land and related resources, in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems.”Hence, the management of water resources should be implemented in a sustainable way by encompassing and balancing water needs among all uses, domestic, industrial, agricultural (irrigation), power generation and ensuring provision for environmental flows for biodiversity and ecosystem services (Tessema, 2011).

1.1.2 The Kenyan context

Kenya is classified as awater scarce country as it has a renewable freshwater supply of 647 m^3 per capita per annum which is below the global threshold of 1000 m^3 per capita per annum for a water stressed country (Akivaga et al., 2010).Kenya is also characterized by high spatial and temporal variability in climate with extremes in droughts and floods (MWI and UN-Water, 2006).A growing economy coupled with a fast growing population has led to increased pressure on limited resources. Of vital importance is the fact that despite the ever increasing demand for water resources the quantity of fresh water has remained more or less constant. This in effect has necessitated the push for better management of water resources in the country especially at the catchment level.With these developments the need to better estimate the fluxes between the various compartments of the hydrologic cycle is always present.

1.1.3 Hydrological modelling

The use of models in decision making applications enables the selection of an optimal course of action. Models are often constructed to enable reasoning within an idealized logical framework about the processes of interest(Shrestha et al., 2010).

Watershed or hydrological models in this case, are vital tools that can be used to study hydrologic processes. Additionally responses to both natural and anthropogenic factors can be investigated, but due to the limitations encountered in the representation of complex natural systems, model calibration and validation ordinarily must be undertaken prior to the application of these models in order that their output may match reality (Shrestha et al., 2010).

The estimation of these fluxes are not only important because of management concerns of available water resources, but alsofor analysis of impacts due to the severity of hydrological events caused by the variability and frequency of the changing climatic conditions (Githui, 2008). Further, the correct estimation of the runoff volume draining out of catchments is an important issue in hydrology and engineering, as it is often the basis for the planning, design and management of river, water supply, irrigation and flood protection works (El-Nasr et al., 2011).The choice of the method to be used for the assessment of the catchment hydrology is thus the first step.

Hydrological modelling is an approach used to forecast and predict the quantity and quality of water for decision makers (Chow et al., 1988).A model can simply be described as a representation of a physical system or processes. Models are simple representations of a complex hydrological system (Bahremand, 2006) and thus aim to represent and predict the response to input for a hydrological system.

In hydrological modelling, different modelling approaches exist. These approaches vary from lumped models to fully distributed models, and from statistical, stochastic models to deterministic models. These modelling approaches attempt to describe the dominant or mostimportant components to the catchment rainfall-runoff process. Components of the hydrologic cycle, include direct and indirect runoff, physical processes such as soil infiltration, groundwater recharge, soil moisture storage, surface and subsurface flow, interception and evapotranspiration. These models can be applied to simulatevarious fluxes at various times steps, for instance,hourly, daily, monthly or annual time steps(Staes et al., 2011).

1.1.4 Lumped models

In the lumped hydrologic modelling approach, there is no spatial variability considered in the catchment rainfall-runoff processes.Characteristically, the lumped rainfall-runoff model lumps or averages spatially, in a general sense, the highly complex land use, precipitation and soil processes and properties into a limited number of processes and parameter values that are representative of the whole catchment. In a spatially aggregated or lumped way the model parameters represent the physical features of the basin and the hydrologic processes, in a some what empirical nature (Staes et al., 2011).Data input in lumped models consist of spatially averaged values of precipitation, evapotranspiration and the size of the basin area. The observed river flow data at the outlet of the basin is then used for calibration.Due to the afore-mentioned qualities, the main advantage of the lumped modelling approach is that due to its simple structure, the data requirements are minimal and the model setup and calibration of model parameters is fast (Staes et al., 2011). This means that it is easily implemented.

1.1.5 Distributed models

The spatially and fully distributed hydrological models on the other hand consider that the parameters vary completely in space at a resolution usually selected by the modeler. Distributed models require large amounts of data for each grid cell thusincreasing the amount of data and computational requirements. It is expected that because the physical and hydrological processes are modelled in full spatial detail, they then will provide a high degree of accuracy. In reality however, data availability is limited to the extent that it might be difficult to identify all parameter values from the available data (Staes et al., 2011).This leads to a situation where the number of parameters is too large for an accurate calibration on the basis of the limited amount of data. Therefore it means that no unique set of 'optimal' parameter values exists as different sets of the model parameters will lead to an equally good fit to the observed model output. The model is then called "over parameterized" (Staes et al.,2011).

Rainfall runoff estimation from a watershed is of vital importance as these values are required in most hydrologic analysis. Such purposes include water resources planning, flood forecasting and pollution control.Modelling studies therefore contribute to our understanding of model structures and hydrological processes (Tanner and Hughes, 2013).

1.1.6 Data scarcity

Model input consists of raw or preprocessed data collected from weather stations and river gauging stations which due to a number of reasons may contain errors and thus increase uncertainty in model results. A challenge that is experienced at the moment in Kenya is the incompleteness of existing records (MWI and UN-Water, 2006).

This problem of lack of data is depicted in the Integrated Water Resources Management and Water Efficiency Plan by the Water resources Management Authority (WRMA, 2009). It noted that in the 20 years following independencein 1963, the operational number of hydrological, meteorological and water quality stations in Kenya remained relatively stable and experienced a commensurate increase.Based on the demand for river gauging stations (RGS) the number rose from 377 in 1963 to 381 by 1973 to 446 stations by 1983. A drastic drop however was experienced thereafter with 110 operational stations being left active by 1996 and 50 stations by 2005 as represented in Figure 1.1.

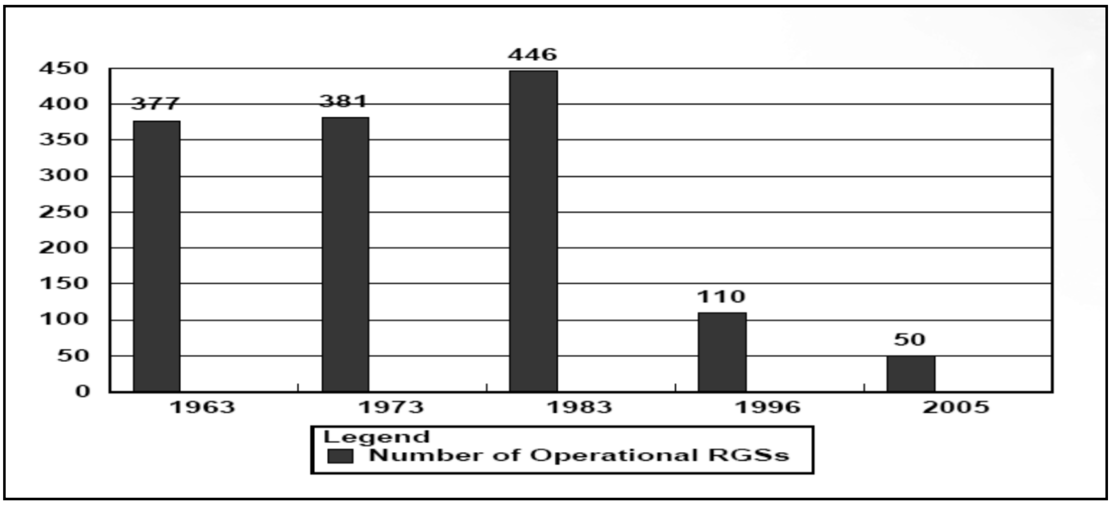


Figure 1.1: The number of RGS stations in Kenya (WRMA, 2009)

This state of affairs makes it challenging for a modeler or a water resource manager who wants to make decisions presently based on sound data.The catchment of interest in this study is the Sergoit catchment and it's a good example for it faces the same challenge of lack of continuous data and inconsistency, as the time series captured at the outlet of the catchment, River Sergoit RGS ID: 1CA02 is incomplete.

1.2 Scope of the study

The scope of this study covers the application of hydrological modelling approaches to the determination of the water yield of the catchment based on currently limited hydro-meteorological datausing a lumped modelling approach and the semi distributed physically based modelling approach during calibration and validation. Each model was applied to generate synthetic discharge data based on more recent meteorological data. The resulting discharge data generated was evaluated to obtain current catchment yield estimates for both cases. It is envisaged that the research will also contribute to the understanding of the hydrology of the Sergoit basin and also serve as a baseline study for Moi University, School of Engineering, Department of Civil and Structural Engineering which is at the initial stages of setting up an experimental watershed in the same catchment.

1.3 Problem statement

Knowledge of the water yield in a river catchment is an indispensable prerequisite in the sustainable management of water resources at watershed level (Adeniyi et al.,2014). At the same time,calibration of hydrological models in ungauged basins is a current research focus in the field of hydrology (Xingqi, et al., 2014).The Sergoit catchment is currently ungauged thus it is currently difficult to quantify its water yield. Given this scenario it is important to identify a hydrological modelling approach that can best describe the hydrological processes in the catchment to sufficiently determine the basins water yield given its limited hydro-meteorological data.The decision on which modelling approach to employ poses a problem to many water resource managers and researchers. This is due to their different structures and varying data requirements. Although hydrological models have been widely used in hydrological related studies, more information is needed to determine the impact of the structural differences between these hydrological models on the hydrological predictions forming their outputs (Vansteenkiste et al., 2012). While there have been various investigations or studies conducted dealing with the comparison of hydrologic simulations between distributed models and lumped models, their results have been inconclusive. The results indicate that distributed models may or may not provide any improvements over those obtainedby lumped models (Shultz, 2007).

Having established this it is important to carry out hydrological modelling research to provide solutions to the problems faced in the Sergoit catchment that may be replicated in other catchments at various scales.

1.4 Justification

Understanding hydrological processes and developing suitable models for a watershed is a vital part of water resource development and management programmes. These watershed based hydrologic simulation models are likely to be used for the assessment of the quantity and quality of water (Shawul et al., 2013).

As a backdrop to the study, the Sergoit basin is important as it is located astride the Uasin Gishu County.It is estimated that in Uasin Gishu County, 90% of the land is arable. Uasin Gishu is endowed with good land resources and varied agro-ecological potential. It is the bread basket for the country; producing over 4.5Million bags of maize and about 1Million bags of wheat annually. It is also estimated that agriculture supports over 80% of the rural population of Uasin Gishu County in terms of household income and food security. The Sergoit basin is thus an important contributor to the socio-economic activities in the Uasin Gishu County and the entire Country as well (Korir, 2010).

In the field of hydrological sciences, it is recognized that the available approaches for the representation of rainfall-runoff transformation are often still far from satisfactory and that more complex hydrologic modelling does not always lead to better results (Linde, 2007). A key issue to operational users of hydrological models and engineering hydrologists is the selection of the most appropriate model and modelling approach to apply for a catchment based on the need for accurate analysis. Limiting constraints like resources, nature of the problem and limited time among others, further complicates this endeavor.

Many authors like Linde et. al, (2007), Anh et al., (2008), Kovacs et al., (2005), Shultz et al.,(2007), have critiqued the use of distributed models with their main concern being the many parameters that need to be altered during the calibration phase. They have even argued that they consider models which are usually claimed to be distributed physically based as in fact being lumped conceptual models with more parameters. A key observation of the distributed model is that the problem of over parameterization is greater (El-Nasr et al., 2011).

Even though a variety of rainfall-runoff models are available, the selection of a suitable rainfall-runoff model for a given watershed is essential to ensure efficient planning and management of watersheds(Verma, 2010). Therefore this study attempts to contribute to the understanding of models and modelling approaches discussed herein, especially in Kenya where there is an increasing need for tools used in the management of water resources. This will be done while expounding on their level of accuracy and the ease of development in their application to a catchment with limited data. The choice of these two particular models is based on their availability, their representation of the model structures to be tested and their suitability for use in areas where hydro-meteorologic data is a constraint.

1.5 Objectives

1.5.1 Main objective

The main objective of this study is to set up and evaluate the performance of twomodelling approaches for the Sergoit basin; a lumped conceptual model MIKE 11-NAM and a semi distributed physically based model SWAT, in estimating the catchment yield given by the two approaches.

1.5.2 Specific objectives

i. To set up, calibrate and validate a lumped conceptual model MIKE 11NAM for the Sergoit catchment.

ii. Toset up, calibrate and validate a semi distributed physically based SWAT model for the Sergoit catchment.

iii. To evaluate model performance based on observed data during the calibration and validation periods.

iv. To estimate the catchment yield based onthe twomodelling approaches for a more recent time period between the years 2005 to 2009.

1.6 Outline of the Research

The desertation is divided into six chapters. Chapter one provides the general introduction of the study, scope of the study, problem statement, and objective of the research, chapter two gives a detailed description of the study area and the data used. Chapter three covers a literature review of the relevant issues in water resource management and hydrological modelling, the various classification of models and modelling approaches and the importance of GIS in hydrological modelling. Also reviewed are the methods in data preprocessing, the SWAT and the MIKE 11-NAM models,Model performance evaluation,Model sensitivity analysis and finally a review of previous research into comparative hydrological model analyses. The fourth chapter outlines the methods applied to this study including data collection and preprocessing, the setup of the SWAT and the MIKE 11-NAM models and finally the application of these models. Chapter five presents the results of each model's calibration and validation evaluation and the simulated estimates of the basin water yield for the model calibration, validation and application periods.The sixth chapter reports the conclusions and recommendations drawn for this research.

CHAPTER 2 : STUDY AREA AND DATA

2.1 Introduction

This chapter gives a general introduction to the study area which is the Sergoit catchment.The characteristics of study area are given including the location, topography and drainage, population, landuse and soil classifications found in the area.

2.2 Study area

2.2.1 Location

The Sergoit catchmentis located in Kenya and lies between longitudes 35.05 and 35.57 East and latitudes 0.44 and 0.73 North. It is part of the greater Nzoia Catchment that lies on the western regions of Kenya (Fig.2.1).Administrative regions arround the study area are shown in Appendix A.

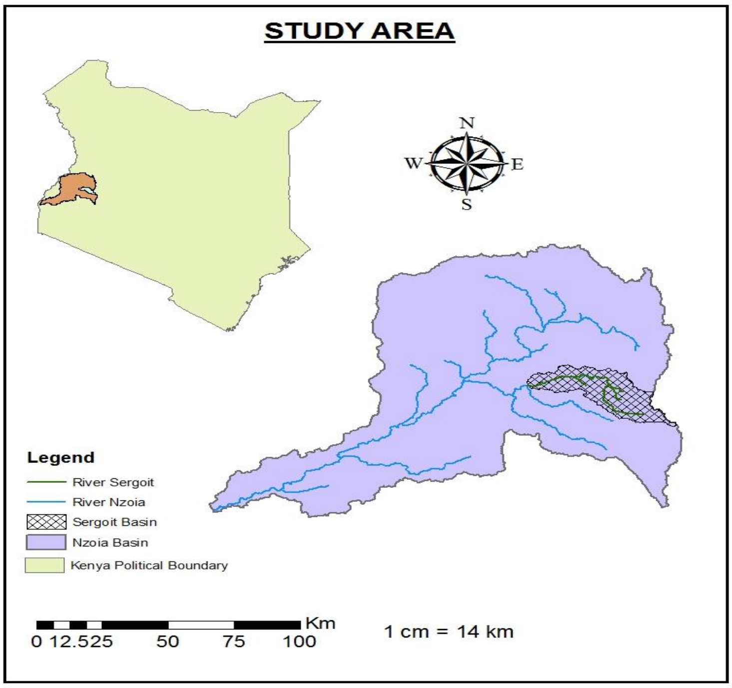


Figure 2.1: The location of Sergoit catchment

It forms part of the upper Nzoia catchment that is part the Lake Victoria and the greater Nile basin.

2.2.2 Topography and drainage

The Sergoit catchment has a mean elevation of 2140m with an elevation that varies from 1806m to2676m above mean sea level. The main drainage feature is the River Sergoit whose length is about 96.42 km based on DEM processing, (Fig.2.2). As part of the drainage in the Sergoit basin, River Chepkoilel has three tributaries; Chepkosom, Chepkoilel and Koitoror. Kisonei River is a tributary of Chepkosom River. Sergoit River has its source on the western slopes of the Kerio Escarpment near Iten and is joined by Chepkoilel River near Kuinet to drainout of the Sergoit River basin.

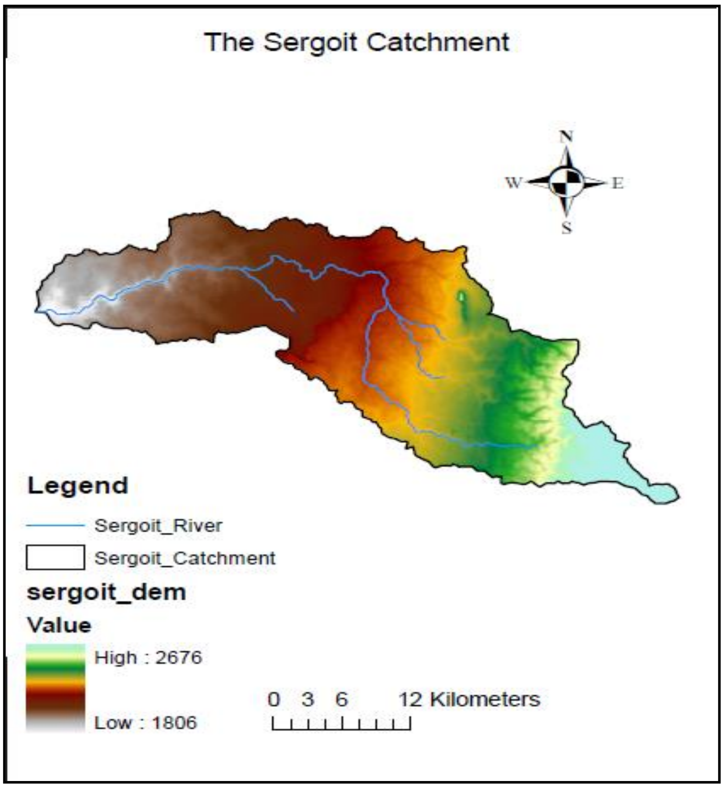


Figure 2.2 : Sergoit Catchment DEM

The Sergoit River drains an area of about 716.3Km^2(691.325Km^2 from the RGS point) which joins the Sosiani River then the Kipkaren River further downstream. These rivers join the Nzoia River which finally drains into Lake Victoria. This catchment is bounded by the Cheranganyi hills to the North East and the Kerio valley to the Eastern side.

2.2.3 Population and Land use

Based on the 2009 census results,Uasin Gishu County, which covers a major part of the catchment area has a population of 894,179 persons and a population density of 267.3 inhabitants per square kilometer. The population growth rate from the year 1999 to 2009 is 3.68%.Based on the sub-counties (Appendix A) that cover most of the Sergoit catchment, Moiben and Soy have populations of 138,409 and 171,941 persons with population densities of 244.3and 251.9 inhabitants per square kilometers respectively (County Govt U.G, 2013).

As earlier stated, it is estimated that Uasin Gishu has about 90% of the land in the county as arable, with about 2,000 km^2 and 1,000 km^2 categorized as high potential and medium potential agricultural land respectively (Korir, 2010). As much of the catchment falls within this region most of the land use is given to agriculture as represented by Figure 2.3. The land use in the catchment is predominantly dense agriculture and plantations according to the land use maps prepared by JICA in 1987. Other land use types include forests and woodland as depicted on the land use map (Fig. 2.3)

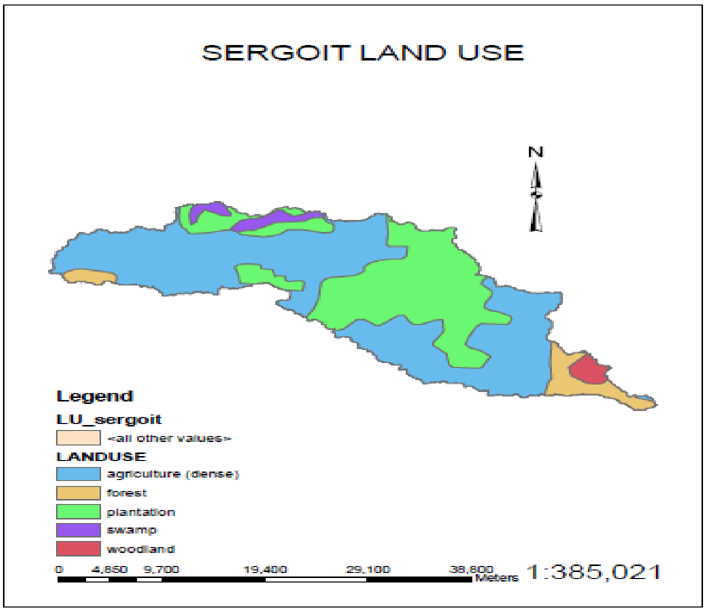


Figure 2.3: Sergoit Basin Land Use Map

2.2.4 Soils

The geology in the region is dominated by tertiary volcanic rock with no known commercially exploitable minerals(County Govt U.G, 2013). The soil types found within the county include Red loam, red clay, brown clay and brown loam (Korir, 2010).The textural descriptions of the dominant soil classes in the Sergoit basin include, very clayey, clayey and loamy soils. This is represented in the Figure 2.4, showing the soils codes which represents the soil mapping unit indicating the physiographic conditions e.g. whether the soil is well drained, shallow or very deep, the color, type of clay (eutric, nitisols). The textural descriptions found within the basin are Loamy soils which include; loam, sandy clay loam, clay loam, silt, silt loam and silty clay loam and,Very clayey soils which hasmore than 60% clay content (Kenya Soil Survey, 1997),(Table 2.1).

Table 2.1 Soil types found in Sergoit Basin (Source; Kenya Soil Survey, 1997)

Soil Name	A1	F14	L5	L8	Pv3	Ux7
LAYERS	5	4	5	5	5	4
Hydrologic Soil Group	B	B	B	B	B	B
Max. Depth	1000	800	900	1000	1000	700
Textural Class	Clayey	Sandy	V.Clayey	Clayey	V.Clayey	Loamy
Bulk Density	1.33	1.4	1.1	1.3	1.3	1.61
Hydraulic Conductivity	7.38	20.73	17.35	8.73	8.15	10.48
CLAY%	52	19	59	50	60	14
SILT%	22	13	17	22	12	18
SAND%	26	68	24	28	28	68

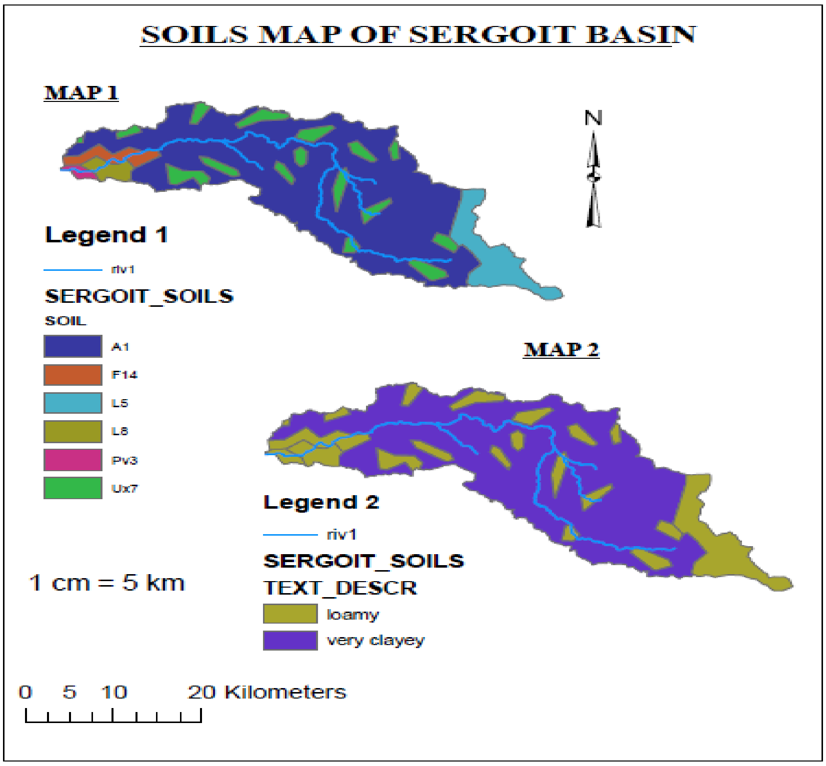


Figure 2.4: Soil types within the Sergoit basin (Source; Author generated Maps)

2.2.5 Climate

The Kenyan climate is primarily controlled by the Inter-Tropical Convergence Zone(ITCZ) and the wide range of topographic relief. As a result of the ITCZ, most parts ofthe country are characterized by two rainy seasons, March to May (long rains) and October to December (short rains)(Karani, 2005). The Temperatures in the area around Sergoit basin and the larger Uasin Gishu, range between 8^{0}C and 26ºC(Korir, 2010) and an annual average Temperature of 24^{0}C. The monthly average temperatures (1960-1990) are depicted in the Figure 2.5.

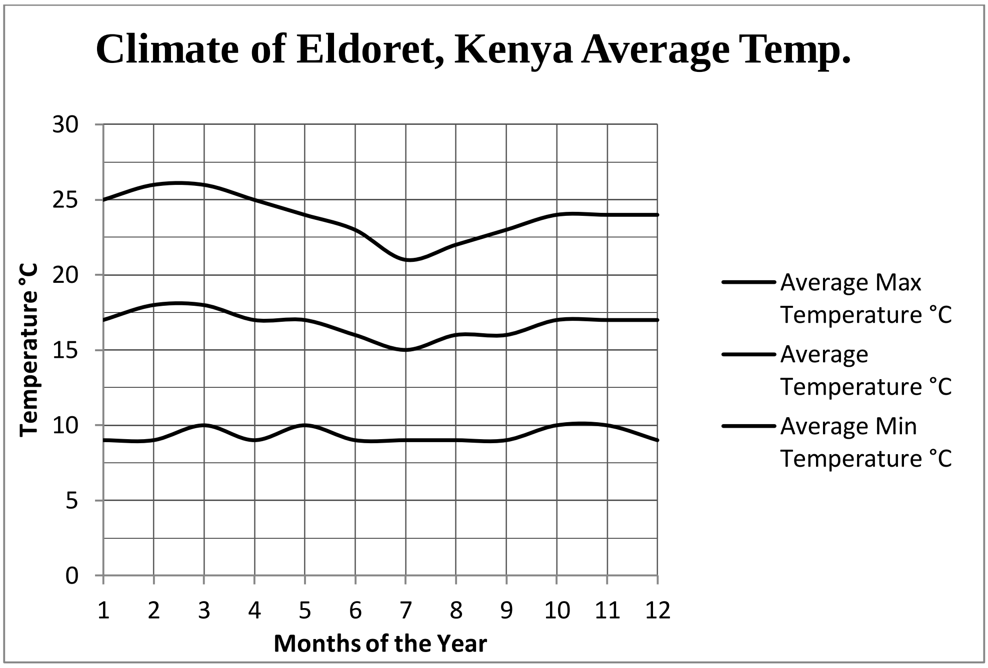


Figure 2.5:Monthly mean Max andMintemperatures.(Climatemps.com, 2013)

The area around Sergoit basin and the larger Uasin Gishu,receives an average annual rainfall of 900-1,200 mm (Korir, 2010). The Average monthly (1960-1990) precipitation in the year is represented in the Figure 2.6

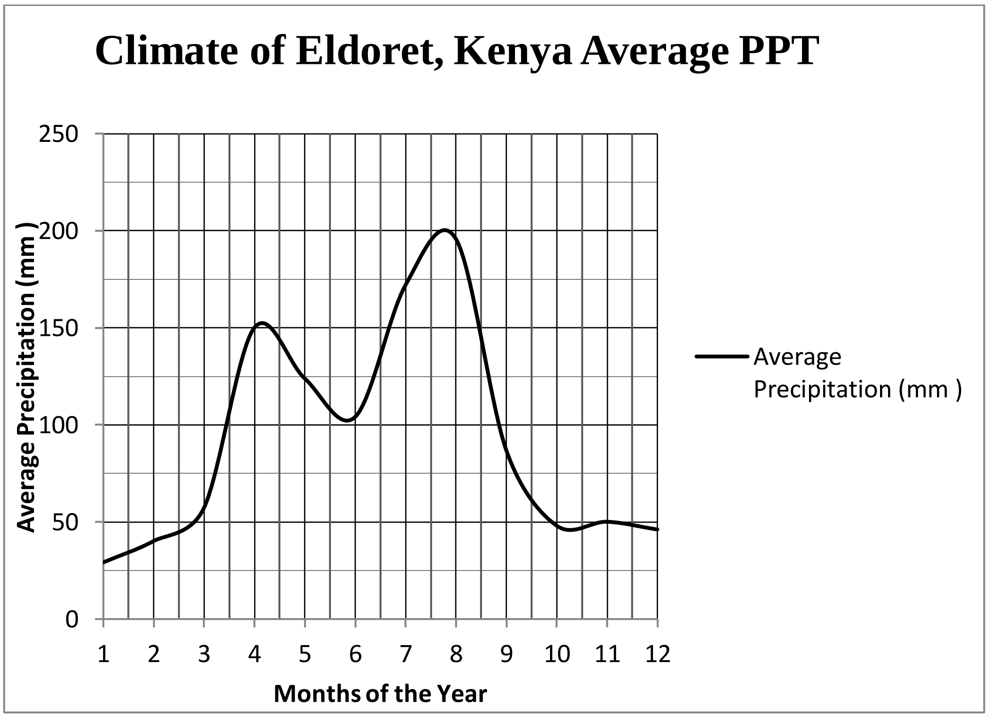


Figure 2.6:Monthly mean precipitation. (Climatemps.com, 2013)

2.3 Data

2.3.1 Data collection

It is difficult to collect extensive data sets on all hydrological process variables at the required time and at the spatial-scales needed to capture vital catchment wide hydrological processes. The engineering hydrologist, therefore as a modeler faces enormous challenges brought by limited availability of good data. In an effort to overcome this problem, data used in this research was collected from a numberinstitutions and downloaded frominternet sources. Meteorological data was sourced from both the Kenya Meteorological Department (KMD) and internet sources including the National Oceanic and Atmospheric Administration (NOAA).Soiland land cover GIS data sets were obtained fromFAO and ILRI while the digital elevation model (DEM) was downloaded from CGIAR - Consortium for Spatial Information (CGIAR-CSI).

2.3.2 Rainfall data

The available rainfall data sourcedfrom Kenya Meteorological Department (KMD) was analyzed for use based on the periods with high percentages of complete data. This was done for a number of stations (Table 2.2) that fell within and around the Sergoit catchment.

Table 2.2: Selected Rainfall stations(KMD, 2005)

STATION NAME	Station Number	Lat.	Long.	Year Opened	Year Closed
Soy Kipsomba Estate	8935016	0.46	35.11	1914	----
Abai Farm,Cheplaskei	8935108	0.48	35.26	1950	----
Kipkwen D.O.'S Office,Chepkorio	8935131	0.22	35.33	1954	----
Eldoret,Institute of Agriculture	8935133	0.34	35.18	1954	----
Kessup Forest Reserve,Elgeyo	8935134	0.39	35.31	1955	----
Boimet Farm,Turbo	8935157	0.36	35.9	1964	1977
Kaptagat,Sabor Forest Station	8935164	0.30	35.29	1965	----
Turbo Forest Nursery	8935170	0.38	35.3	1966	----
Eldoret Met.Station	8935181	0.32	35.17	1972	----

Stations with little data were eliminated and the remaining stations with data were checked and compared with the data available from theWRMA River Gauging station on River Sergoit 1CA02. As an initial step the available rainfall and discharge data was summarized as annual rainfall values, represented in Figure 2.7. The years with missing data are coded in yellow while years with complete data are in green.

An initial period 1960 to 1990 was checked for completeness on a coarser annual scale then on a finer time scale of daily values.

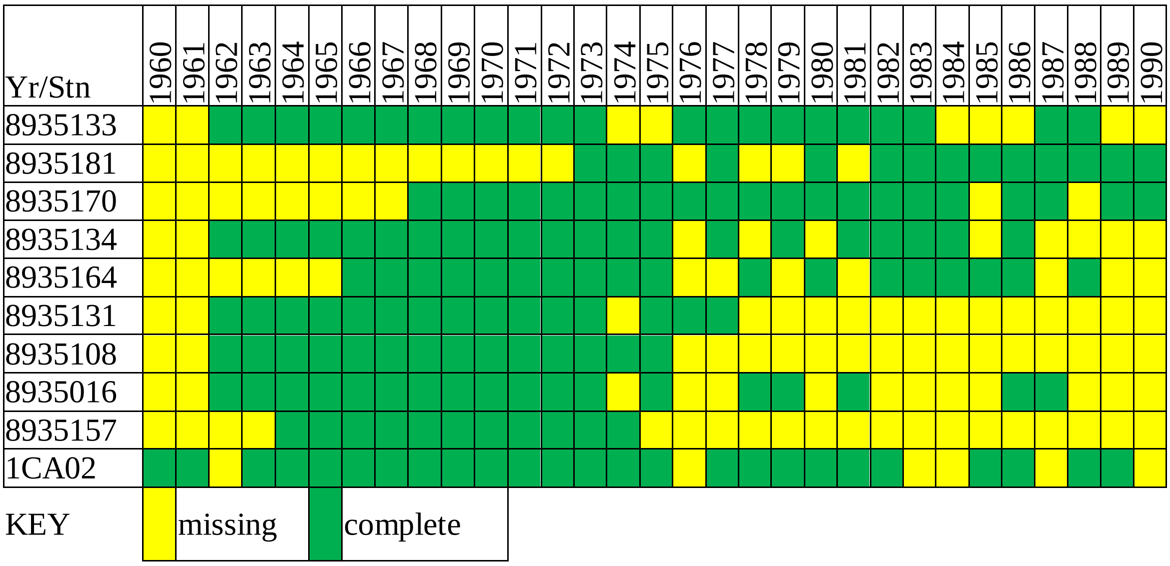


Figure 2.7 Available Rainfall and Discharge Records.

2.3.3 Discharge data.

The measured discharge data from River Sergoit taken at the RGS Station ID: 1CA02 (Figure 2.8) was used in the calibration of the models. The gauging station is located on longitude 35.06 E andlatitude 0.642 N.The available data was from January 1975 to December 1984 with periods of missing data as represented in Figure 2.7 above.

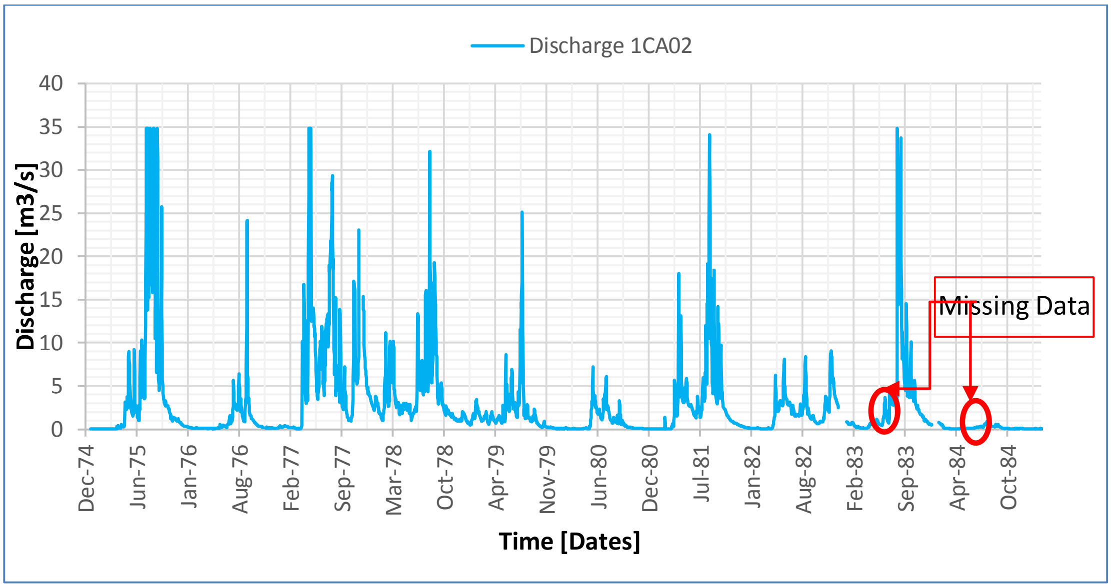


Figure 2.8: Discharge from River Sergoit 1975-1984: RGS 1CA02(WRMA)

2.3.4 Topographical data

A digital elevation model was used to derive topographic information on the Sergoit basin. The Shuttle Radar Topography Mission (SRTM) 90m resolution DEM's have a ground resolution of 90 meters by 90 meters at the equator and a horizontal resolution of 10 to 16 meters. These data sets were sourced from http://srtm.csi.cgiar.organd was used in this study to derive the physical characteristics of the study area that were required for hydrological modelling like elevations, catchment boundaries, catchment area and stream networks.These DEM's were processed in a GIS environment using ArcGIS 9.3.1.

2.3.5 Land use maps

Land use maps were sourced from the FAO website http://www.fao.org/ geonetwork. The land cover map shows general land use classes derived from 1980 Landsat satellite imagery data. The land use map data is provided in shape files and comes along with database files. The database files contain map identification values that are assigned to various land use types.

2.3.6 Soils maps

The soils map was sourced from Kenya soil survey (KSS) of 1982. The maps coverage represents the soil physical and chemical properties of Kenyan soils. Additionally Soil data was obtained from the Kenya Soil and Terrain (KENSOTER) database at a scale of 1:1,000,000 that was compiled by the Kenya Soil Survey (KSS).Thesoil parameter estimates and associated soil analytical data were derived from soilsurvey reports.The data is provided in shape files and is accompanied by database files. Some of the parameters included in the data files include: the bulk density, percentage of sand, silt clay, by mass and depth of soil layer among others.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

This chapter reports a review of literature into the relevant issues of water resource management and hydrological modelling, the various classification of models and modelling approaches and the importance of GIS in hydrological modelling. Also reviewed are the methods in data preprocessing, the SWAT and the MIKE 11-NAM models, model performance evaluation, model sensitivity analysis and finally a review of previous research into comparative assessments of hydrological models.

3.2 The management of water resources

In the past few decades there has been a global push to promote better management of water resources. In 1992 the United Nations Conference on Environment and Development (UNCED) held in Rio de Janeiro covered a wide spectrum of developmental issues. Among the main issues was globalwater resources which was informed by the International Conference on Water and the Environment that formed the "Dublin Principles". "Agenda 21" resulted from UNCED in which Chapter 18 Section 2 on freshwater emphasizes a holistic and integrated approach to sectoral water plans and programs that are within the national and social policy framework(UNEP, 2012).

The river basin or the catchment area, is the most appropriate unit in the management of water resources. It is the best unit to monitor effects of physical developments, technical management choices of water resources, and it is most appropriate for water accounting. Since, water resources in Kenya are considered as scarce it is more important to ensure continuous monitoring, assessment and evaluation to facilitate planning for water security(MWI and UN-Water, 2006).

This raises a need for hydrological research within the country to betterquantify the available water resources and support catchment management programs that provide better safeguards and decision support tools for water managers. These tools are mainly climatic, hydrological hydro-geological and soil erosion and sediment transport models(Setegn et al., 2008). Complex modelling of watershed hydrology is an efficient tool to provide information on the impact of natural and anthropogenic phenomena on the status of water and to facilitate decision-making in water management Hydrological processes (Kovacs et al.,2005).

3.3 Mathematical models

There are different types of models that exist for different uses. They can be distinguished or classified according to whether they are conceptual, physically based,spatially distributed, lumped, deterministic or stochastic models.

The general structure of mathematical modelsseeks to describe a physical reality in hydrology or waterengineering. For each mathematical modelling application, the general structure represented in Figure 3.1 holds.

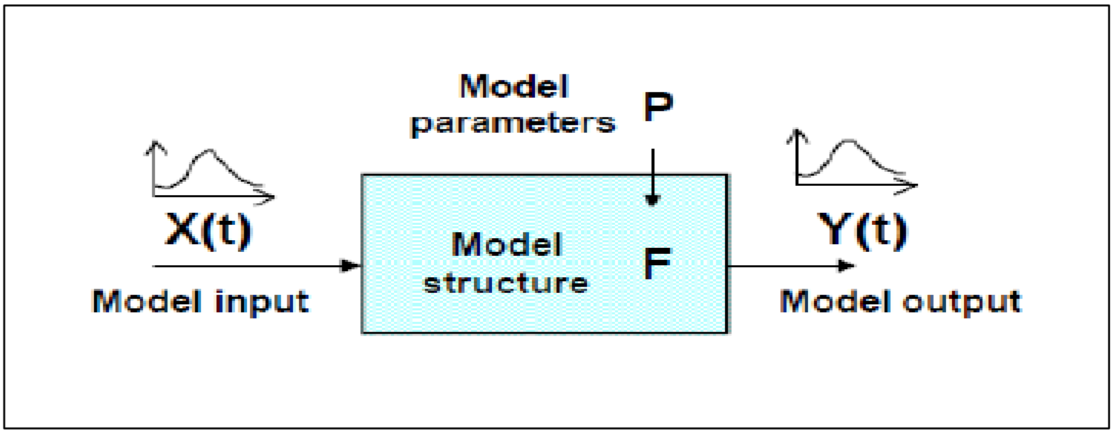


Figure 3.1 General structure of a mathematical model

Some physical processes are captured in the model structure, indicated by the box and are represented by a number of mathematical functions *F*,to describe some output variables Y in that physical space. The variables Y are the ones which the model user is interested in, and are usually the unknowns which are often referred toas model-output variables or simulated variables. In the generation of these variables (model output variables), use is made of other more easily known variables X. These are variables which are easily obtained or measured and are called model input variables.

The model structure or the model body is a set of mathematical relations used to describe therelationship between the input and output variables. The model structure is usually parameterized using a number of model parameters P. These parameters control the nature of the relationship between the model inputs and the model outputs, and thus determine the response of the system represented with respect to the inputs.

3.4 Hydrological models

Hydrological models involve the application of mathematical expressions to relate precipitation to stream discharge or runoff. These expressions define quantitative relationships between inputs,like factors inducing flows and outputs which are mostly flow characteristics like depths and volumes. The scope of hydrologicmodelling and itsapplications has broadened dramatically over the past decades.

From the late 1950's numerous models have been developed to simulate the hydrologic processes that occur within watersheds(Bengtson and Padmanabhan, 1999). Many types of these models have been developed for various processes, though some may inherently have structural similarities occasioned by similar underlying assumption in the development of the models while others may not.

Hydrologic modelling is related to the spatial processes of the hydrologic cycle and is often used to estimate basin water resources as well as for impact assessment or more precisely water resource management (Githui, 2008).

A basic concept is application of the water balance computed through the system that is represented as interrelated storages comprising of canopy, soil surface and sub-surface storages. Hydrologic models compute runoff from excess precipitation falling within the watershed's divides which is then routed to the basins outlet. The excess precipitation is obtained by subtracting that part of precipitation volume that is intercepted by vegetation, stored in various storages, lost to evapotranspiration or lost to deep percolation.

As with most models, hydrological models require inputs which in this case are the driving variables in the hydrologic cycle. These inputs are mainly climatic variables like precipitation, temperature and evapotranspiration. The output from hydrological models are mostly discharge values or runoff depths at various time steps leading to a hydrograph from which peak flow magnitudes, time to peaks and recessions can be displayed.

In order for these outputs to be relied upon they must be compared with actual observations of the observed variables from the outlet of the watershed basin or a specified time period similar to the period of the input variables. The process of calibration which is the adjustment of parameters associated to the model outputs is undertaken until an acceptable match between the model output and the actual observed values is sufficiently achieved.

3.5 Application of hydrological models

Hydrological modelling can be applied to a number of objectives, depending on the problem under investigation(Pechlivanidis et al., 2011).Applications of hydrological modellinginclude:

a) Extrapolation of point measurements in space and time.

b) Improving the essential understanding of existing hydrological systems and ;

c) Assessing theimpact of change (e.g. climate and land cover change) on water resources.

3.6 Classification of hydrological models

3.6.1 Statistical versus Deterministic

Hydrological models can be classified as either statistical models or deterministic models. Statistical models include consideration of uncertainties in both the parameters and input data. Simple statistical analysis could include techniques such as double mass curve analysis, regression, and flood frequency analysis. They simply aim to relate the input variable to the outputs by deriving statistical relationships between the two.

These techniques can be used to show changes in hydrologic response in a watershed, but it may be very difficult to determine what underlying factors have contributed to the changes(Bengtson and Padmanabhan, 1999).

Deterministic simulation models on the other hand describe the behaviour of the hydrologic processes taking place in a watershed through mathematical functions. These expressions interrelate the various phases of the hydrologic cycle. These models are verified or calibrated by comparing the model output with existing data (Bengtson and Padmanabhan, 1999).

3.6.2 Empirical Models, Lumped Conceptual Models and Physically based models

Hydrological models may also be classified depending on the level of detail captured in the model structure to represent physical processes within a catchment. Thus the models vary from detailed physically-based models to simplified conceptual models to empirical models. In Table 3.1, they are classified according to how well and to what detailed the model structure represents the physical processes in the hydrology of the catchment (Willems, 2012).

Table 3.1 Modelling types (Willems,2012)

MODELLING TYPES			
Increasing level of physically-based modelling	Detailed physically-based models Partly physically-based models	White box	Most model parameters can be measured
	Conceptual models	Gray box	Model parameters need calibration (e.g. using measurements for model output variables)
	Empirical models Black-box models	Black box	Also the model-structure building depends on the measurements for the model output variables

In a physically-based model, the relation between model input and output is described by a number of equations, which represent physical processes. Due to this, the model structure is transparent and it thus mayalso be called a white box model. For a detailed physically-based model, most parameter values can be measured and calibration is not so necessary, unless measurements are not available as is frequently the case.

A conceptual model means that the hydrological processes are represented in the way they are perceived to occur. The processes and properties within the catchment are lumped together in a few processes and values to represent the system in a spatially averaged manner. In this way, process description and model parameters are more conceptual than physical in nature, and cannot be directly obtained from field observations or measurements. Because the physical reality and underlying assumptions of the processes are less transparent, a conceptual model may also be called a gray-box model (Willems, 2012). Conceptual models need calibration because the model parameters are from a lumped representation of the physical characteristics of the catchment and their values cannot be measured directly.

As opposed to the physically-based models and conceptual models, empirical models do not have an internal description. They are built and calibrated based on the simultaneous evaluationof the model input and output. Because a physical basis is missing for these models, the model structure may depend on the period that was selected for calibration (Willems, 2012).

It is worthwhile noting that most models combine most of these approaches as sub models or sub routines and some model structures have both a physically-based part and an empirical part, while some even have stochastic models incorporated.

3.6.3 Single event models and Continuous models

Hydrological models can also be classified as single event-simulation models when they are used for modelling a single precipitation or rainfall- runoff event. These models generally use short time steps in the order of hours or even minutes. These models produce a single event runoff hydrograph, with the main interest usually being only the peak flow.

These models do not account for Precipitation that infiltrates into the soil, interflow or groundwater flow from infiltrated water, although they mayinclude a baseflow component from groundwater recharge into a river reach (Bengtson and Padmanabhan, 1999). They also generally do not model evaporation and transpiration, or changes in the soil moisture. This is because these processes are considered not to contribute significantly to the runoff over the short duration that runoff occurs from a precipitation event.

Continuous models on the other hand, are generally used to represent the generation of flow overlong periods of time such as months and even years while accounting for all theprecipitation-runoff events during the period. In addition to the hydrologicprocesses included in the event-based models, continuous models keep anaccounting of soil moisture by routing infiltration into the soil and partitioning it tosubsurface flow, groundwater flow, and evapotranspiration. (Bengtson and Padmanabhan, 1999). The Classification of hydrologic models, as suggested by Bengtson and Padmanabhan, (1999), is represented in Figure 3.2.

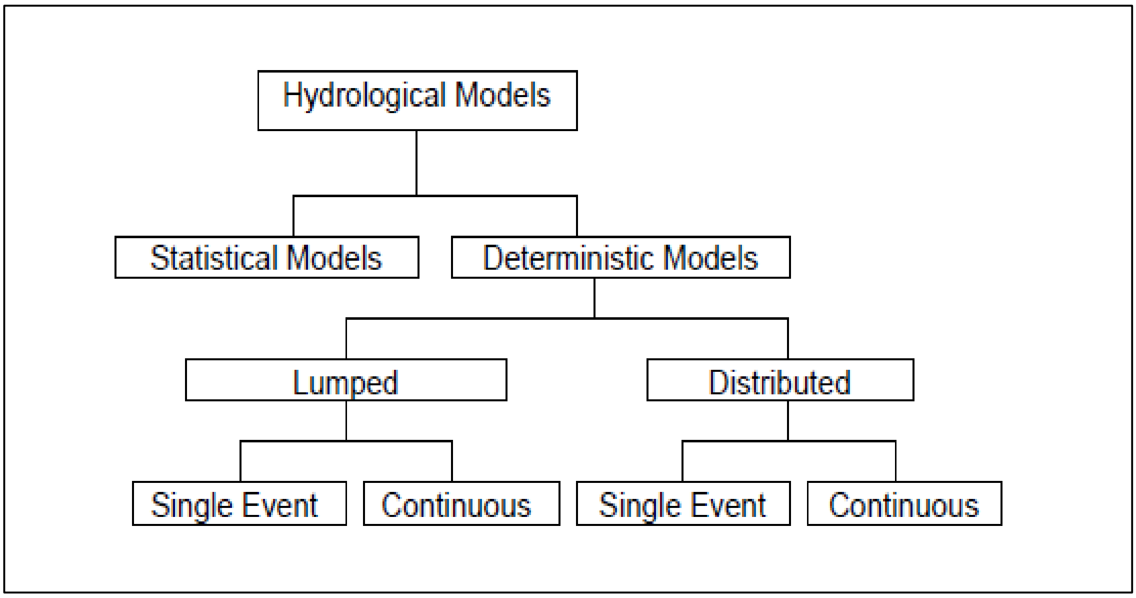


Figure 3.2 Classification of hydrologic models (Bengtson and Padmanabhan, 1999).

3.6.4 Application based classification

Models can alsobe classified according to their typical application. These uses vary from agricultural applications, urban storm runoff, sedimentapplication models, pesticide application models to pollutant and water quality models(Bengtson and Padmanabhan, 1999).

3.7 Hydrological modelling

There are some common modelling approaches that are based on how a model represents the hydrology and the physical properties and characteristics of a catchment. These approaches include, lumped modelling, semi-distributed modelling and distributed modelling approaches.

3.7.1 Lumped hydrological models

Lumped conceptual models have been widely used in hydrology for many years. The models are typically able to describe the most essential processes in a catchment through a set of solvable equations. They are usually preferred because they have such advantages as their basic physically-based nature and simplicity(Anh et al., 2008). For lumped models however, their parameters cannot always be measured directly from the basin as conceptual models are lumped on a catchment level and the catchment is treated as a solitary unit. This means that model variables and parameter sets are values averaged for the entire catchment (Chow et al., 1988).

An assumption made in Lumped models includes, uniformly distributed rainfall i.e. mean areal precipitation is averaged over a watershed basin in both a spatial and temporal manner over a given time step. This assumption almost never happens in reality although there could be a limited number of cases where this may come close(Shultz etal., 2007). Other assumptions in lumped modelling include uniformity soil types and texture, averaged slope and other catchment characteristics such as vegetation types and land-use practices. In reality, these parameters may vary very widely across the entire basin. Due to the averaging together of these parameters across the basin, the results are uniform conditions that create a lumped model(Shultz et al., 2007).Examples of lumped models are the Stanford model, the problem-oriented computer language for building Hydrologic Models, HYMO, the flood hydrograph package of the Hydrologic Engineering Center, HEC-1, the model for runoff and stream flow routing in river basins, RORB, the Tank model, and the Erosion-Productivity Impact Calculator, EPIC model among others(Krysanova et al., 1999).

3.7.2 Fully distributed hydrological models

Distributed models are models that are able to explicitly represent the spatial variability of the important land surface and climatic characteristics(Rubarenzya et al., 2007).

There are several distributed physically based hydrological models. These include among others, WetSpa, MIKE SHE, and Topmodel(Willems, 2012). The basic idea behind the distributed modelling approach is the discretization of the modeled space into grid cells with the use of model equations with finite differential equations. The equations applied in the distributed approach are the continuity and the momentum equations.The momentum equation is used to describes the flow or the water balance from one block to another. This equation can be described as;

$$\sqrt{1-S_o^2}\frac{\partial h}{\partial s}+\alpha\frac{U}{g}\frac{\partial u}{\partial s}+\frac{1}{g}\frac{\partial u}{\partial t}=S_o-S_f-\frac{2\alpha^2 Q}{gA^2}q \qquad \text{Equation 3.1}$$

The continuity equation is used in the models to describe the water storage in the blocks or grid cells. The continuity equation is given by;

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial s}=q \qquad \text{Equation 3.2}$$

These model equations are solved in a two dimensional way and assumptions like the kinematic wave assumption are applied, where the dynamic terms related to time is neglected and the water surface slope is assumed to be equal to the bottom slope. Further simplification assumes uniform flow conditions, meaning that there is no variation of the flow in time. The movement of ground water is also represented in the model by the equation;

$$\frac{\partial}{\partial x_i}\left(K_{ij}\frac{\partial h}{\partial x_j}\right) = S\frac{\partial h}{\partial t} + q \qquad \text{Equation 3.3}$$

Where the terms, K_{ij} is the hydraulic permeability coefficients, S is the storage coefficient and,$q$is the additional discharge.

The main advantage of the distributed modelling approach is the high detail captured in terms of the spatial representation of the processes. This also will be reflected in the results where the spatial distribution of model results will also be available. The disadvantages to this approach is the large amount of data required, long calculation times and computational resources needed to run these models. Additionally there are a large number of model inputs and parameters needed for the model setup. Examples of The distributed physically-based models are represented by the Système Hydrologique Européen, MIKE SHE, the Institute of Hydrology Distributed Model, IHDM, and the WetSpa model (Krysanova et al., 1999;Willems, 2012).

3.7.3 Semi distributed hydrological models

Semi-distributed models are considered somewhat as intermediate models. This modellingapproach differs significantly with regards to the representation of hydrological processes and accompanying spatial representation. Different semi-distributed models have different approaches to achieve a form of spatial representation. For example, the Precipitation-Runoff Modelling System, PRMS and the SWAT model subdivides the basin first into sub-basins then further into Hydrologic Response Units, HRU’sbased on land-use, soil data and slope. The SLURP model (Simple Lumped Reservoir Parametric) divides a watershed into "Grouped Response

Units", while the semi-distributed hydrological model, HBV-96 subdivides a basin into sub-basins based on elevation and vegetation zones (Krysanova et al., 1999).

3.8 Comparison of lumped conceptual and distributed modelling approaches.

Traditionally hydrologic research has been done using lumped models. However recent technological advancements especially in computing and Geographical Information Systems (GIS), have made the use of distributed models easy with the improved access to spatial data. Distributed models are seen as a way to capture the various hydrologic conditions and processes is a spatial manneracross drainage areas and ultimately the response the hydrologic basin to climatic input (Shultz et al., 2007).

Given that, there is an ongoing debate in hydrological research on the use and application of different hydrological modelling approaches, it is imperative to test these approaches to evaluate which approach represents the system (catchment) we are interested in better. The sense of usingmore complex distributed models that aim to describe all physical processes taking place within a catchment, betweenland and atmosphericinteraction and feedback processes, in rainfall-runoff modelling is still a question best tackled by comparative studies. The general idea ofdistributed modelling is that it represents reality better than lumped model approachesas it takes into account spatial information and more importantly it uses physical laws like mass balance and energy equations to describe the hydrological processes(Te Linde et al.,2007).

However, while the use of complex models may look appealing in representing the rainfall-runoff process, the lack of adequate hydro-meteorological, soil and land cover data and the large spatial and temporal variability strongly hinders the use of distributed modelling approaches(Célleri et al., 2010).

Though distributed modelling approaches remain the most objective in answering to questions related to problems with the need for spatial representation, researchers in recent years have cast doubts on the misperception that model complexity is positively correlated with confidence in the results. This has been based on these reasons given by (Xu, 2002). One reason given is that hat the current representations in process-based models are often too crude to enable accurate application to predictive problems. Secondly the difficulties he states, relate to both the perception of model capabilities and the fundamental assumptions and algorithms used in the models. Additionally the scale of measurement for many parameters is often not compatible with their use in hydrologic models. The choice of models for particular catchments should generally be based on the availability of data, the project objective and the structure of the model (Anh et al., 2008; Xu, 2002).

The available approaches are still far from providing a satisfactory representation of rainfall-runoff transformation and that more complex modelling does not always lead to better results (Linde et al., 2007).As absolute objective methods of choosing the best model for a particular problem have not yet been developed, the choice remains as a part of the art of hydrological modelling(Xu, 2002). This shows that it is essential to try out the different models and modelling approaches to identify the best representation for the hydrological processes taking place in the catchment of interest to address the problems or challengesencountered in the specific area.

3.9 GIS and hydrological modelling

It is important to mention that developments in computer technology, remote sensing and geographical informationSystems (GIS) have provided an effective and less costly way to study hydrologic systems. In many applications, results from remote sensing and/or GIS analyses serve as input into hydrological models. GIS also serves as a way of displaying and analyzing outputs from hydrological models. Thus GIS serves as both a pre-processor and post-processor for hydrological models.

GIS has also contributed significantly by providing tools for effectiveand efficient storage and manipulation of spatially referenced information and othernon-spatial information. One of the usual applications of GIS is the use of adigital elevation model (DEM) for the accurate extraction of hydrologic catchment propertiessuch as flow accumulation and direction, elevation, slope, and the delineation of thecatchment boundaries(Githui, 2008).

3.10 Model data preparation

Data processing is the most important task in modelling. It is of great importance to ensure that models have the best possible data set available. This is to ensure that the modeled results are reliable and the calibration process speedy(Anh et al., 2008).

3.10.1 Homogeneity testing

Before analysis of rainfall data, it is required that the data be homogeneous and independent. The restriction of homogeneity assures that the observations are from the same population. One of the tests of homogeneity is based on the cumulative deviations from the mean:

$$S_k = \sum_{i=1}^{n}(X_i - \overline{X}) \quad k = 1, \dots, n \qquad \text{Equation 3.4}$$

Where; X_i are the records from the series X_1, X_2... X_n and $\bar{X}$is the mean. The initial value of S_k=0and last value S_k=n are equal to zero. When the values of $S_k$are plotted, i.e. the residual mass curve, changes in the mean are easily detected. For a record *Xi* above normal, the Sk=i increases, while for a record below normal, Sk=i decreases. For a homogenous record the residuals fluctuate around zero because there is no systematic pattern in the deviations of the records from their average value$\bar{X}$(Raes, 2006).

3.10.2 Filling of missing values

There are methods that can be applied to fill in missing data in rainfall time series data. These methods include Inverse Distance Weighting (IDW),Arithmetic Mean method, Normal Ratio method, Areal Precipitation Ratio (APR) method. The Arithmetic Mean method and the normal ratio method can both be used if the normal annual precipitations at surrounding gauges are within the range of 10% of the normal annual precipitation at station of interest (De Silva et al., 2007).Inverse distance weighted (IDW) interpolation is based on the assumption that the missing value at a given point can be approximated by a weighted average of observed values of surrounding points. The weights used for averaging are a decreasing function of the distance between the points. The common weighting function is the inverse of the distance squared, and the equation used by IDW to estimate a missing value (P_x) at a point is given by;

$$P_x = \frac{\sum_{i=1}^{n} \frac{1}{d_i{}^p} Z_i}{\sum_{i=1}^{n} \frac{1}{d_i{}^p}} \qquad \text{Equation 3.5}$$

Where;Z_i (i = 1, 2,. . .,n),d_i is the distance between the *i*th point $Z_i$and the point with a missing value, and *p* is the power (exponent) variable. The power variable dictates the significance of the surrounding points upon the interpolated value. A higher power leads to a lesser influence from distant points and a stronger influence from points that are closer to the point of interest. The number 2 is the most commonly used value for *p*(Ruelland et al.,2008).

3.10.3 Estimating areal rainfall

There are three main methods of extending point rainfall estimates to areal averages. These are station-averaged, Thiessen polygon and Isohyetal methods. The station averaged method is easy to apply, however it may not provide good estimates that reflect the actual spatial distribution of rainfall when rain gauges are not uniformly distributed throughout the watershed. The Isohyetal method on the other hand assigns weights on the basis of storm morphology, spatial distribution of the rain gauges, and orographic effects. The Thiessen polygon method which was applied in this study, assigns weights to the rain gauges based on the ratios of the area (polygon) influenced by a particular gauge to the total watershed area. Polygons are constructed about each gauge by constructing perpendicular bisectors between each pair of nearby gauges. The equation to obtain areal rainfall is thus;

$$\mathrm{P} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{a_i} \times \mathrm{p_i}}{\mathrm{A}} \qquad \text{Equation 3.6}$$

WhereN is the number of sub areas (polygons) coinciding with the number of gauges, a_i is the area of polygon i, A is the total area of the watershed andp_i is the precipitation value for the gauge located within the area (polygon)a_i.

3.11 MIKE 11-NAM

NAM is an abbreviation of the Danish "Nedbør-Afstrømnings-Model", meaning precipitation-runoff-model. This model was originally developed by the Department of Hydrodynamics and Water Resources at the Technical University of Denmark.It forms part of rainfall-runoff modules in MIKE 11 River modelling system.

The NAM model can be applied independently as done in this study or used to generate lateral inflows to a river network for other MIKE 11 modules. The NAM model is characterized as a deterministic, lumped, conceptual model with moderate input data requirements. This model has been found suitable to basins whose surface area ranges between 10 and 2000 km^2(Gautam, 2004; DHI, 2009;Anh et al., 2008).

3.11.1 Nam model inputs

The basic input requirements for the NAM model consist of:

1. Model parameters
2. Initial conditions
3. Meteorological data
4. Stream flow data for model calibration and validation

The basic meteorological data requirements are:

a) Rainfall
b) Potential evapotranspiration

In the cases of snow modelling there are additional meteorological data required.

Meteorological data requirements are;

a) Rainfall time series

In many cases applied to the NAM model, daily rainfall values in mm are required. The rainfall data are treated as accumulated daily totals. Generally the time resolution of the rainfall input depends on the objective of the study and on the time scale of the catchment response. Also acceptable is rainfall data with variable time increments as long as it is specified in the rainfall input.

b) Potential evapotranspiration

Potential evapotranspiration data in mm is also required.When daily time steps are used, monthly values of potential evapotranspirationare sufficient. The evapotranspiration data is treated as accumulatedtotals where the evapotranspiration associated with any particular time isthe evapotranspiration since the last entered value.

3.11.2 Model structure

The model structure is a set of linked mathematical equations that describe thebehavior of the land phase of the hydrological cycle in a simplified way. The hydrologic model represents various components of the rainfall-runoff process by continuously accounting for the water content in four different and mutually interrelated storages:

- snow storage,
- surface storage,
- root zone storage (subsurface)
- groundwater storage

These storage zones represent different physical elements of a catchment. In NAM, total flow is a sum of the overland flow, interflow and baseflow.

The concept of the linear reservoir is applied to route overflow and interflow through two linear reservoirs in series with their time constants while the baseflow is calculated as the outflow from a linear reservoir with baseflow time constant.

The NAM model can be used for simulating single events or for simulating continuous hydrological processes over a range of flows (El-Nasr et al., 2011; DHI, 2009). The NAM model structure is represented by Figure 3.3.

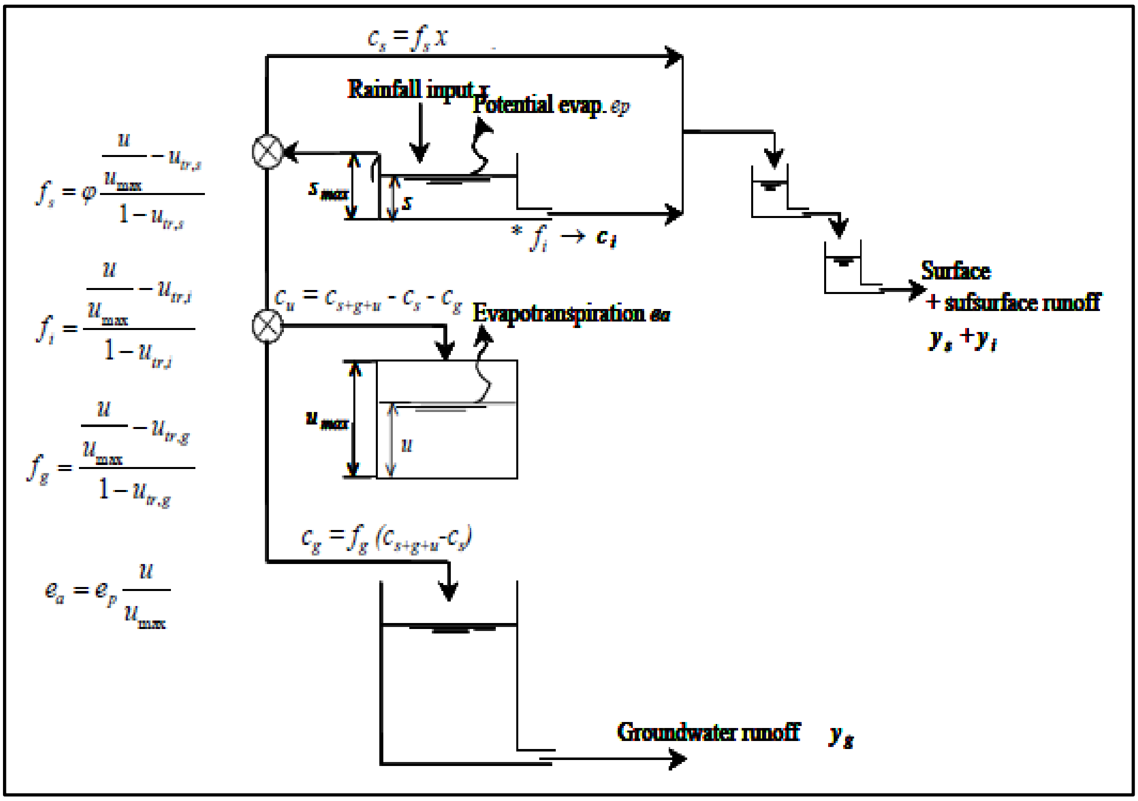


Figure 3.3 MIKE 11-NAM model structure(DHI, 2009;Willems et al., 2014)

i. Surface storage

This is the first storage is the NAM model structure. The NAM model may be considered to have two main storage reservoirs apart from the ground water storage(Willems et al.,2014). The surface storage has a maximum storage capacity S_{max} (represented as U_{max}in the model)and a second storage reservoir representing soil water storage with a maximum capacity L_{max}.

Spatially averaged rainfall (Areal rainfall) forms input that first fills up a surface storage reservoir. The maximum surface storage is represented by the parameterU_{max}.The surface storage represents water stored on surface depressions and the top or upper layer storage of the soil surface. Overflow occurs when$U \geq U_{max}$, meaning that the reservoir becomes full and overflows. The surface storage reservoir is then emptied by potential evapotranspiration e_p and by reservoir through flow c_i which is the contribution to interflow. (Willems et al., 2014) When the surface storage capacity is depleted, the reservoir overflow volume is separated into overland flow $c_s$and interflow$c_i$contributions.

The part of the overflow volume that contributes to quick or surface runoff is controlled by the fraction f_s. The rainfall fraction f_s, linearly depends on the relative soil water content$\frac{U}{U_{max}}$. A threshold value $U_{tr,\, s}$is provided and it should be taken into account that no surface runoff will occur when the relative soil water content has a value lower than a threshold value $U_{tr,\, s}$. The equation describing this relationship is equation 3.7:

$$\mathrm{f_s} = \frac{\frac{\mathrm{U}}{\mathrm{U_{max}}} - \mathrm{U_{tr,s}}}{1 - \mathrm{U_{tr,s}}}$$ Equation 3.7

The overland flow is modeled after the concept of the linear reservoir and using the linear reservoir equation. The surface runoff and interflow is routed through two linear reservoirs in series. The recession constants of these reservoirs (C_{k1} and C_{k2}) are the controlling parameters that affects the response time of surface runoff to rainfall. These recession constants combined with the recession constant of the surface runoff reservoir determine the response time of interflow to rainfall

ii. Root zone storage

The second storage is the root zone soil storage. The maximum water content is represented byL_{max}. When the soil is saturated the actual evapotranspiration equals the potential evapotranspiration i.e.

$$\mathrm{e_a} = \mathrm{e_P}.$$ Equation 3.8

The actual evapotranspiration is a fraction of the potential evapotranspiration and is linearly dependent on the relative soil water content. This can be represented as seen in equation 3.9:

$$e_a = e_p \times \frac{U}{U_{max}} \qquad \text{Equation 3.9}$$

After overland flow is extracted, the remaining rainfall fraction $(1 - f_s)$infiltrates into the soil. The sub surface soil storage reservoir is filled by infiltration into the soil storage. This reservoir is then emptied by actual evapotranspiration e_a, which is a fraction of e_p, depending on the relative soil saturation level as represented by equation 3.9.

Interflow or subsurface runoff, also contributes to the total flow and is controlled by the threshold value for interflow $U_{tr,\,i}$. This value sets the condition for interflow to occur by determining the fractionf_i . The inflow is then routed through the two overland flow routing reservoirs. $f_i$is linearly dependent on u and its value can be determined through the equation 3.10

$$f_i = \frac{\frac{U}{U_{max}} - U_{tr,i}}{1 - U_{tr,i}} \qquad \text{Equation 3.10}$$

iii. Groundwater storage

Part of the infiltration water contributes to the groundwater (c_g). This is controlled by the fraction (f_g).This fraction is linearly dependent on the relative soil water content. Here again a threshold value $U_{tr,g}$is used to control this movement. Only when the relative soil water content attains a value higher than a threshold value does percolation occur. The equation representing this relationship is given by equation 3.11.

$$f_g = \frac{\frac{U}{U_{max}} - U_{tr,g}}{1 - U_{tr,g}}$$ Equation 3.11

As was done with the surface and interflow contributions, the outflow of the groundwater reservoir is modeled by means of a linear reservoir, where the groundwater reservoir recession constant C_{KBF} determines the response time of groundwater to rainfall.

3.11.3 The NAM model parameters

The NAM model has nine main parameters that are adjusted during the calibration process. These parameters are discussed as summarized below from the R.R. Reference manual byDHI, (2009).

The surface and root zone parameters

1) U_{max}

This is the maximum water content in the surface storage. It depends on the type of soil, vegetation cover, and land use pattern. This storage represents interception storage (on vegetation), surface depression storages, and storage in the uppermost few centimeters of the ground. Typical values of $U_{max}$are in the range 10-35 mm. When the value of U_{max} is increased, then there is a corresponding increase in infiltration and, the overland flow is reduced.

2) L_{max}

This is the maximum water content in the lower root zone storage and can be physically defined as the maximum soil moisture storage in root zone. It usually depends on the type of soil. $L_{max}$and U_{max} are the main parameters controlling the water balance as actual evapotranspiration is highly dependent on the water content of the surface and root zone storages.The consequence of increasing $L_{max}$is that, there will be less overland flow, higher infiltration, and small base flow values. L_{max}ranges from 100 to 300mm.

3) Overland flow runoff coefficient (CQOF)

This is a dimensionless value parameter lying between 0 to 1 that determines to which extent excess rainfall runs off as overland flow and the magnitude of infiltration. It depends on the permeability of the soil and the average slope of the basin. For high permeable soils with flat terrain, the value is near to zero and for steep terrain with rocky soil; the value is near to one. This value is crucial for the overland flow and infiltration. The higher value of *CQOF* leads to higher overland flow and vice versa.

4) Time constant for interflow (CKIF)

It is the interflow time constant together with U_{max} that determines the interflow.*CKIF* is dependent on the quantity of surface water content U that is drained to interflow every hour. The increase in *CKIF* will lead to higher interflow, less infiltration, and small overland flow. The normal value of CKIF varies from 500 to 1000 hours.

5) Time constant for routing interflow and overland flow C_{K1} and C_{K2}

C_{K1} and C_{K2} are defined as routing time constant for overland flow and interflow in the basin. This parameter determines the shape of the hydrograph peaks. Generally, the value of C_{K1} and C_{K2} depend on the basin size, and how fast the response of runoff is to precipitation. Mostly, the value of C_{K1} and C_{K2} are the same.

6) Root zone threshold for overland flow (TOF)

This is the threshold value for overland flow as no overland flow is generated if the relative moisture content ($^{L}/_{L_{max}}$) in the lower root zone storage is below this value. This value is normally varies from 0 to 1. The consequence of high a *TOF* value is higher infiltration and a later start of overland flow during the wet season. Similarly, the root zone threshold value for interflow *TIF* and ground water recharge *TG* act as threshold values for generation of interflow and recharge respectively.

7) Root zone threshold value for interflow (TIF)

Similar to *TOF*, the *TIF* is a threshold value for interflow, and this value ranges from 0 to 1.This parameter dictates when interflow occurs, the higher the TIF, the higher will be the overland flow.

8) Root zone threshold value for ground water discharge (TG)

The threshold value for ground water flow is an important parameter for simulating the rise of the groundwater table in the beginning of a wet season. Higher value of *TG* indicates the later start of groundwater recharge.

9) Time constant for base flow CK_{BF}

The time constant for base flow, CK_{BF}in hours, is the parameter that determines the shape of the simulated hydrograph during the dry periods. Generally, the value of $CK_{BF}$is higher than C_{K1} and C_{K2}. The consequence of increasing $CK_{BF}$is longer duration of the base flow component with flatter recession curves in the dry seasons.

3.12 SWAT

The Soil and Water Assessment Tool (SWAT) is a continuous time model that operates on a daily time step at catchment scale. It is a physically based semi-distributed hydrological model developed by the US Department of Agriculture (U.S.D.A) in order to quantify the impact of land management practices on water quantity, sediment and water quality in large complex watersheds with varying soils, land use and management conditions over a long time durations (Nietsch et al., 2005; Arnold et al., 1998).

SWAT is an easily available public domain model,and has been in usewidelyin hydrological research. The main users have been hydrologists interested in watershed hydrology andrelated issues. Several studies have been conducted using SWAT to address several hydrological challenges by various researchers including; Githui(2008), Zakayo (2009), Setegn et al., (2008), Alansi et al., (2009) and Shrestha et al., (2010).

The SWAT model is capable of simulating a high level of spatial detail. This is accomplished through the division of a catchment into a large number of subcatchments and further into HRU's. During the implementation of SWAT, a single large watershed is divided into a number of sub watersheds. These sub watersheds are then further subdivided into smaller units referred to as Hydrologic Response Units (HRUs) that consist of homogeneous slope, land use, management, and soil physical characteristics (Gassman et al., 2003; Arnold et al., 1998).

3.12.1 SWAT model inputs

The basic SWAT model inputs include rainfall (mm), maximum and minimum temperature (^{0}C),solar radiation (MJ/m^2), wind speed (m/s), Relative Humidity, Land Cover, Soil and Elevation (DEM). The watershed is subdivided into subbasins that are related to one another spatially. This way the natural configuration of the natural channels and flow paths of the watershed are preserved.

SWAT model outputs include, flow generation, sediment yield, and non-point-source loadings from each HRU in a sub watershed which are then added up or combined. The summed up loadings are then routed to the watershed outlet, through channels, ponds, and reservoirs that may be defined within the watershed. The key component of SWAT that is of interest to this study is hydrology, although there are other components include plant growth, erosion, nutrient transport and transformation, pesticide transport and management practices.

3.12.2 SWAT model structure

Simulation of the hydrology of a watershed in SWAT can be separated into two major divisions. The first division is the land phase of the hydrology cycle and the second division is the routing phase of the hydrologic cycle. The land phase of the hydrologic cycle controls the amount of water, sediment, nutrient and pesticide loading to the main channel in each sub basin, while the routing phase can be defined as the movement of water, sediments, nutrients and bacteria, through the channel network of the watershed to the outlet (Nietsch et al., 2005).The soil water balance equation is the basis of accounting for soil water in the model:

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{deep} - Q_{gw}\right) \quad \text{Equation 3.12}$$

Where; SW_t is the final soil water content (mm), SW_0 is the initial soil water content on day *i* (mm), t is the time (days), R_{day} is the amount of precipitation on day *i* (mm), Q_{surf} is the amount of surface runoff on day *i* (mm), E_a is the amount of evapotranspiration on day *i* (mm), W_{deep} is the amount of water percolating into the deep aquifer on day *i* (mm), and Q_{gw} is the amount of return flow on day *i* (mm). Runoff is predicted separately for each HRU and routed to obtain the total runoff for the watershed (Figure 3.4).

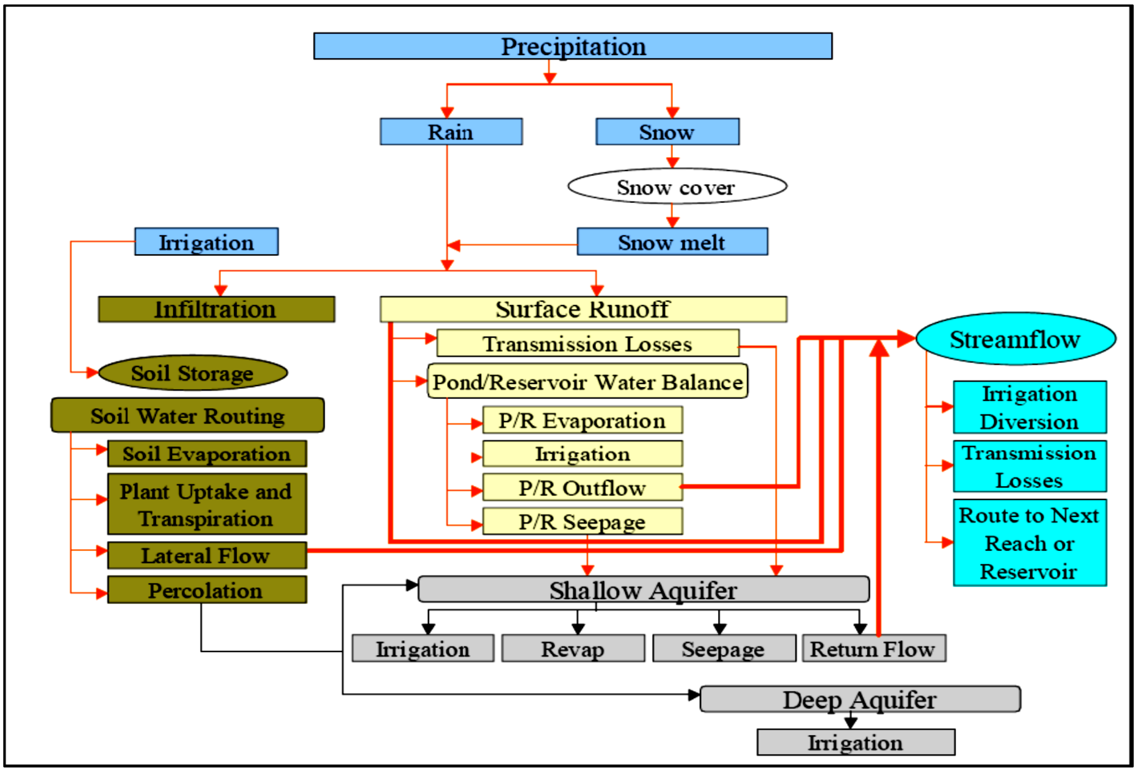


Figure 3.4 Pathways for water movement within SWAT (Neitsch et al., 2004)

SWAT is a semi distributed model in the sense that sub basins are spatially related to one another and will contain at least one HRU, a tributary channel and a main channel. The next subdivisions are the HRU’s. These are portions of a subbasin that have unique landuse/ land cover, slope and soil characteristics. It is important to note that they are not geographically or spatiallyreferenced (thus semi distributed).

Additionally, although individual HRUs may be scattered throughout a sub basin, their areas will be lumped together to form one HRU. These units are the ones that account for the spatial diversity in the basin characteristics. The assumption made is thatHRU’s in one sub basin do not interact with each other. The contributions from each HRU are calculated discretely and thensummed together to determine the total loadings from each subbasin.

Inputs used to model processes within the catchment in the SWAT model aredefined at three levels. These are the watershed level, the subbasin level and the HRU level. The method used to model each process is uniform for all HRUs in the catchment, while inputs likerainfall and temperature are set at the same valuefor all HRUs in the particular subbasin. At the HRUlevel, land use and soil inputs are set to unique values for each HRU in the catchment

In SWAT, surface runoff amounts can be estimated by using either the SCS curve number or the Green Ampt infiltration method. The SCS curve number method is an empirical model that estimates the amounts of runoff under varying land use and soil types. The SCS curve number (CN) is a function of the soil's permeability, land use and antecedent soil water conditions(Arnold et al., 1998).

$$Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)} \qquad \text{Equation 3.13}$$

Ia is approximated as *0.2S* therefore the accumulated excess runoff becomes

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \qquad \text{Equation 3.14}$$

Where, Q surf is the accumulated runoff or rainfall excess (mm), R_{day} is the rainfall depth for the day (mm),I_a-is the initial abstractions which includes surface storage, interception andinfiltration prior to runoff (mm), and S is the retention parameter (mm). The retention parameter varies spatially due to changes in soils, land use and slope. Temporally variations to this parameter also occur due to changes in soil water content. The retention parameter is represented by;

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \qquad \text{Equation 3.15}$$

Calculation for the peak flow rates is done using the modified rational formula which is;

$$q_{peak} = \frac{\alpha_{tc} \times Q_{surf} \times Area}{3.6 \times t_{conc}} \qquad \text{Equation 3.16}$$

Where, q_{peak} is the peak runoff rate (m^3/s), $\alpha_{tc}$is the fraction of daily rainfall that occurs during the time of concentration, Q_{surf} is the surface runoff (mm H2O), Area is the sub-basin area (km^2), t_{conc} is the time of concentration for the sub-basin (hr.) and3.6 is a unit conversion factor.

In this study SWAT was implemented through the ArcSWAT graphical userinterface. This program provides an interface withinthe ArcGIS geographic information systems (GIS) software to facilitate Data input and SWAT input file preparation. ArcSWAT uses the topographic data (DEM’s) to delineate the watershed into sub basins and extract other inputs like slope classes, stream geometry and elevations. More details can be found in the SWAT Theoretical Documentation byNeistch et al., (2011) andArnold et al., (1998).

3.12.3 SWAT model parameters

SWAT model parametersrelated to hydrology can be summarized by the Table 3.2.

Table 3.2 SWAT parameters for simulation of flow (Nossent, 2010)

Flow related parameters				
Parameter	Definition	Process	Level	Range
ALPHA_BF	Base flow recession factor (1/day)	Groundwater	HRU	0–1
BLAI	Maximum potential leaf area index for crops	PlantGrowth	HRU	0–12
CANMX	Maximum canopy index (mm)	Evapotranspiration	HRU	0–10
CH_K2	Hydraulic conductivity in main channel (mm/h)	Routing	sub basin	0–150

CH_N	Manningcoefficientforchannel	Routing	sub basin	0.001–0.1
CN2	SCS runoffcurvenumberformoistureconditionII	SurfaceRunoff	HRU	35–98
EPCO	Plantuptakecompensationfactor	Evapotranspiration	HRU	0.01–1
ESCO	Soilevaporationcompensationfactor	Evapotranspiration	HRU	0–1
GW_DELAY	Groundwaterdelay(days)	Groundwater	HRU	0–100
GWQMN	Thresholdstorageinshallowaquiferforreturnflow(mm)	Groundwater	HRU	0–5000
GW_REVAP	Groundwater‘revap’coefficient	Groundwater	HRU	0.02–0.2
RCHRG_DP	Groundwaterrechargetodeepaquifer(fraction)	Groundwater	HRU	0–1
REVAPMN	Thresholdstorageinshallowaquiferfor‘revap’(mm)	Groundwater	HRU	0–500
SLOPE	Averageslopesteepness(m/m)	LateralFlow	sub basin	
SLSUBBSN	Averageslopelength(m)	Concentration Time	sub basin	
SOL_ALB	Soilalbedo	Evapotranspiration	HRU	0–1
SOL_AWC	Availablewatercapacityofthesoillayer(mm)	Soil Water	HRU	0–0.3
SOL_K	Soilconductivity(mm/h)	Soil Water	HRU	0–15
SOL_Z	Depthfromthesoilsurfacetothebottomlayer (mm)	Soil Water	HRU	0–12
SURLAG	Surfacerunofflagcoefficient	Surface Runoff	sub basin	0.01–1

The parameters related to snowthat are not included in the calibrationare,TIMP- for Snow pack temperature lag factor , TLAPS- Temperature laps rate (°C/km) , SMFMN -Minimum melt rate for snow (mm/°C/day)SMFMX -Maximum melt rate for snow (mm/°C/day), SMTMP Snow melt base temperature (°C) and SFTMP- Snowfall temperature (°C).

For estimating potential evapotranspiration, the SWAT model uses three different methods for estimating PET and AET; namely, Hargreaves, Priestley-Taylor, and Penman-Monteith.

The SWAT model uses seven main databases. Five databases are used to store the required information about land use/ land cover, plant growth, tillage, fertilizer components and pesticide properties. Two databases, the user soil database and the user defined weather generator database (userwgn) have to be created for regions outside the United States of America (USA) to store custom soil characteristics and weather parameters. These databases must be created and edited to the required content before setting up the SWAT model. More detailed information can be found in the SWAT user manual 2005 and ArcSWAT interface for SWAT 2005 user's guide byWinchell et al., (2007).

3.13 Model uncertainties

3.13.1 Model input uncertainties

There are a lot of uncertainties associated with model input data due to the associated errors during their estimation, collection or representation. The estimation of point rainfall values is prone to error. Rainfall spatial and temporal variability isa basic reason for uncertainty in precipitation data. Other model inputs such as evapotranspiration also increase uncertainty in model predictions. Another source of uncertainty arises from the discrete time nature of the data, which provides no information about the variation within time steps which can affect parameter estimates(Pechlivanidis et al., 2011).

3.13.2 Model structure uncertainties

The model structure in hydrological models considers the hydrological processes through mathematical representation. This structure is however controlled by our understanding of the hydrological system, based on the information and the data available. It is thus common to ignore unobserved processes. This has the effect of introducing uncertainties to modelling results(Pechlivanidis et al.,2011).

3.13.3 Model parameter uncertainties

Model parameters in essence control the model output and it is essential to understand their effect during model calibration. Parameter uncertainty therefore cannot be ignored during model development due to the fact that it is still difficult to determine how representative a model parameter is (Quan, 2006). This is because most model parameters representing physical catchment characteristics or hydrological processes cannot fully capture the extent of spatial and temporal variation within a catchment and the hydrological system.

3.14 Model calibration and validation

3.14.1 Model calibration

The process of selecting suitable values of model parameters such that the models simulations are close compared to the observations is called model calibration. Two types of model parameters can be identified in most models. These are physical parameters which represent physical properties and can be measured, and process parameters that represent catchment characteristics and cannot be directly measured.There are also some physical parameters which are measurable in theory but difficult to measure in practice, such as the hydraulic conductivity and porosity. These parameters hence have to be calibrated.

Calibration is vital to the process of modelling, due to the fact that in reality it is impossible to measure all hydrological properties of a catchment. Model calibration generally aims to ensure that the model represents the hydrological processes while retaining a physically sensible meaning.During calibration it is important to identify a unique set of parameters. Failure to attain this leads to the problem of equifinality. This is a case where different model parameter sets yield equally “good” results.This will pose significant constraints to development and application of the model(Pechlivanidis et al., 2011).

There are two approaches to model calibration. This process can either be carried out manually, using a trial and error process of parameter adjustments, or by using computer based or automated approach or automatic procedures(Zakayo, 2009).In practice however a combination of the two is often applied.

3.14.1.1 Manual calibration

Manual calibration involves altering the values of a number of input parameters within their specified ranges and then running the model and analyzing or critically looking at the behavior of the model outputs with the aim of observing whether the said changes leads to the improvement in the fit between the simulated and the observed flows.

From other studies it has been observed that itis possible for an experienced hydrologist to obtain very good model parameters that are hydrologically sound by applying manual calibration. It is also noted that manual calibration is tedious, subjective, time-consuming, and easily excludes the effects of theinteraction between the modelparameters (Zakayo, 2009; Xu, 2002; Pechlivanidis et al., 2011).

It is generally difficult to determine the “best fit” or to determine a clear point to indicate the end of the calibration process; this has often led to different results being obtained by different modelers(Xu, 2002). Given the time consuming nature of manual calibration, the “heuristic”(based on one’s knowledge of the catchment hydrological and physical processes) approach however, makes the use of modelers' knowledge and experience and, therefore, can prove to be useful (Shrestha at al., 2010).

3.14.1.2 Automated calibration

The need to speed up the calibration process has partly motivated the development of computer-based methods for automatic calibration of hydrological models. This has vastly improved computational efficiency and has sped up the process of calibration (Pechlivanidis et al, 2011; Xu, 2002).

Automated calibration is carried out by using optimization algorithms. Optimization algorithms for calibration can be classified into two categories. These categories are the local search and theglobal search optimization objectives. Literature reports that local search procedures offer some limitations and therefore global search procedures have been developed(Zakayo, 2009).

With automated calibration the prediction error is first computed using an equation which is the objective function and is usually one ora combination of goodness of fit statistics. Then an automatic optimization procedure or a search algorithm is used to locate parameter values that optimize the value of the objective function.Depending on the objective function, the automated calibration procedures can be classified as single objective procedures and multiple objective procedures. Single objective function procedures usually defines an objective function with a goodness of fit measure such as Mean Squared-Errors (MSE) estimator, Nash and Sutcliffe Efficiency (NSE), or others, and tries to maximize or minimize this value depending on the case in order to obtain a better fit between predicted and observed time series of discharges. The concept of multi-objective optimization has evolved and has been applied to many models as many real-world problems involve multiple measures of performance, or objectives, which should be optimized simultaneously(Zakayo, 2009).

Despite automatic calibration being fast and less subjective it has major limitations depending on the assumptions made for the objective function and the existence of local minima which is closely related to the number of model parameters. Taking this into account, automated calibration should be used with caution(Shrestha et al.,2010).

A typical automatic parameter estimation procedure consists of four major elements: the selected objective function (or performance measure); the optimization algorithm; the termination criteria; and the calibration data. The purpose of automatic calibration is to find those values of the model parameters that optimize (minimize or maximize, as appropriate) the numerical value of the objective function.

3.14.2 Model validation

Model validation also called model verification is done after the model has been calibrated. The purpose of validation is to test if the model performs well on a portion of independent data, which was not used in calibration.

The aim of model verification is to check the model's robustness and its capability to describe the hydrological response of a catchment under a different set of data. This can also further detect any biases in the calibrated parameters(Pechlivanidis et al., 2011). It has been noted however that, the model's performance is usually better during the calibration period than the validation period. This phenomenon is known as "model divergence". In the event the degree of divergence is considered unacceptable, the model structure and the calibration is examined and revised.

3.15 Split sample tests

Split sample tests arefrequentlyused in hydrological model calibration and validation.The test is done by having one period ofobservations used in the calibration of the modelwhile another separate period is used to verify thatthe model predictions are satisfactory.Several tests have been proposed including different splitsampling tests, proxy catchment testing and proxy catchment split sample tests.

3.15.1 Split-Sample (SS)

This test can be applied when, testing river flow in a gauged basin with adequate time series of data that is sufficiently long. The available record is split in two equal portions, one for calibration, and theother for validation. Ordinarily, the record should be split 70% forcalibration, 30% for validation. The model is deemed acceptable if both calibration and validation results are similar and errors areminimal.

3.15.2 Types of Split-Sample tests

The other split sample tests include the Differential Split Sample (DSS) test, which is done when the model is to simulate flows in a gauged basin under conditions different from those corresponding to the available flow record (e.g. change in climate).Here two periods with the different climatic parameter of interest are selected from the available record (e.g. high and low mean precipitation). If the model is intended to simulate wet climate flow then it must be calibrated on dry record and validated with the wet record and vice versa.

Another test is the Proxy Basin (PB) test. This is a basic test for geographic transpose-ability to a separate basin. For an un-gauged basin C, two gauged basins A and B are selected within the same region. The model is calibrated on basin A, and validated on basin B. Minimal errors on both accounts then indicate that the model is considered sufficient and therefore the model parameters are transferable to basin C.

A Proxy Basin Differential Split-Sample (PB-DSS) on the other hand is applied where the model is meant to be both geographically, climatically or even in terms of land use,transferrable to a different basin. Two gauged basins, A and B with characteristics similar to those of C are identified with Wet and Dry periods for each basin selected i.e. A-wet, A-dry and B-wet, B-dry. To assess a wet climate in basin C, A-dry /B-wet and B-dry/A-wet need to be undertaken for calibration and validation respectively. The model is judged adequate if results from B-wet and A-wet are similar or satisfactory.

3.16 Model evaluation

3.16.1 Goodness of fit statistics and calibration plots

A good model calibration and validation process requires the use multiplestatistics with each covering a different aspects of the simulated and observed hydrographs so that the entire hydrograph is captured. This is important because the use of a single evaluation statistic can lead to over-emphasis or an exageration on the matching of one atribute of a hydrograph at the expense of otheraspects(Moriasi, et al., 2007; Arnold, et al., 2012).

There are several statistical error indices commonly used in model evaluation. These mainly include; Mean absolute error (MAE), Mean square error (MSE) and Root mean square error (RMSE). These indices are valuable because they indicate error in the units (or squared units) of the constituent of interest, which aids in analysis of the results. RMSE, MAE, and MSE values of 0 indicate a perfect fit and RMSE and MAE values less than half the standard deviation of the measured data may be considered low. A number of goodness of fit statistics are considered:

1. Percent bias (PBIAS)

Percent bias (PBIAS) measures the average tendency of the simulated data to be larger or smaller than their observed values. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation, while negative values indicate model overestimation. PBIAS is calculated as;

$$\mathrm{PBIAS} = \left[\frac{\sum_{i=1}^{n} Y_i^{obs} - Y_i^{sim} \times 100}{\sum_{i=1}^{n} Y_i^{obs}}\right] \quad \text{Equation 3.17}$$

Where; Y_i^{obs} are the observed values and Y_i^{sim} are the simulated values. PBIAS is the deviation of data being evaluated expressed as a percentage.

2. RMSE-observations standard deviation ratio (RSR):

RMSE is a commonly used error index. RSR standardizes RMSE using the observations standard deviation, and it combines both an error index and some additional information. RSR is calculated as the ratio of the RMSE and standard deviation of measured data as;

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\mathrm{STDEV_{obs}}} = \frac{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}\right]}{\left[\sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{obs\ mean}\right)^2}\right]} \quad \text{Equation 3.18}$$

Where; Y_i^{obs} are the observed values and Y_i^{sim} are the simulated values,$Y_i^{obs\ mean}$is the mean of observed data values, and *n*is the total number of observations.

3. Nash-Sutcliffe efficiency (NSE):

For the comparison of the evaluation of performance of the models and further to unify the presentation of the different models, the modeled results were evaluated based on the same statistical measures.The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance. NSE indicates how well the plot of observed versus simulated data fits the 1:1 line.It is a measure of how well the observed and simulated values match. NSE is given by;

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{obs\ mean}\right)^2}\right] \qquad \text{Equation 3.19}$$

Where; Y_i^{obs} is the i[th] observation value, Y_i^{sim} is the i[th] simulated value $Y_i^{obs\ mean}$ is the mean of observed data values, and *n* is the total number of observations.NSE values range between $-\infty$ and 1. Values between 0.0 and 1.0 are generally viewed as "acceptable" levels of performance, and values less than 0 indicates that the mean observed value is a better predictor than the simulated value, which suggests unacceptable performance. NSE values that are moving towards 1 indicate better model performances (Anh et al., 2008; Krause et al.,2005; Amir, et al., 2013; Moriasi, et al., 2007).

4. Coefficient of determination R^2

The coefficient of determination R^2 measures the proportion of variability in the observed stream flows that is accounted for by the model. The value for R^2 can range from 0 to 1, with higher values indicating a better model performance(Wang et al.,2010).

$$R^2 = \frac{\left(\left(Y_i^{obs} - \overline{Y}^{obs}\right) \times \left(Y_i^{sim} - \overline{Y}_i^{sim}\right)\right)^2}{\sum\left(Y_i^{obs} - \overline{Y}^{obs}\right)^2 \times \sum\left(Y_i^{sim} - \overline{Y}^{sim}\right)^2} \qquad \text{Equation 3.20}$$

5. Index of agreement (IA)

The index of agreement IAwas proposed to overcome the insensitivity of NSE's and R^2 to differences inthe observed and predicted means and variances. The index of agreement represents the ratio of the mean square error and the potential error and is represented as;

$$IA = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2}{\sum_{i=1}^{n}\left(\left|Y_i^{sim} - Y_i^{obs\ mean}\right| + \left|Y_i^{obs} - Y_i^{obs\ mean}\right|\right)^2} \qquad \text{Equation 3.21}$$

Where; $Y_i^{obs}$is the i[th] observation value, $Y_i^{sim}$is the i[th] simulated value $Y_i^{obs\ mean}$is the mean of observed data values. The range ofIA lies between 0 for no correlation and 1 indicating a perfect fit (Krause et al., 2005).

3.16.2 Graphical plots

In addition to the traditional goodness of fit statistics between simulated and observed discharges the properties of the flow time series are also analyzed using goodness-of-fit plots (Willems, 2005).Goodness-of-fit statistics, such as those discussed above are most widely used for evaluating model performance. They however have the disadvantage that they largely summarize the goodness-of-fit information only for a few numbers and values. It is thus better to complement these statistics with graphical goodness-of-fit plots. Generally, these plots compare the simulated and observed values, as used on the basis of the statistics in a graphical way, and provide the modeller with far more complete information about the goodness-of-fit. Model residuals or model errors typically increase with higher flow values. This means that the higher flow values receive more weights in evaluations based on the goodness of fit statistics due to the squared error terms in the equations. They are clearly oversensitive to peak values. To remedy this problem one can apply weighting coefficients to the squared terms or use transformations of the variable of interest, without the need to modify the equations.

There are different types of transformation that can be found in literature. These transformations include, non-parametric normal quantile transformations applied to transform the model residuals into a normal distribution, the square root transformation, the logarithmic or ln-transformation and the Box-Cox transformation byBox and Cox, (1964). The Box-Cox (BC) transformation is a very flexible onedepending on its parameter value and can cover a whole range of weak and strong transformations. The BC-transformation, when applied to a variable Q, is given by;

$$\mathrm{BC(Q)} = \frac{\mathrm{Q}^{\lambda}-1}{\lambda} \qquad \text{Equation 3.22}$$

Where the parameter λ needs to be calibrated in an attempt to reach homoscedasticity (or homogeneity of variance) in themodel residuals. The value of λ ranges from 0 to 1.For the best λ, the standard deviation is constant i.e. it is independent of the flow magnitudes.For runoff discharges the parameter λ usually falls around a value of 0.25 (Willems , 2005).

As a summary, graphical techniques including hydrographs and percent exceedance probability curves, and other plots provide visual model evaluation overviews. The first steps in model evaluation should typically involve the use of these techniques. Generally a visual agreement between observed and simulated data indicates adequate calibration and validation.The next step should be to calculate values of the goodness of fit statistics selected. With these values, model performance can be judged based on general performance ratings(Moriasi et al., 2007).The Table 3.3 indicates some performance ratings adopted in this study.

Table 3.3 Performance ratings(Moriasi et al., 2007)

Performance Rating	Goodness of fit statistics		
	RSR	NSE	PBIAS (%)
Verygood	0.00 ≤ RSR ≤0.50	NSE ≥ 0.75	PBIAS ≤ ± 10
Good	0.50 ≤ RSR ≤ 0.60	0.65 ≤ NSE ≤ 0.75	±10 ≤ PBIAS ≤ ±15
Satisfactory	0.60 ≤ RSR ≤ 0.70	0.50 ≤ NSE ≤ 0.65	±15 ≤ PBIAS ≤ ±25
Unsatisfactory	RSR≥0.70	NSE ≤ 0.50	PBIAS ≥ ±25

3.16.3 Extreme Value Analysis

Models can be evaluated based on how well they simulate both peak flows and low flows. Estimation of various probabilities of exceedance of high discharges with corresponding return periods is required for a wide range of engineering problems. Pickands, (1975) showed that, for a set of ordered and independent observations, the values above a sufficiently high threshold tends towards the Generalized Pareto Distribution (GPD). A more detailed review can be found inWillems, (2009). The Water Engineering Time Series PROcessing Tool (WETSPRO) software was used in this study for the comparative evaluation of the two models abilities to predict extreme flows.

3.17 Sensitivity analysis

Sensitivity analysis refers to the process of identifying a set of parameters that have the most effect in the model. It is a step carried out prior to model calibration. It speeds up the optimization process by concentrating on finding the optimum values for a limited number of parameters that govern the model outputs. The process of sensitivity analysis determines the rate of change in model output with respect to changes in model parameter inputs. Sensitivity analysis is required to investigate how the hydrological models outcomes are sensitive to its parameters. Some hydrological models are complex and over-parameterized; especially the semi-distributed or the fully distributed models, which have many model parameters that can pose a challenge during the calibration process.

Therefore, the sensitivity analysis is essentially important in most of hydrological models since it reduces the number of parameters that have to be calibrated byidentifying the parameters that the model output is sensitive to, thus helping to reduce a lot of the time required to calibrate a model.

Sensitivity analysis actually evaluates how parameters influence model predicted outputs.Sensitive parameters are then identified for use in model calibration. This procedure in short serves as a process for narrowing down the wide number ofparameters in a particular model to only the important ones so that a focused analysis is directed to a modelled problem. The ability of a watershed model tosufficiently predict constituent yields and stream flow for a specific application isevaluated through sensitivity analysis, model calibration, and model validation.

A number of sensitivity analysis techniques are available. These include differential analysis, Manual sampling, one-at-a-time (OAT) design, factorial design, the derivation of sensitivity and importance indices, subjective analysis, construction of scatter plots, the relative deviation methods, partial correlation coefficients, regression techniques, the Smirnov test statistic, the Cramer-vonMises test, Mann-Whitney test and others (Zakayo, 2009; Githui, 2008). In this study, a LH-OAT (Latin Hypercube-One At a Time) method that is integrated in the ArcSWAT interface was applied for the SWAT model.

3.17.1 Manual sampling

Manual sampling is an easy method applied to carry out sensitivity analysis. It starts by changing the parameter values and checking the effect of those changes on the model simulated output results (Saleh, 2008).The parameters which cause significant changes to the overall results with small variations in their values are then considered sensitive. This method is mainly suited for models that have few parameters like lumped models. Manual sampling sensitivity analysis was done for the NAM model.

3.17.2 Automated sensitivity analysis

Sensitivity analysis can become too complex when done manually in complex models with many parameters. There are thus automatic techniques developed to handle this challenge. These automated methods are embedded in hydrological model packages to carry out sensitivity analysis by running the model several times with different sets of parameter values then noting the change in model output. After this is done parameters are ranked according to their sensitivities. An example is the LH-OAT algorithm in SWAT.

As indicated in the SWAT "Sensitivity, auto-calibration, uncertainty and model evaluation in SWAT2005" manual (Griensven, 2008), the LH-OAT sensitivity analysis method combines both the robustness of the Latin Hypercube sampling which ensures that the full range of all selected parameters has been sampled with the precision of aone at a time (OAT) design. This ensures that the changes in the output in each model run can be clearly attributed to the changed parameters in a simulation run. This method requires several model runs to obtain the required parameter sensitivities. Form intervals in the LH method, and p parameters to be considered, a total of m*(p+1) runs are required (Griensven, 2008).

3.18 Water yield and water balance

The total volume of water that can be expected from a stream or river within a given period such as a water year is called the yield of the stream or the catchment basin.

Estimation of water yield and water balance in a river basin is critical to the sustainable management of water resources at watershed level in any countryand is an indispensable prerequisite in the sustainable management of water resources at watershed and basin levels(Adeniyi et al., 2014). A basin's yield calculated in water resources development studies can be done using; hydrograph method, runoff – rainfall correlation method, empirical equations, and watershed modelling. For this research two watershed models, the lumped MIKE 11-NAM and the semi-distributed SWAT model will be applied.

3.19 Lumped and Semi-Distributed Approaches

This study applied a lumped conceptual NAM hydrological model and a semi-distributed physically based SWAT model to the Sergoit catchment. As NAM is a lumped model it treats the catchment as a single unit. The represented model parameters are therefore, average values for the whole catchment. This means that most parameters in their final parameter estimation must be performed by calibration against time series of hydrological observations. This is done because the model parameters do not have a direct physical catchment meaning.

On the other hand the semi- distributed hydrological model structure applied in the SWAT model enables the spatial variations in catchment characteristics to be represented first by sub catchments and then by hydrologic response units which represent homogeneous units of similar soils, slope and land use. For each HRU several parameters and variables are extracted.

The use of process based, easily accessible, public domain modelling software like SWAT is an easy option for hydrologists while considering watershed modelling (Shrestha et al.,2010). This however has to be balanced with the data availability for the area of study and the skills required of the modeler to set up the model.

3.20 A review of comparative studies on hydrological models

There have been some research efforts in conducting hydrologic model comparison.
On face value it can be generally accepted that the distributed modelling approach represents reality and in more spatial detail better than the lumped model approach and more importantly it uses the physical laws of mass balance and energy equations to describe the hydrological processes, while the lumped approach uses averaged values and conceptual representations of the hydrologic processes over an entire basin.
Despite the ongoing debate, it is important to study the available modelling approaches applied to the specific catchment of interest and assess which modelling approach provides a more satisfactory representation of rainfall-runoff transformation in the particular area of interest and which model structure best captures the complex hydrological processes taking place in the catchment under study. Several comparative researches are discussed below.

3.20.1 NAM (DHI), FEH (UK) and TVM

Anh et al., (2008) evaluated the performance of three lumped conceptual rainfall-runoff models at catchment scale. The selected models were the NAM and FEH models which represented continuous modelling while the TVM model was an event based model. The selected catchment was the Bradford catchment in the UK and the models were applied on a seasonal basis i.e. summer and winter. The time steps for the models were the hourly and the quarter hourly time intervals. For the comparison of the evaluation of performance of the models and further to unify the presentation of the different models, the modeled results were evaluated based on the same statistical measures. These measures included the water balance error (*WR*), NSE proposed by Nash and Sutcliffe (1970), peak flows (quick flow) and low flows (slow flow) statistics including MSE, RMSE and the coefficient of determination (R^2). They concluded that the study showed that generally TVM model having an NSE of 0.79 and 0.54 performed better than the NAM model with an NSE of 0.53 and 0.45 during calibration and validation respectively. Additionally the hydrological models represented the catchment well and gave reasonable results in terms of accuracy. They however noted that, the selection of models for particular catchments should be based on data availability, project objective and model structure (Anh et al., 2008). For this study the NAM model was taken for its suitability for continuous modelling as recommended.

3.20.2 VIC and HBV

In a research by Linde et al., (2007) the hydrological models HBV (Hydrologiska Byråns Vattenbalansavdelning) and VIC (Variable Infiltration Capacity) models were compared for the Rhine basin by testing their performance based on observed runoff. HBV is a semi distributed lumped conceptual model while VIC is a distributed physically based model. In this paper it was argued that even for a well-documented river basin as the Rhine, the available approaches were still far from providing a satisfactory representation of rainfall-runoff transformation and that more complex modelling approaches do not always lead to better results. From the results on the research, the hydrological models HBV and VIC were compared for the Rhine basin by evaluating the model’s performances for simulating discharge. Overall, the semi-distributed lumped conceptual HBV model performed much better than the distributed physically based VIC model. Additionally, it concluded that deviations between the observed and simulated discharge in many cases resulted from errors or deviations in forcing data rather than from a structural problems in model definition (Linde et al., 2007)

3.20.3 MIKE 11-NAM and MIKE SHE

El-Nasr at al., (2011) compared two different methods for predicting rainfall-runoff. The models implemented in their study represented modelling approaches with a gradual increase in complexity, ranging from a lumped conceptual approach to a fully distributed physically based approach. The model that represented a lumped semi-empirical approach was the NAM-module of the MIKE 11 model, and the MIKE SHE model represented the fully distributed, physically-based deterministic catchment model. The two modelling approaches were applied to the Jeker River basin, in Belgium. The size of the catchment area is 465 km^2. The model performance was tested based on each model's ability to simulate peak flows(El-Nasr et al., 2011). A good analysis on the agreement between the model simulated and the observed river flow in the two split sample conditions of calibration and validation periods was conducted. The quantitative evaluation on the models performance by use of statistical performance indices including the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (CD), Modelling Efficiency (EF) and Goodness of Fit (R^2) statistics was carried out. Also the examination of the model's long-run prediction of the high peaks through extreme value analysis and using different performance criteria was utilized to perform the analysis on the river discharge at the basin outlet station.

The study results showed that the lumped conceptual NAM model (NSE of 0.74) behaved better than distributed physically based MIKE SHE model (NSE of 0.60) for the calibration period. In the validation period there was a marginal improvement in the

NAM results (NSE of 0.76) compared with a greater improvement in the MIKE SHE model output (NSE of 0.76). There was an inclination to underestimate flow values for MIKE SHE model. This was observed in the validation period .This trend however was observed in both calibration and validation periods in the NAM model.

It was observed that on the basis of an extreme value analysis of simulated values from both models, the MIKE SHE model performed much better than the NAM model. It was noted that for the NAM model there was increasing underestimation for larger peak values which indicated a poor performance for use in extrapolation purposes (El-Nasr et al., 2011).

3.20.4 SWAT, HSPF and DWSM

Borah and Bera, (2004) compared three watershed−scale hydrologic and nonpoint−source pollution models, all having the three major components which included hydrology, sediments, and chemical, that were selected based on a review of eleven models whichh included AGNPS, AnnAGNPS, ANSWERS, ANSWERS−Continuous, CASC2D, DWSM, HSPF, KINEROS, MIKE SHE, PRMS, and SWAT, presented in a companion article.The models selected were SWAT, a model for long−term continuous simulations in predominantly agricultural watersheds;HSPF, also model for long−term continuous simulations in mixed agricultural and urban watersheds; and DWSM, a rainfall event simulation model for agricultural and suburban watersheds. They reported that as supported in literature, the SWAT and HSPF models require a significant amount of data and empirical parameters for development and calibration. DWSM on the other hand has efficient physically (process) based simulation routines and thereforehas a small number of calibration parameters. SWAT and HSPF were found suitable for predicting yearly flow volumes,sediment, and nutrient loads. Monthly predictions were generally good, except for months having extreme storm events andhydrologic conditions(Borah and Bera, 2004). Daily simulations of extreme flow events were poorly represented. In their assessment, the DWSM model reasonably predicted distributed flow hydrographsand the concentrations or discharge graphs of sediment, nutrient, and pesticides at small time intervals resulting fromrainfall events. The finally concluded that the combined use of these complementary models and perhaps other models having different strengths was warranted to adequately address water quantity and quality problems and their solutions. Their research effort demonstrates the need for evaluation and assesement of hydrological models before their application in waterhed analysis.

CHAPTER 4: METHODOLOGY

4.1 Introduction

This chapter describes the methodology that was applied in this research for the two modelling approaches. The first and second schematic (Figure 4.1 and Figure 4.2) represents the methodology applied in the lumped modelling approach and the semi distributed approach respectively.

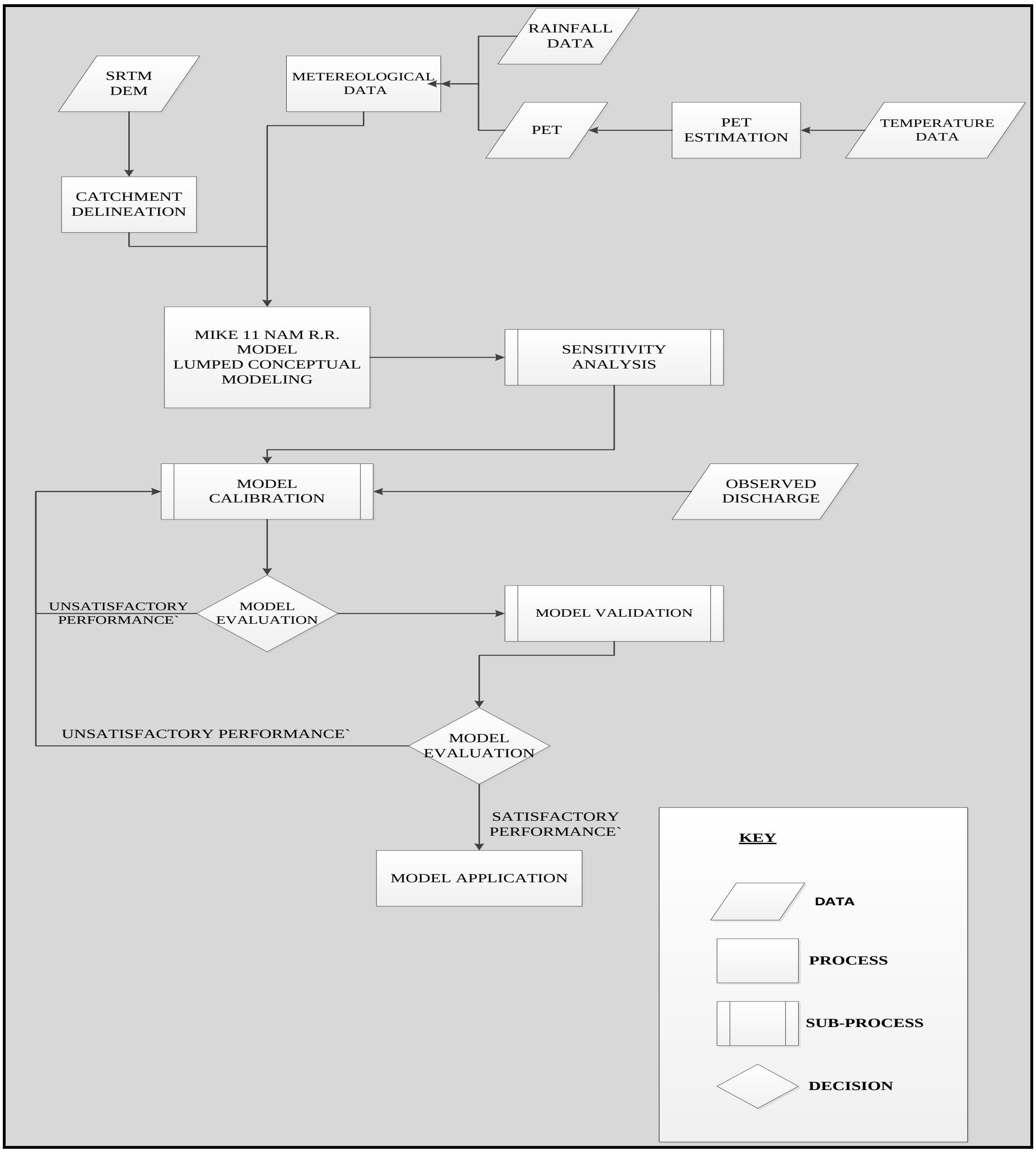


Figure 4.1 Lumped Conceptual Modelling Approach using MIKE 11-NAM.

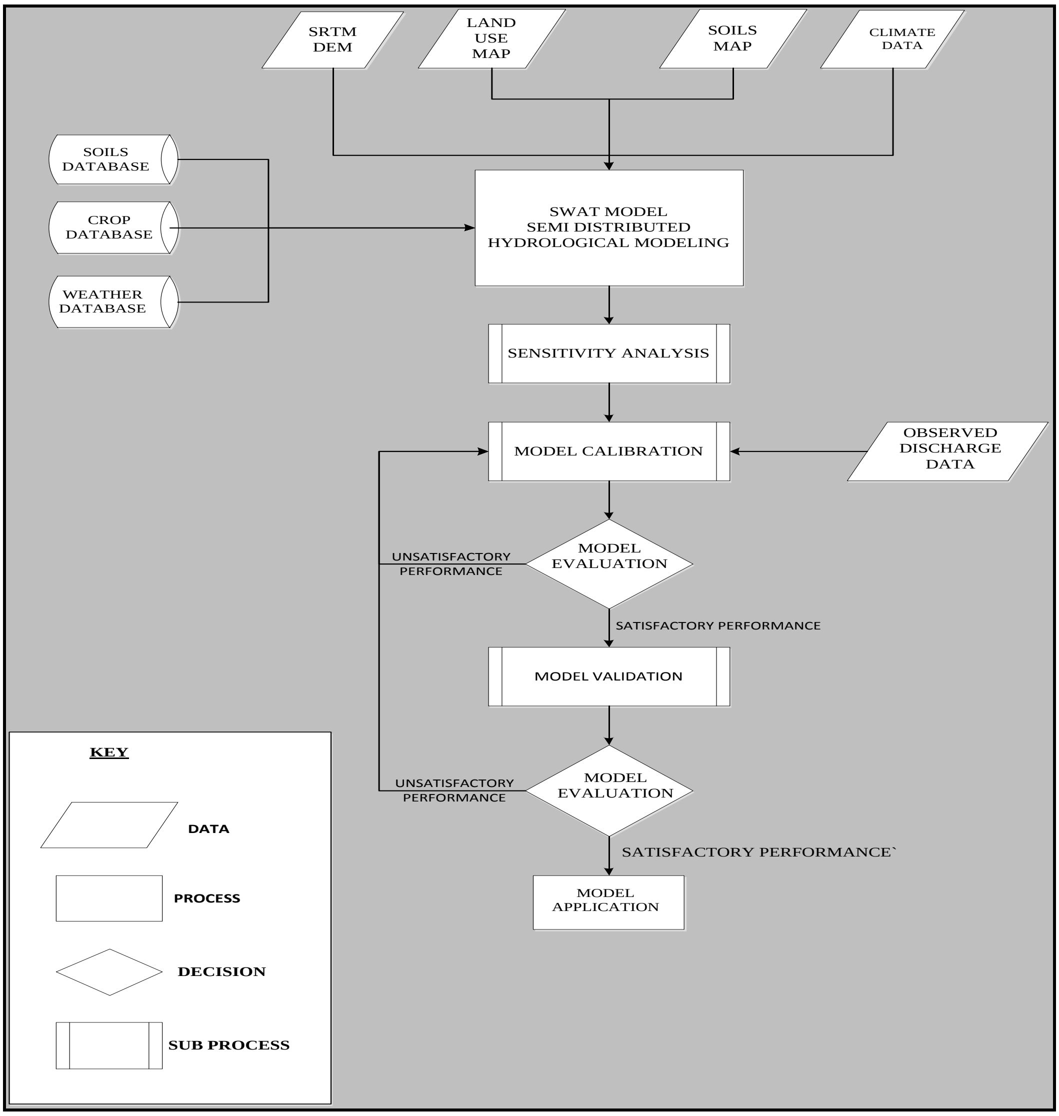


Figure 4.2 Semi Distributed physically based Modelling Approach using SWAT

Both modellingapproaches were set up andapplied to the Sergoit basin and then their performance evaluated using statistical and graphical methods.

4.2 Data pre-processing

4.2.1 DEM Processing and Catchment delineation

After the DEM data was identified and downloaded from the http://srtm.csi.cgiar.org web site, ArcGIS 9.3.1 with the Arc Hydro tools extension was used to process the DEM after creating a raster from the mosaic of the four raw DEM tiles and extracting the area of interest using a mask. This was followed by projecting the resulting DEM raster file into an appropriate projection coordinate system. Here UTM projection 36N was used. The process of catchment delineation involved the following processes using the Arc Hydro tools extension. The DEM was first filled for sinks to eliminate pits. This was followed by processing for flow direction for each cell using the D8 algorithm. This process determines the relative elevation of one cell with respect to other cells surrounding it. The next process was flow accumulation. Using the information from flow direction processing, it is then possible to establish how many cells drain to a particular cell. This results in a flow accumulation raster file which is used as an input to obtain the stream network file which is formed on the basis of a threshold value which represents the minimum number of drained cells that can form a stream. When a low threshold value is set, it implies that only a few cells are required to form a stream and this leads to a dense stream network and vice versa.

To determine the catchment boundaries, the coordinates of the river gauging station were used to create a point shape file having a similar projection coordinate system with the base DEM. This formed the pour point or outlet point to the watershed and was used together with the stream links file and the flow accumulation file generated earlier to delineate the catchment of interest in this case the Sergoit basin. The delineated basin boundaries were thereafter used for other spatial analysis using various tools in ArcGIS. These included the clipping and extraction of soil maps, land use/land cover maps and estimating the area of the Sergoit basin.

4.2.2 Rainfall data processing

From the initial time period an excel sheet enabled macro was utilized to check data completeness. The period was then reduced to between 1975 and 1984. This was done based on the collection periods of other data sets like the soils and the land use data. The results on the data completeness for this period are shown below (Table 4.1).

Table 4.1: Data completeness of selected period 1960-1990

Station ID	Station Name	% Complete
8935133	Eldoret Institute of Agriculture	86.64
8935181	Eldoret Met.Station	90.28
8935170	Turbo Forest Nursery	100.00
8935134	Kessup Forest Reserve,Elgeyo	85.35
8935164	Kaptagat Sabor Forest Station	85.09
8935131	Kipkwen D.O.'S Office,Chepkorio	37.50
8935108	Abai Farm,Cheplaskei	12.48
8935016	Soy Kipsomba Estate	81.27
8935157	Boimet Farm,Turbo	1.61
1CA02	River Sergoit RGS	80.10

According to the World meteorological organization (WMO) standards, it is not recommended to fill more than 10% of missing data(Githui, 2008). But due to the scarcity of data, a threshold of 20% was used because of the limited data.

From Table 3.2, above the stations that did not meet this threshold were eliminated from the study.Other climatic data required included; maximum and minimum temperature, wind speed, relative humidity, solar radiation and dew point temperature. Eldoret Institute of Agriculture (station ID 8935133) is the only station that is near the catchment under study that has temperature, wind speed and relative humidity data recorded. Therefore solar radiation and dewpoint temperature data required was sourced from the National Oceanic and Atmospheric Administration (NOAA) website (NOAA, 2014). These data sets were necessary to build a user weather database for the inbuilt SWAT weather generator.

The rainfall data used to represent rainfall in the Sergoit basin are from the rainfall stations represented in the map below (Figure 4.3).

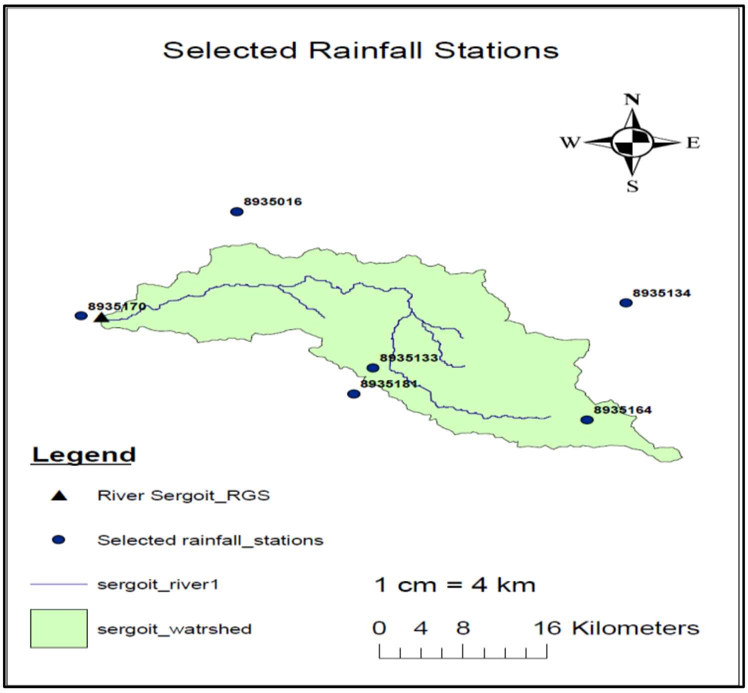


Figure 4.3: Selected Rainfall stations and the Sergoit RGS.

For the selected stations and period of study the missing values were filled using Inverse Distance Weighting (IDW) discussed in section 3.10.2.

4.2.3 Estimation of aerial rainfall

The Thiessen polygon method as discussed in section 3.10.3 was used in this study to convert daily point rainfall values for the selected stations into daily areal rainfall values for input into the MIKE 11-NAM model. The map (Figure 4.4) represents the areas of influence for each rainfall station within the Sergoit basin. The Thiessen weights for each station were calculated (Appendix B).

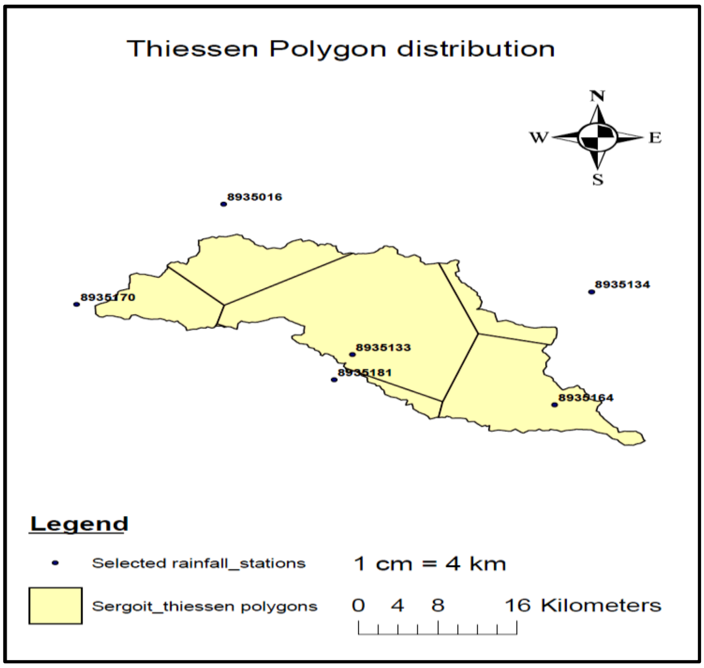


Figure 4.4 Thiessen Polygons covering Sergoit catchment

4.2.4 Potential Evapotranspiration

Temperature data from Eldoret Institute of Agriculture (station ID: 8935133) and Eldoret Meteorological Station (Station ID: 8935181) were used in the estimation of potential evapotranspiration (PET) using the Hargreaves-Samani (1985) Method(Lu et al.,2005) given by;

$$\lambda \mathbf{PET} = \mathbf{0.0023} \times \mathbf{R_a} \times \mathbf{TD^{0.5}} \times (\mathbf{T} + \mathbf{17.8})$$

Equation 4.1

Where PET is the daily PET (mm/day); λ is the latent heat of vaporization (MJ/kg); T is the daily mean air temperature (°C); Ra is the extraterrestrial solar radiation (MJ/m^2/day; and TD is the daily difference between the maximum and minimum air temperature (°C). The Hargreaves method was used as it requires only tepmerature data to estimate PET.Unlike rainfall data, the evaporation data can be assumed to be the same for the entire watershed (Willems et al., 2014).

4.2.5 Sub flow filtering

This exercise was done to get an idea of the main hydrologic components that contribute to the runoff process.Sub-flow filtering was done iteratively and with a stepwise approach using the processing tool WetsPRO.

4.3 Mike11 NAM model setup

As an initial step the data was split into two sets. One set covered the three year calibration period from January 1975 to December 1977 and the three years validation period from January 1982 to December 1984. Inorder to setup a MIKE 11-NAM model, four files input prepared. The first file was a time series file. This file contained the input rainfall, potential evapotranspiration and observed discharge time series data for the calibration period January 1975 to December 1977 and the validation period between January 1982 and December 1984. The next file was a rainfall runoff parameter file that contained the NAM model parameters and within it was the location of the time series file as input. This file specified the catchment area and the model that was applied (NAM) and this was where the NAM parameters were adjusted during the calibration process(Figure 4.5).

The simulation file wasthe third and last file created. In this file Mike 11 module of interest in this case the rainfall runoff module was selected. The main input to thisfile is rainfall runoff parameters file. Also this was where the results file was specified, the simulation period (1975-1977 for calibration)and the daily time stepselected.

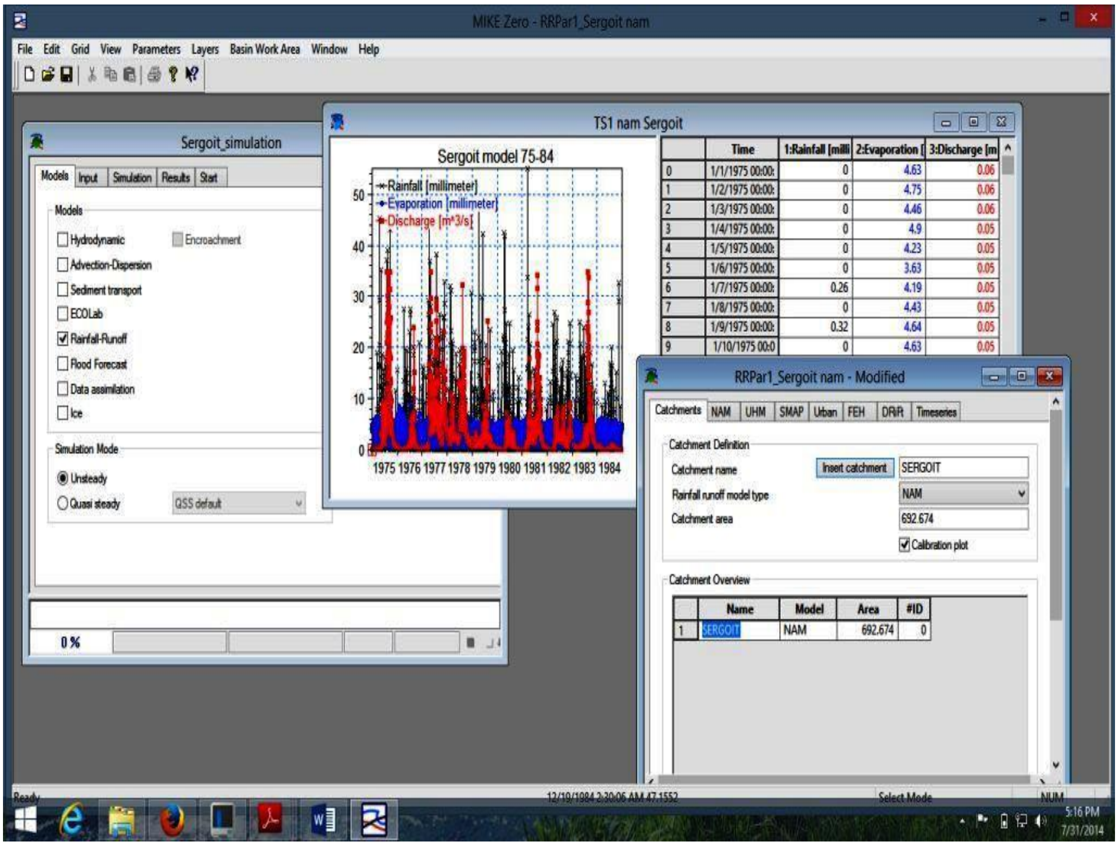


Figure 4.5. MIKE 11-NAM model Screen Shot

After this set up the model was run and the results viewed using Mike View for visual comparison with the observed flows. From here the simulated values were transferred to an excel workbook to calculate the goodness of fit statistics when compared with observed flows as discussed in section 3.16.

4.3.1 Model sensitivity analysis and model calibration

Before calibration the model parameters were manually changed as discussed in section 3.17.1. to evaluate each model parameter's sensitivity. This was done by varying each of the model parameters within the parameter limits and observing the change in the objective function. The objective function in this case is the NSE. The NAM model was then calibrated by first keeping the threshold parameters TOF, TIF, and TG at 0 while varying the timing constants CKIF, CK_{BF}, the storage parameters U_{max},L_{max} and the runoff coefficient CQOF. After achieving a visually reasonable fit between the observed and simulated flows the threshold parameters were then varied and used in this way to fine tune the calibration. Automatic calibration was also done along with the manual calibration. This process was done iteratively while observing the goodness of fit statistics and graphical plots as discussed in section 3.16.

4.3.2 NAM Model validation

After calibration and achieving a good performance rating (depicted in Table 3.3), the model was then validated using an independent period from 1982 to 1984 while using the same model parameters attained during the calibration period.The simulated results were then compared with the observed discharge values from the same validation time period and evaluated based on the same goodness of fit statistics used earlier for comparison. The WetsPRO tool was also used to check on the performance of the model using graphical plots.

4.4 SWAT model set up

4.4.1 SWAT model user database set up

SWAT requires user databases to be created first for SWAT applications outside the United States. One database is the “usersoil” database that requires the soil types of the modeled area and accompanying attributes like, the hydraulic soil group, the number of soil layers and their thicknesses, bulk density, hydraulic conductivity, sand, silt and clay percentages (by weight)among others.

The other database needed before simulation was the weather generator database “userwgn”. The SWAT model using this database has an ability to generate missing weather data. The statistical data required was generated based on weather data from the Eldoret Meteorological Station. The data included rainfall, wind speed, minimum and maximum temperature, dew-point temperature, relative humidity and solar radiation data. The data was processed for the required statistical parameters using a macro enabled excel worksheet that was used to obtain parameters listed below:

- average daily maximum and minimum temperatures,
- standard deviation of both maximum and minimum temperatures-
- average total monthly rainfall (pcpmm)
- standard deviation of daily precipitation of each month (pcpstd)
- Skew coefficient of daily precipitation in each month (pcpskw)
- The probability of a wet day following a dry one (pr_w(1))
- The probability of a wet day following a wet day (pr_w(2))
- Average number of days of precipitation in a month (pcpd)
- Average daily wind speed in a month(windav)
- Average daily dew point temperature for each month (dewpt)
- Average daily solar radiation in a month (solarav)

After this process the SWAT 2009 database was updated with these parameters representing the local weather to make the user defined databases.SWAT data inputs are requiredin specific file types as either as database (.dbf) files or ascii text (.txt)files. The numbers within the files also need to be in a specified format. These data input formats are presented in the manual ArcSwat Interface for SWAT 2005(Winchell et al., 2007).

4.4.2 SWATmodel set up

The SWAT model requires many input files. In order to generate these files the ArcSWAT interface was used to extract information from geographically referenced maps in the ArcGIS 9.3.1 environment. The process of setting up the SWAT model included defining a project folder, loading the DEM, rainfall, temperature, soil and land use data(described in section 2.3.4 to 2.3.6) through the ArcSWAT interface. The interface is used to generate the stream network and delineate the catchment boundary from the DEM and further subdivide the catchmentinto subbasins. The land cover and soil layers were used to generate HRUs. Theclimatic data was also integrated spatially to assign these data as the main drivers ofthe model to the various subbasins.

The first step was to load the digital elevation model (DEM) that was projected to the UTM zone 36N projection system. A mask covering the Sergoit catchment was used to focus on the watershed area. After this DEMprocessing which includes filling sinks, slope generation, flow direction and flow accumulation was done.The stream network was generated after assigning a threshold area that determined the number of cells required to initiate a stream. Lower threshold values lead to denser streamnetworks and vice versa. In order to delineate the Sergoit catchment the location coordinates of the Sergoit River RGS point was added to the map. Once the sub basins were delineated the sub basin parameters (longest flow path, basin centroid and slope) were calculated. This resulted in 9 subbasins are shown in Figure 4.6.

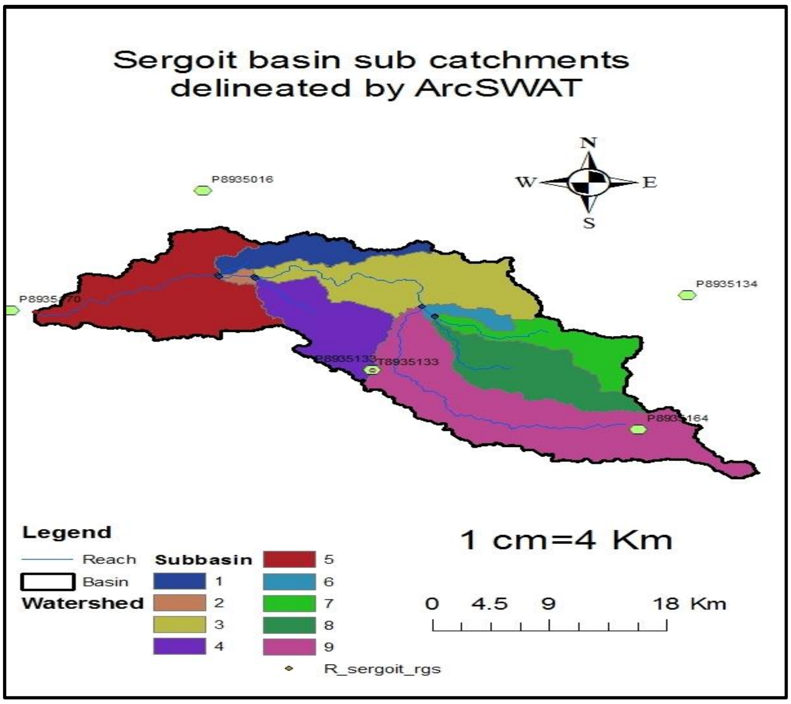


Figure 4.6 SWAT generated sub basins

4.4.3 Land use and soil type definitions

This was followed by land use, soils and slope definition. The landuse and soil maps were first loaded then followed by a lookup table for each map that wasusedto relate the default map classification with the SWAT crop database classification. After the land use and soil mapswereadded and clipped to the basin size and coverage, they werereclassified, andthen overlaid. This resulted in the catchments landuse and soil definitions as shown in Figures 4.7 and 4.8.

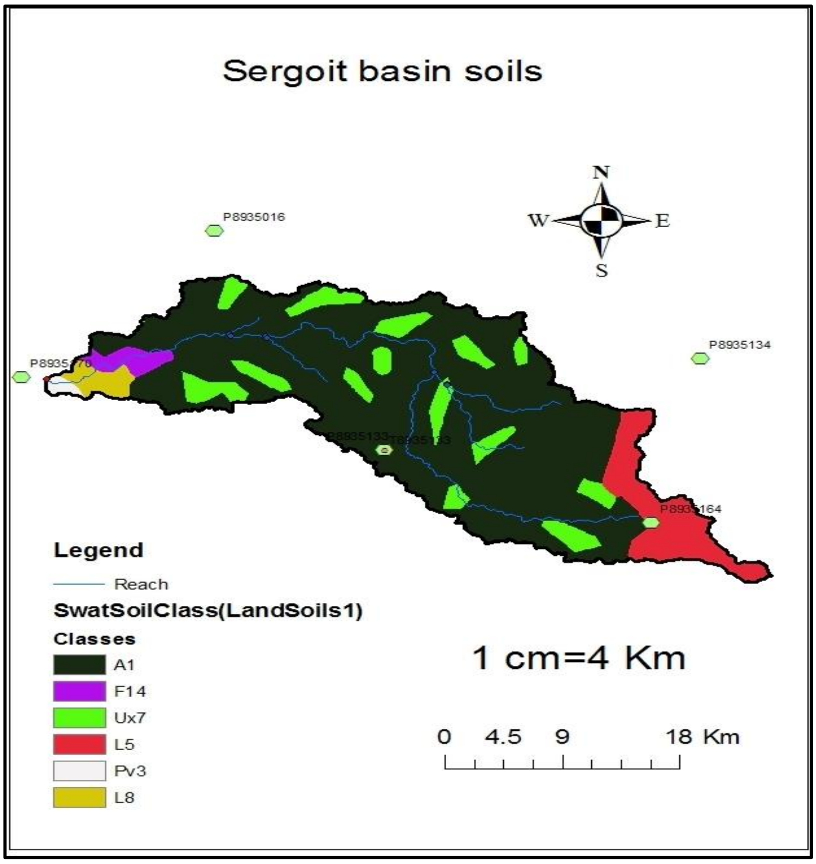


Figure 4.7 Soils class definition.

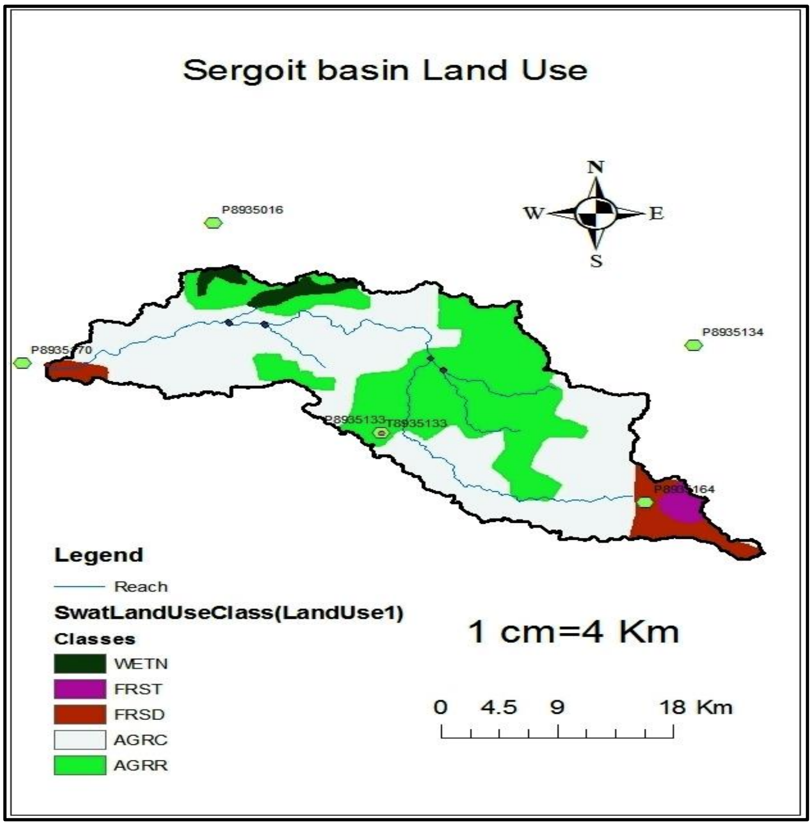


Figure 4.8 Land use class definition.

4.4.4 Definition of HRU’s

The definition of HRU’s was achieved by defining threshold percentage areas below which the land use and soil types would be discarded. Here the landuse threshold of 5%, a soils threshold of 5% and a slope threshold of 5% was selected. These values ensured that most land use and soil types in the basin were represented for a fully semi distributed model. Based on this criteria 78 HRUs were created (Figure 4.8). Table 4.2 shows the land use, soils and slope distributions.

Table 4.2 Land Use, Soils and Slope distribution

Land use / Soils / Slope definitions		Area [Km^2]	% Area
LANDUSE:	Wetlands-Non-Forested	11.370	1.64
	Forest-Mixed	10.498	1.52

	Forest-Deciduous	36.177	5.23
	Agricultural Land-Close-grown	396.094	57.29
	Agricultural Land-Row Crops	237.186	34.31
SOILS:	A1	529.824	76.64
	Ux7	70.785	10.24
	L8	14.091	2.04
	Pv3	3.964	0.57
	F14	13.203	1.91
	L5	59.459	8.6
SLOPE:	0-4	553.084	80
	0-6	63.338	9.16
	6-9999	74.903	10.83

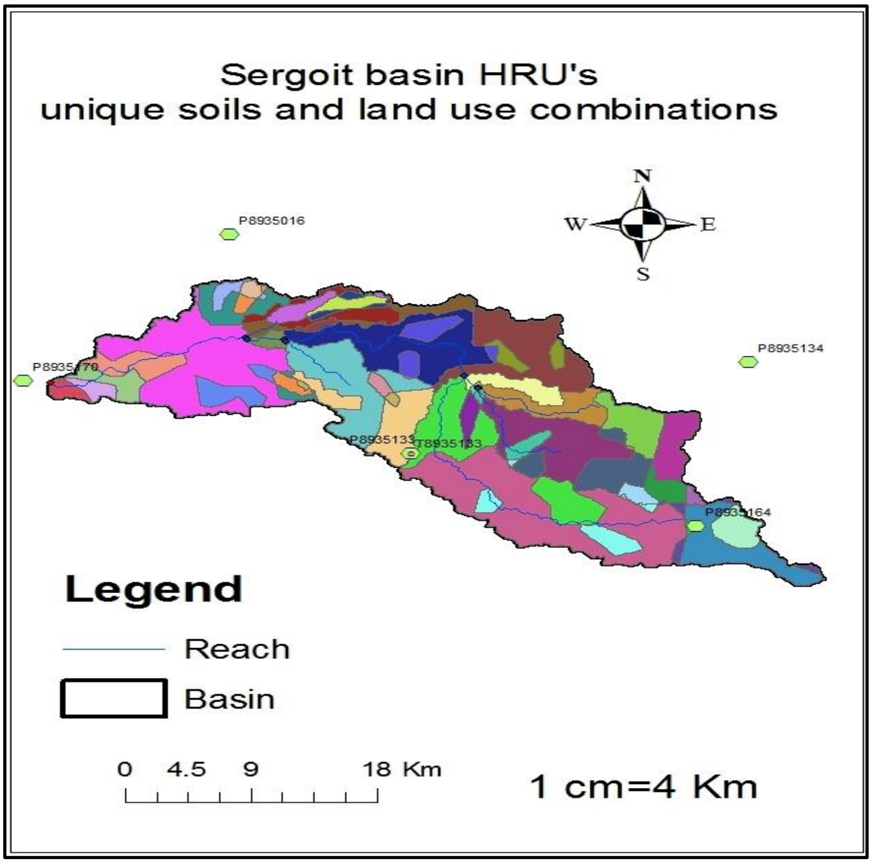


Figure 4.9 SWAT HRU's

4.4.5 Weather data definition

Before loading the climatic data the user weather generator station from the SWAT user weather generator database (created in section 4.4.1) must be selected. Rainfall and temperaturedata was then loaded through the ArcSWAT interface.Here the different weather station data sets were saved separately as text files with an accompanying batch file which contains the name, location and elevation of each station (Figure 4.10). These stations are assigned to the subbasins in the watershed based on how close a station is to the sub basin. The last stage in the model set up is the writing of all the SWAT input files and executing the model run after selecting the calibration period from 1975 to 1979 with 1975 as the warm up period.

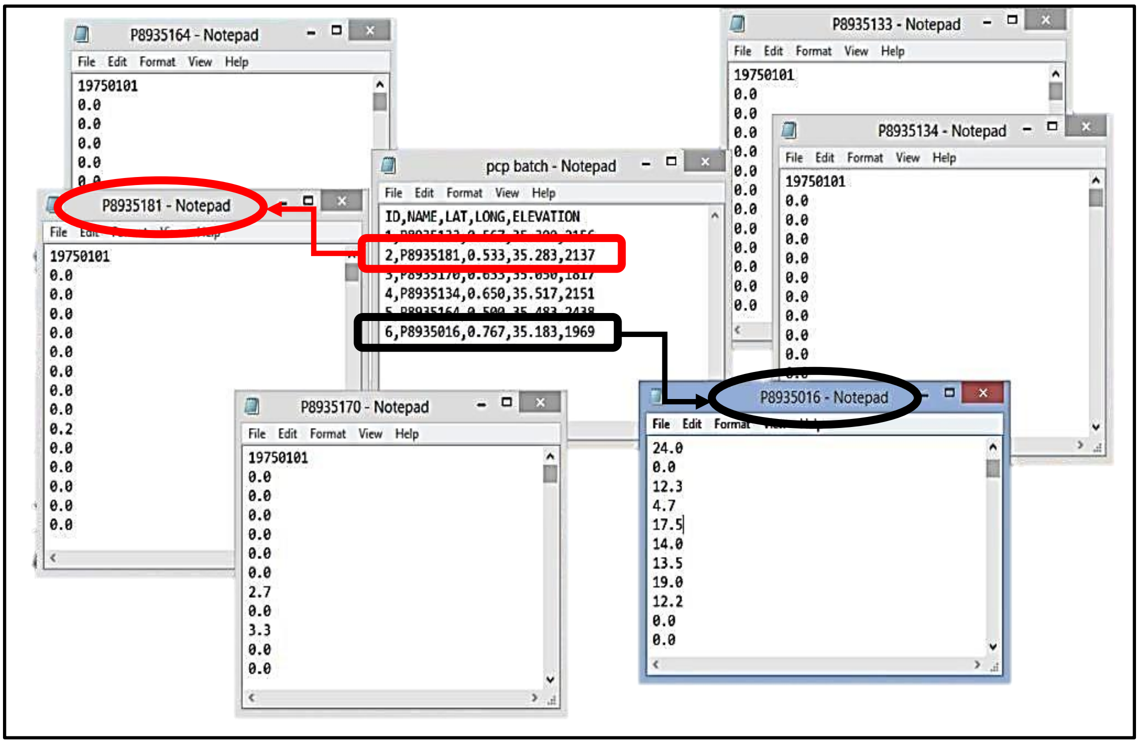


Figure 4.10 Rainfall input files (text files)

4.4.6 SWAT model calibration and sensitivity analysis

The SWAT model was calibrated using 1975 to 1979 data. This is because the SWAT model requires significantly more data and empirical parameters for development and calibration.For ideal calibration, awarm up period of one year plus 3 to 5 years of data that includes average, wet, and dry years, is suggested by Moriasi et al., (2007). Model climatic inputs were based on data from six rainfall stations and one temperature station in and around the study area for this period. Prior to model calibration an automated sensitivity analysis was carried out prior to the calibration exercise. This was done by use of the LH-OAT method that combines the 'One-factor-At-a Time' (OAT) design and the Latin Hypercube (LH) sampling by taking the LH samples as initial points for a OAT design. (Section 3.17.2). Based on the ranks assigned to the parameters with respect to their sensitivity, the 10 most sensitive parameters were selected and used for automatic calibration. Automatic calibration was done using the parameter solution method (Parasol) that uses the shuffled complex evolution (SCE-UA) algorithm (Griensven, 2008). This was executed in the model by selecting the "Auto-calibration and Uncertainty" option and selecting the simulation target for automatic calibration. The observed discharge for the calibration period was loaded then the sensitive parameters and their ranges within which they'll be optimized selected. Here users have the ability to select a method of updating or changing the parameter values during automatic calibration. Parameters can be modified by replacement or by addition for an absolute change or by a multiplication for a relative change.

A relative change means that the parameters, or several distributed parameters simultaneously, are changed by a certain percentage. However, a parameter is never allowed to go beyond the predefined parameter ranges. The next step was to set the number of runs which was mainly set between 3,000 to 10,000 model runs and took some hours to execute. The general process of SWAT calibration was conducted by running the sensitivity analysis first, then selecting the sensitive parameters and finally running automatic calibration. This was repeated several times.

4.4.7 SWAT Model validation

Similar to the NAM model, a good enough performance rating was deemed to have been reached after which the model was validated using an independent period. This period was from 1981 to 1984. Here also a warm up period was set as one year (1981), while using the same model parameters attained during the calibration period.The simulated results were then compared with the observed discharge values from the same validation time period and evaluated based on the same goodness of fit statistics and graphical analysis using the WetsPRO tool.

4.5 Model application

After obtaining well calibrated models the next step was to apply the model to generate a time series of synthetic discharges that would be used to determine the catchment yield based on the more recent weather inputs. To this end the available rainfall and temperature data was acquired and processed for the period 2005 to 2009. The same methodology for data preparation and input for both models was followed and the generated discharges at the basin outlet processed to estimate the basin yield using the model output results. For the NAM and SWAT models the basin water yield was estimated by equation 4.2 and 4.3 respectively.

$$\text{Water Yield} = (\text{OF} + \text{IF} + \text{BF}) \qquad \text{Equation 4.2}$$

Where, OF -is overland flow (mm), IF- is interflow (mm) and BF -is base flow (mm)

$$\text{WYLD} = \text{SURQ} + \text{LATQ} + \text{GWQ} - \text{TLOSS} \qquad \text{Equation 4.3}$$

Where, WYLD is the amount of water yield (mm), SURQ is the surface runoff (mm), LATQ is the lateral flow contribution to stream flow (mm), GWQ is the groundwater contribution to stream flow (mm) and TLOSS is the transmission losses (mm) from tributary channels in the HRU via transmission through the stream bed (Nietsch et al., 2005; Adeniyi et al., 2014). These values were further averaged annually and multiplied by the Sergoit catchment area.

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Introduction

This chapter presents the various results obtained data preprocessing and from both models during calibration validation, evaluation and model application. This section presents both goodness of fit statistics and graphical evaluation techniques of the models simulations for these periods.

5.2 Data preprocessing

5.2.1 Homogeneity Testing

The rainfall data from the selected rainfall stations was tested for homogeneity for the study period.The results indicate that the data was found to be homogeneous and from the same population. (Appendix C) A sample homogeneity plot is shown in Figure 5.1.

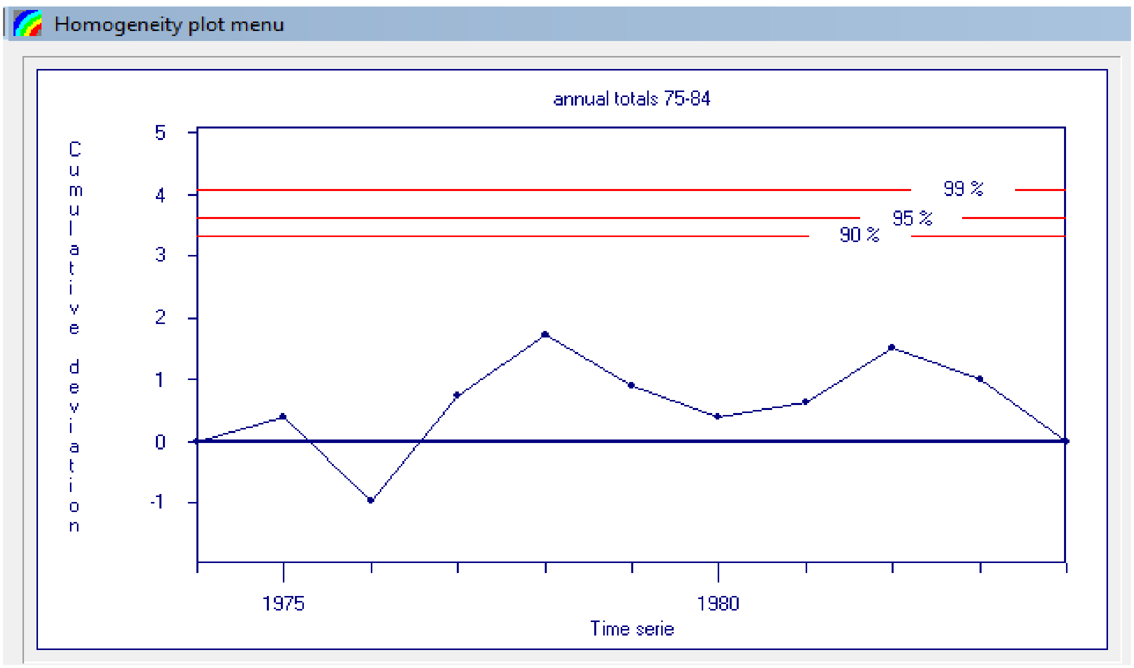


Figure 5.1: Sample Homogeneity plot for station 8935170

5.2.2 Sub flow filtering

The plot of the sub flows is shown in the Figure 5.2. The Quick flow components were found to be about 68% of total flows. With a base flow recession constant of 18 days $^{-1}$. This demonstrates that the dominat hydrologic process is quick surface runoff.

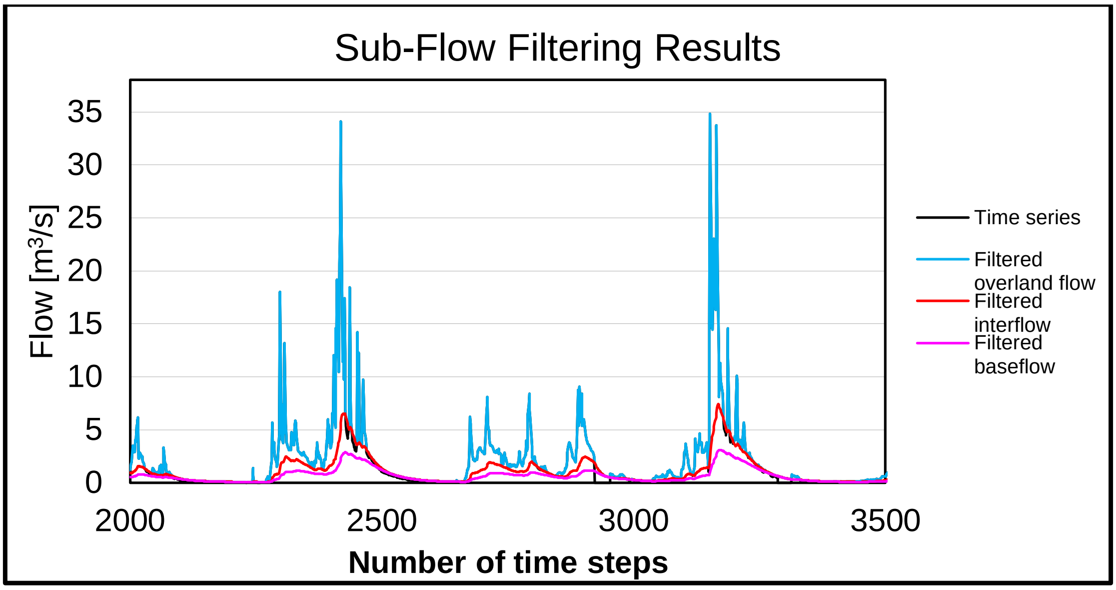


Figure 5.2: Sub Flow Filter Plots

5.3 MIKE 11-NAM model Results

The MIKE 11-NAM model was set up and calibrated using 1975 to 1977 data. The data inputs for this period included River discharge, spatially averaged rainfall or areal rainfall. Potential Evapotranspiration (PET) was estimated using the Hargreaves-Samani(1985) Method given by equation 4.1 from temperature data for the same period.

5.3.1 NAM sensitivity analysis results

The sensitivity analysis of the MIKE11 NAM model was done on all the nine model parameters. This was done by running the model after changing each model parameter over its allowable range. To identify the most sensitive model parameters,one parameterwas changed at a time while the others were heldconstant. This was done while noting the changes in the objective functions. Two objective functions, R^2 and Water Balance Error (WB ERR) were selected to monitor parameter sensitivity. The parameters were first set to their lowest value within the allowable range then a 20% incremental change added until the upper limit was reached.

The incremental 20% change in parameter value was chosen as it has a sufficient resolution to highlight changes in sensitivity with respect to the onjective function. For each simulated run, R^2 and Water Balance Error (WB ERR) was determined from the model output. The results were analysed by plotting R^2 and Water Balance Error (WB ERR) against the respective model parameters (Figure 5.3) and the ranking of parameters was tabulated (Table 5.1 and 5.2) indicating the parameter against the maximum change in the objective function and thus parameter sensitivity.

Table 5.1 Sensitivity to (R^2)

Rank	Parameter	Max.change in R^2
1	L_{max}	1.491
2	CQOF	1.355
3	CKBF	0.353
4	TIF	0.226
5	CKIF	0.164
6	$C_{K1,2}$	0.133
7	U_{max}	0.107
8	TG	0.08
9	TOF	0.007

Table 5.2 Sensitivity to WB Error

Rank	Parameter	Max. change in WB error
1	L_{max}	107
2	TIF	29.7
3	CKBF	28.4
4	U_{max}	25.2
5	TG	22.2
6	CQOF	19.7
7	CKIF	14.3
8	TOF	2.1
9	$C_{K1,2}$	0

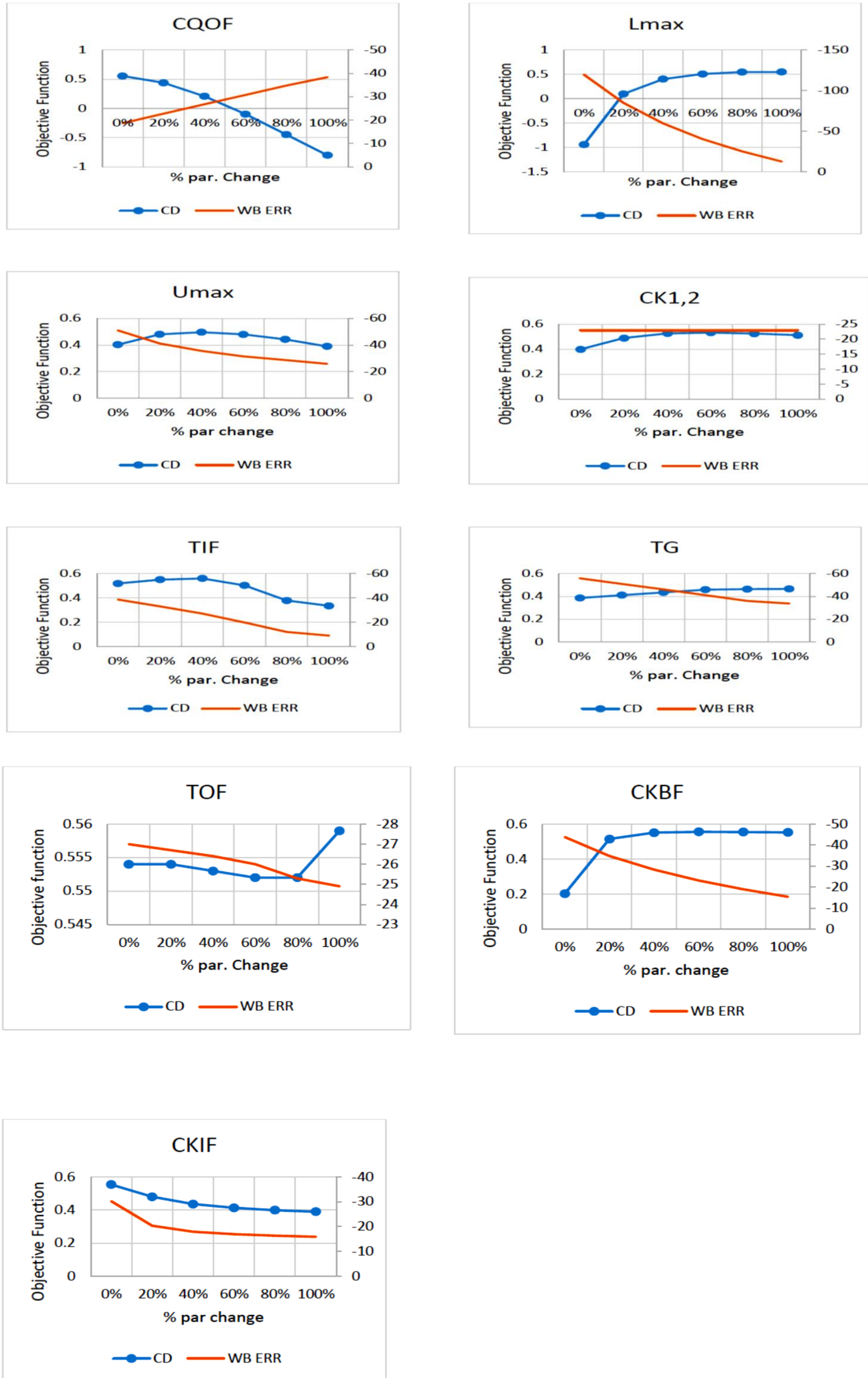


Figure 5.3 Parameter Sensitivity Plots

The results indicate that NAM model parameters have different sensitivities to the two different objective functions. The ranking on Table 5.1 indicates that the L_{max} and the CQOF parameters are the most sensitive and vital in terms of the models ability to account for the variations in observed river flows (indicated by the R^2 value). L_{max} which conceptually represents the spatially averaged maximum root zone storage capacity is key in determining how quick the response is to a rainfall event. This is because a smaller value of L_{max}will represent a lower capacity in the basin to store water from infiltration meaning runoff will be generated faster. CQOF which is the overland flow coefficient, values on the other hand control the overland flow volumes generated in the basin. Similarly L_{max} is also sensitive to the overall water balance due to its role in affecting the available water in the root zone that can be lost through evapotranspiration. TIF which is the threshold value for interflow to occur, controls the movement of the water in the root zone or the lateral flow of water. Higher thresholds for this value mean that more water is kept in the soil before lateral flow can occur thus affecting the overall water balance. $C_{K1, 2}$ is the timing constant for overland flow and does not affect the volumes generated thus a very low sensitivity value to Water Balance Error (Table 4.2). $C_{K1, 2}$ rather affects the fit or the overland flow hydrograph recession slopes. This makes it more sensitive to the response of quick flows and the Coefficient of Determination (R^2) objective function.

5.3.2 NAM Model calibration and Validation

The NAM model was calibrated by both manual and automatic methods and the final parameter estimations are shown in Table 5.3.

Table 5.3 Calibrated parameters

Parameter	Range		Final Value
	Lower	Upper	
U_{max}	5	35	23
L_{max}	50	400	237
CQOF	0	1	0.7
$C_{K1,2}$	3	72	39.4
TOF	0	0.99	0.933
TIF	0	0.99	0.5
TG	0	0.99	0.536
CK_{BF}	500	5000	1030
CK_{IF}	200	2000	229.7

For validation of the model the same parameters were used with an independent set of data inputs from the period 1982 to 1984. The model output was also evaluated against the observed discharge, with the model being accepted as satisfactorily calibrated based on the statistical indices attained.

5.3.3 NAM goodness of fit statistics

For evaluation of model performance during calibration, the Coefficient of Determination ($R^{2)}$, Percent Bias (PBIAS), Nash and Sutcliffe Model Efficiency (NSE), the Index of Agreement (IA), RSR and Pearson's correlation coefficient (r) were used in this study. Tables 5.4 and 5.5 represent these indices attained during the calibration and validation periods for the NAM model for both daily and monthly time steps.

Table 5.4 Goodness of fit statistics for the calibration period

Goodness of fit Statistic	Daily time step	Monthly time step	Range	Optimal
NSE	0.811	0.945	$-\infty$ - 1	1
PBIAS	1.805%	1.633%	$-\infty$ - $+\infty$	0
RSR	0.435	0.24	0 - $+\infty$	0
IA(d)	0.943	0.985	0-1	1
R^2	0.810	0.946	0-1	1
r	0.902	0.972	0-1	1

Table 5.5 Goodness of fit statistics for the validation period

Goodness of fit Statistic	Daily time step	Monthly time step	Range	Optimal
NSE	0.781	0.941	$-\infty$ - 1	1
PBIAS	0.648%	0.309%	$-\infty$ - $+\infty$	0
RSR	0.470	0.243	0 - $+\infty$	0
IA(d)	0.945	0.987	0-1	1
R^2	0.801	0.965	0-1	1
r	0.896	0.982	0-1	1

The NAM model can be said to have attained a “very good” performance rating in both the calibration and validation periods.This is because, NSE$\geq$ 0.75, PBIAS $\leq \pm$ 10% and $0 \leq$ RSR ≤ 0.50. and thus are within the recommended range (Table 3.3).

5.3.4 Hydrograph plots

For visual inspection, observed and simulated flow hydrographs for the calibration and validation periods were plotted for the daily time step as shown in Figure 5.4 and 5.5, and the same was also done for the monthly time step in Figure 5.6 and 5.7.

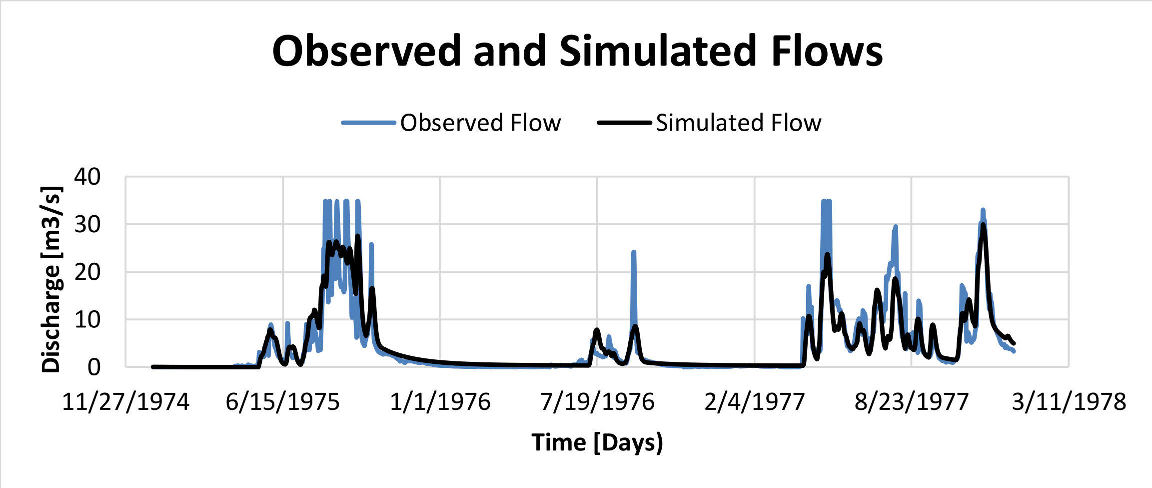


Figure 5.4 Daily observed and simulated flow hydrograph, calibration period

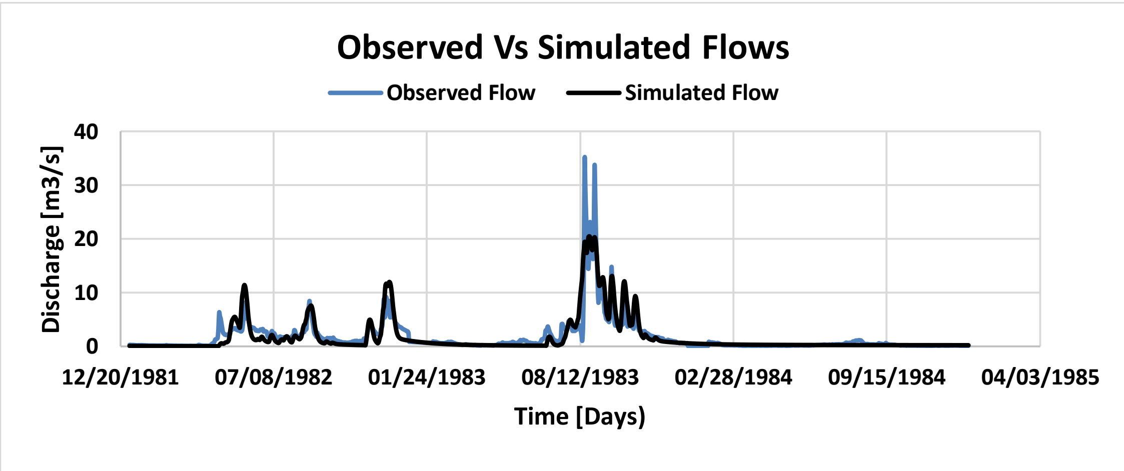


Figure 5.5 Daily observed and simulated flow hydrographs, validation period

For the daily time step the NAM model generally underestimated the peak flows,this trend has been captured by other researchers including (El-Nasr, et al., 2011) and (Anh et al., 2008). The monthly time step hydrographs reveal a better representation of the peaks as also supported by the goodness of fit statistics. This result shows that the model represents the hydrology in the catchment better on a monthly time scale than on the daily scale.

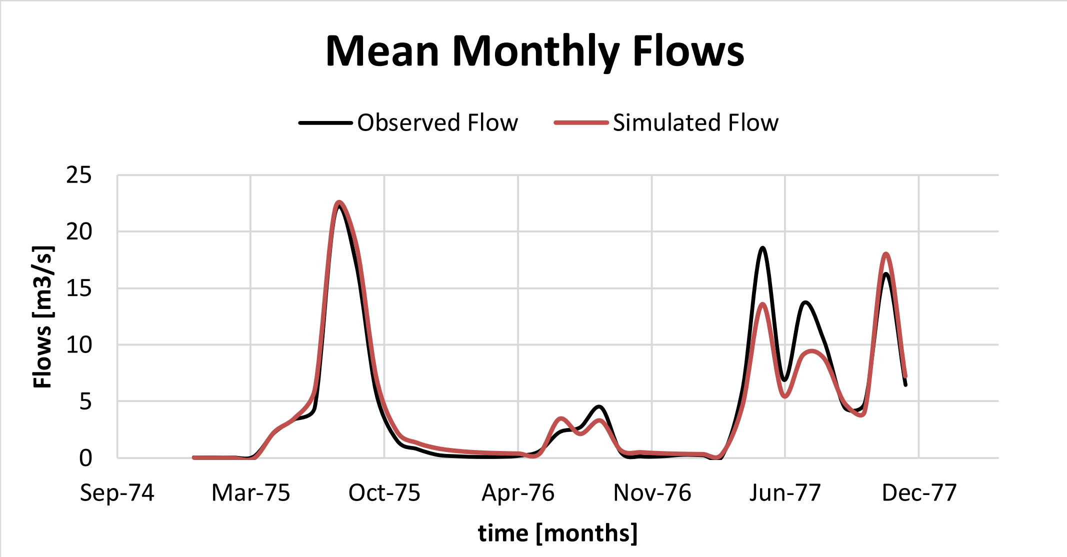


Figure 5.6 Observed and Simulated Mean Monthly flow (calibration period)

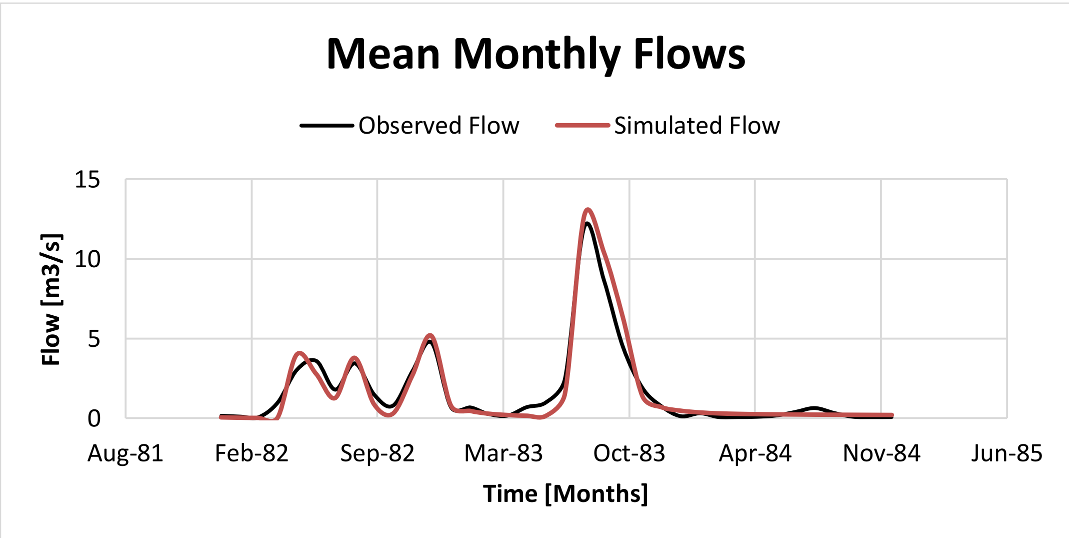
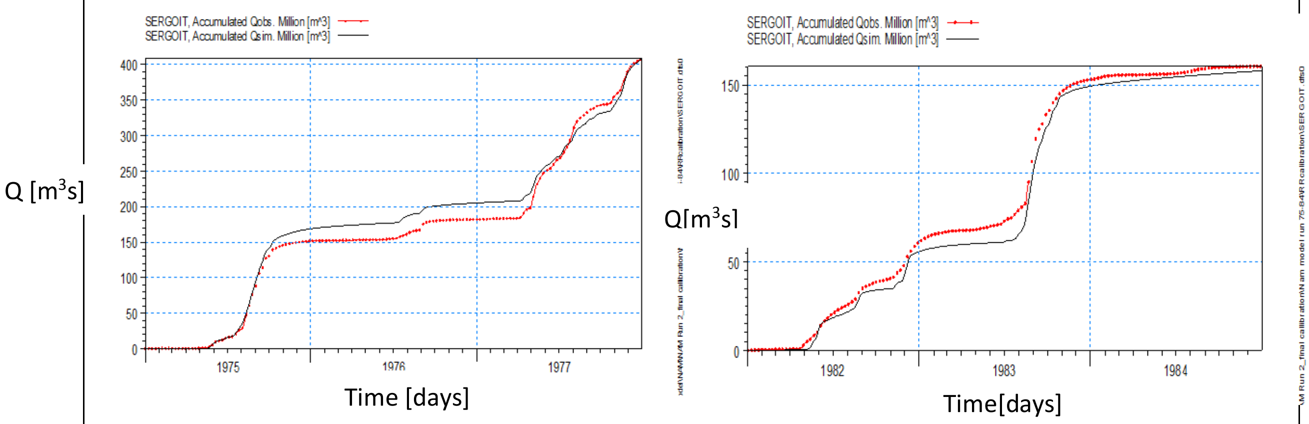


Figure 5.7 Observed and Simulated mean monthly flow (validation period)

Cumulative plots reveal how the model performs with respect to the volume generated at the basin outlet with time. The plots reveal that the NAM model slightly underestimated the volume of runoff generated in both the calibration and validation periods as supported by the positive PBIAS statistic. The model seems to perform poorly during the dry periods by overestimating runoff in the calibration period. The visual comparison of the cumulative runoff discharges are represented in Figure 5.8(a and b)

Cumulative daily flows (calibration period) Cumulative flows (validation period)



(a) (b)

Figure 5.8 Cumulative flows, calibration (a), validation (b) periods

5.4 TheSWAT model results

5.4.1 SWAT sensitivity analysis

The results of the sensitivity analysis for the first round of calibration is represented in Figure 5.9 and ranked in Table 5.6. the sensitive paramaters indicate which processes key to representing the hydrology of the basin using the SWAT model structure. These processess include surface runoff, run off lag time, channel flow and soil water balance.

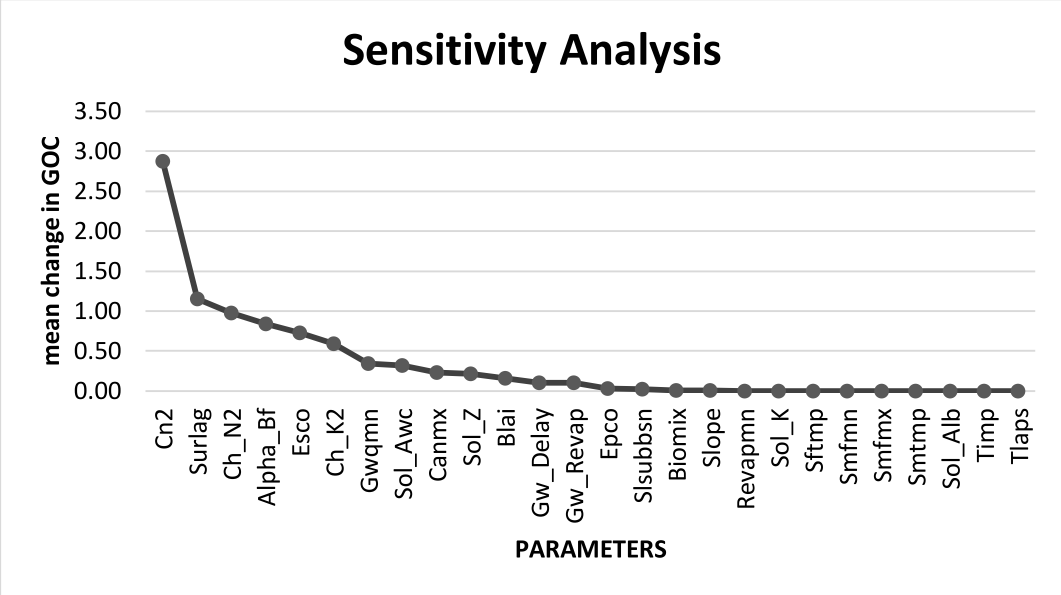


Figure 5.9 Parameter Sensitivity Analysis

Table 5.6 Parameter rank and description

Parameter	Rank	Description
Cn2	1	SCS runoff curve number
Surlag	2	Runoff lag time
Ch_N2	3	Manning's n value for the main channel.
Alpha_Bf	4	Base flow alpha factor (days).
Esco	5	Soil evaporation compensation factor.
Ch_K2	6	Effective hydraulic conductivity in main channel alluvium.
Gwqmn	7	Threshold depth of water in the shallow aquiferfor return flow.
Sol_Awc	8	Available water capacity of the soil layer.
Canmx	9	Maximum canopy storage.
Sol_Z	10	Depth from soil surface to bottom of layer.
Blai	11	Max Leaf Area Index
Gw_Delay	12	Groundwater delay (days).
Gw_Revap	13	Groundwater revap coefficient.
Epco	14	Plant uptake compensation factor.
Slsubbsn	15	slope length

Based on the ranks assigned to the parameters with respect to their sensitivity, the 10 most sensitive parameters were selected and used for manual and automatic calibration.

5.4.2 SWATmodel calibration and validation

The SWAT model was calibrated using 1975 to 1979 data with 1975 as the warm up period. The SWAT model was calibrated using both manual and automated approaches. Table 5.7 shows the fitted calibrated parameters. For validation of the model the same parameters were used with an independent set of data inputs from the period 1981 to 1984 with 1981 taken as a warm up period.

Table 5.7 Calibrated SWAT parameters

Parameter Name. file	Final value	Range	
		Min	Max
CN2.mgt	-18.28%	-25%	25%
ESCO.hru	0.104	0	1
SOL_AWC.sol	-20.59%	-25%	25%
GW_DELAY.gw	412.048	0	500
GW_REVAP.gw	0.049	0.02	0.2
RCHRG_DP.gw	0.507	0	1
EPCO.hru	0.885	0	1
SOL_Z .sol	7.49%	-10%	10%
GWQMN.gw	2570.89	0	5000
REVAPMN.gw	178.723	0	500
SURLAG.bsn	0.549	0.05	24
ALPHA_BF.gw	0.890	0	1
CH_N2.rte	0.205	0.01	0.3
CH_K2.rte	338.530	0.01	500
SLSOIL.hru	130.207	0	150
LAT_TIME.hru	179.256	0	180
SOL_K.sol	4.15%	-10%	10%
OV_N.hru	0.015	0.01	30

5.4.3 SWAT goodness of fit statistics

Similar to the NAM model the same statistical indices were used in the evaluation of the SWAT model. These are the Coefficient of Determination (R^2), Percent Bias (PBIAS), Nash and Sutcliffe Model Efficiency (NSE), the Index of Agreement (IA), RSR, and Pearson's correlation coefficient (r) were used. The model statistical evaluation indices attained during the calibration and validation periods for the SWAT model for both daily and monthly time steps are shown in Table 5.8 and 5.9.

Table 5.8 Goodness of fit statistics for the calibration period

Goodness of fit Statistic	Daily time step	Monthly time step	Range	Optimal fit
NSE	0.697	0.873	-∞ - 1	1
PBIAS	15.110%	15.217%	-∞ - +∞	0
RSR	0.550	0.356	0 - +∞	0
IA(d)	0.901	0.962	0-1	1
R^2	0.704	0.902	0-1	1
r	0.844	0.950	0-1	1

Table 5.9 Goodness of fit statistics for the validation period

Goodness of fit Statistic	Daily time step	Monthly time step	Range	Optimal fit
NSE	0.648	0.856	-∞ - 1	1
PBIAS	-11.822%	-11.801%	-∞ - +∞	0
RSR	0.600	0.379	0 - +∞	0
IA(d)	0.897	0.965	0 - 1	1
R^2	0.653	0.858	0 - 1	1
r	0.813	0.934	0 - 1	1

The SWAT model can also be said to have attained a “Good” performance rating in both the calibration and validation periods, given that, NSE $\geq$ 0.65, PBIAS $\leq$ ±15% and RSR $\leq$ 0.60, which is within the recommended ranges (Table 3.3).

5.4.4 Hydrograph plots

The visual representation of the observed and simulated flow hydrographs for the calibration and validation periods were plotted for both the daily time step and the monthly time step as shown by Figures 5.10 to 5.13.

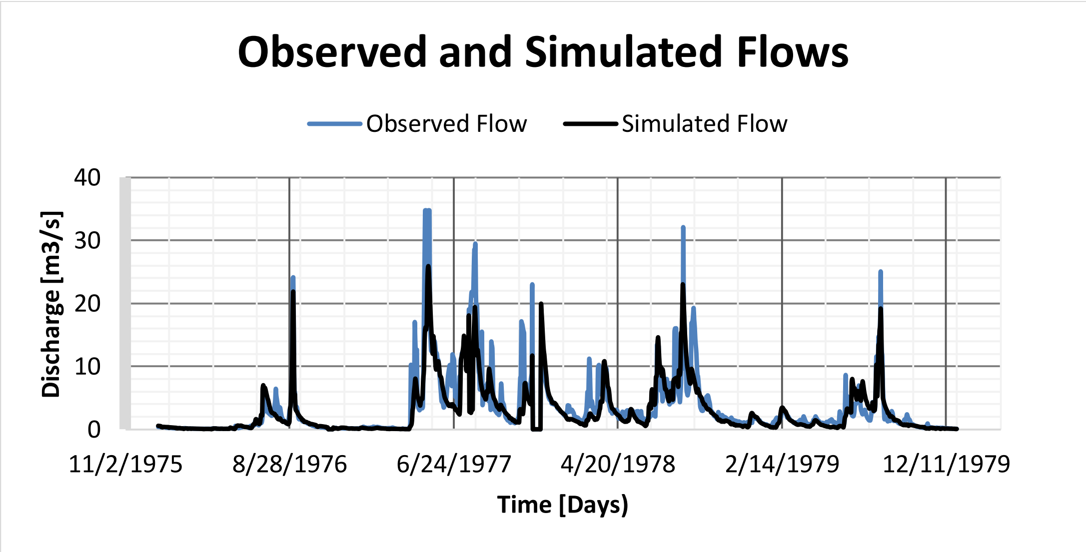


Figure 5.10 Daily observed and simulated flows, calibration period.

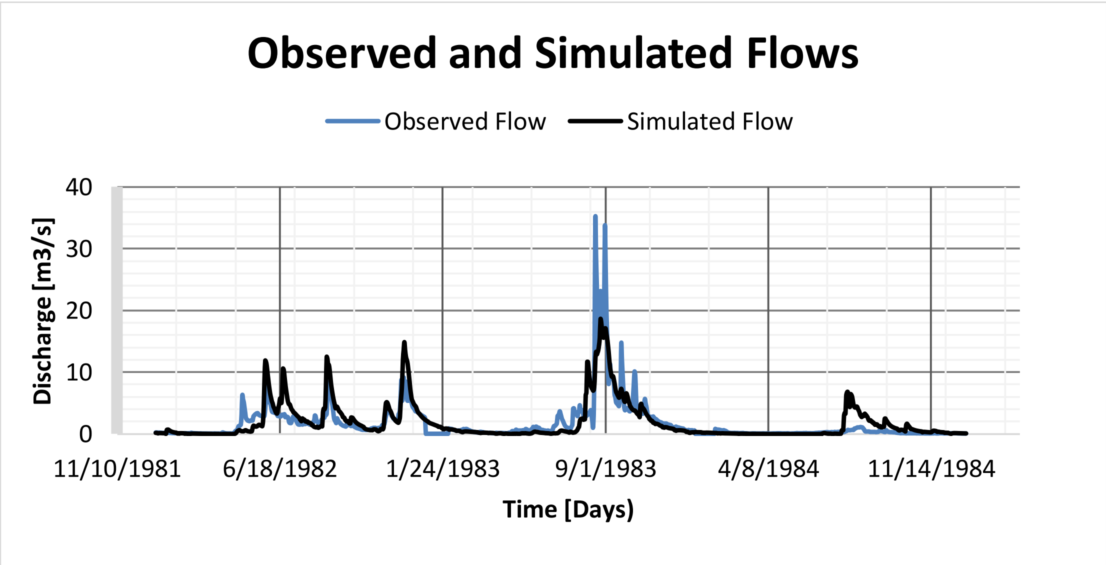


Figure 5.11 Daily observed and simulated flows, validation period.

Both the daily flow hydrographs for the calibration and validation periods (Figures 5.10 and 5.11) show an underestimation of the simulated peak flow values. The recession of the base flow in the dry periods is better represented although what is poorly captured is the catchment's response to the rainfall events both at the inception of the rainy season and during the rainy periods. This could be due to the models poor accounting of the soil water balance. The plots of the observed and simulated discharges also reveal that some flow peaks are not captured at all. This can be attributed to the weak representation of rainfall stations in the catchment, indicating that information on some rainfall events are not captured in the rainfall data input records.

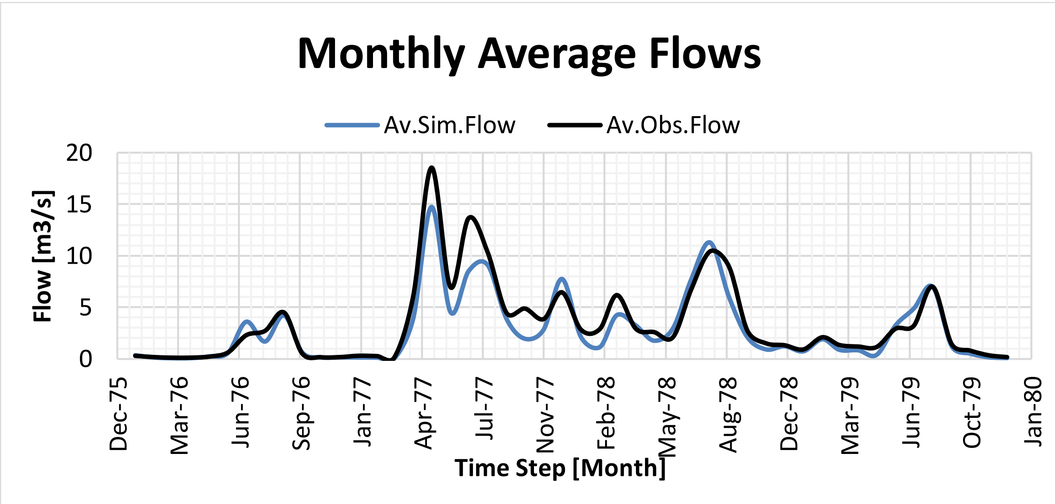


Figure 5.12 Mean monthly observed and simulated, calibration period

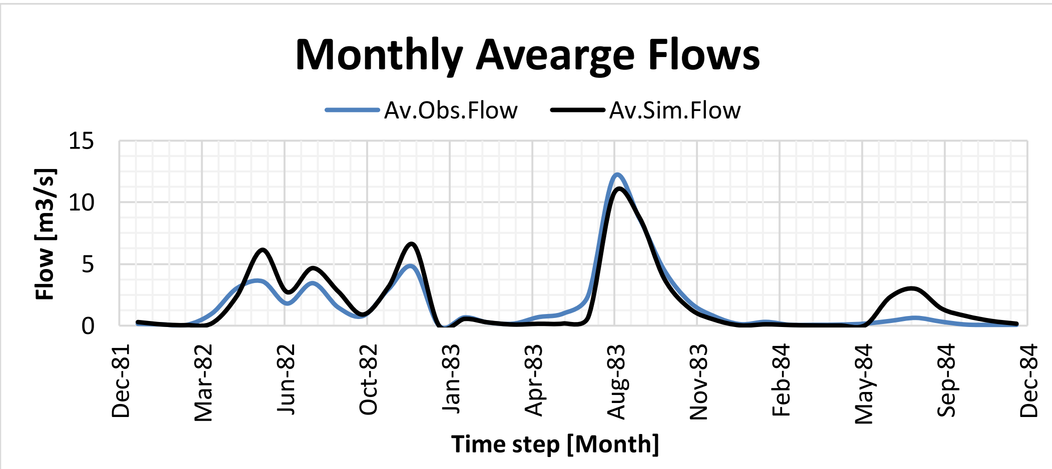
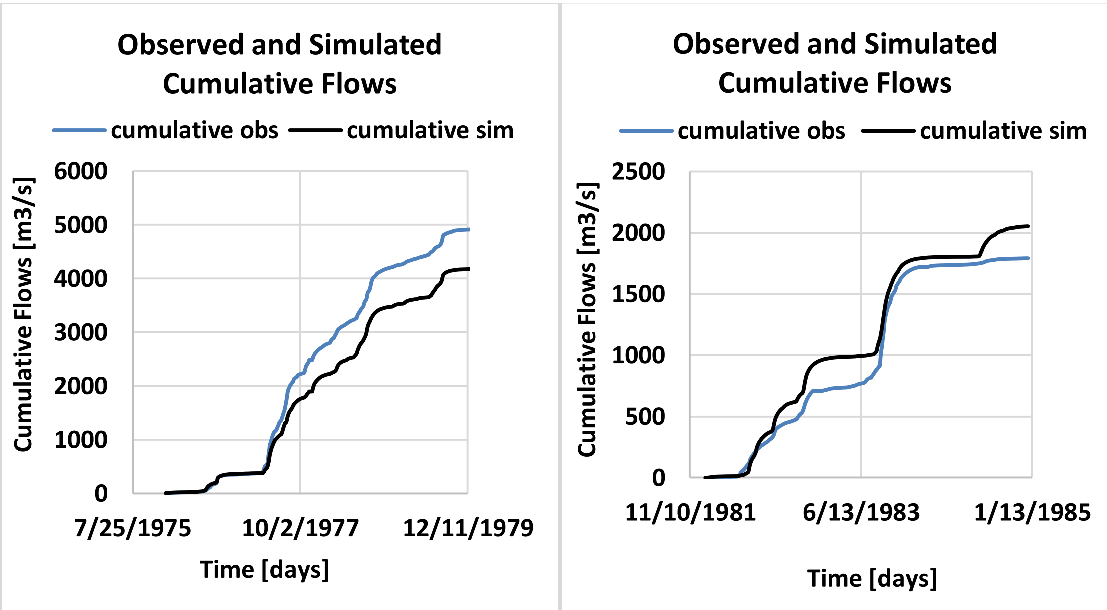


Figure 5.13 Mean monthly observed and simulated flows, validation period.

The monthly plots (Figures 5.12 and 5.13) reveal a better agreement of the monthly averaged outputs of the SWAT model as the peaks are better captured than in the daily time steps both in the calibration and validation periods. The cumulative plots on the other hand reveal how the SWAT model underestimates the volumes generated at the basin outlet in the calibration period (Figure 5.14a) while overestimating the same in the validation period (Figure 5.14b).



(a) (b)

Figure 5.14 Cumulative Plots for the calibration (a) and validation (b) periods.

5.5 Box cox transformation

In order to ensure the model residuals are homoscedastic and that the peak and low flow model residuals have equal weights, a Box Cox transformation was carried out. This allowed the values of the simulated and observed model residuals to be plotted and analyzed on equal weighting.

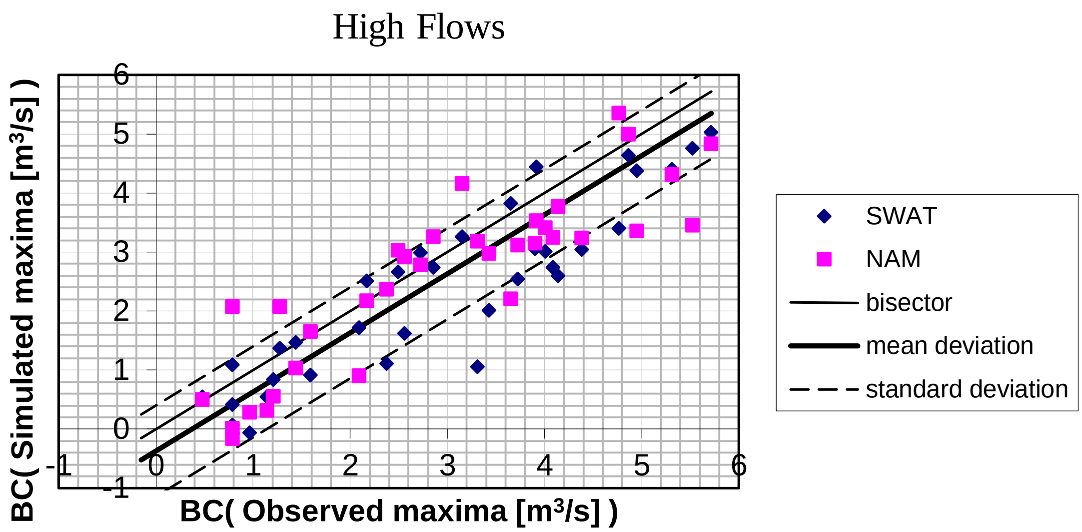


Figure 5.15 Model Residual plot (Box Cox Transformation) high flows

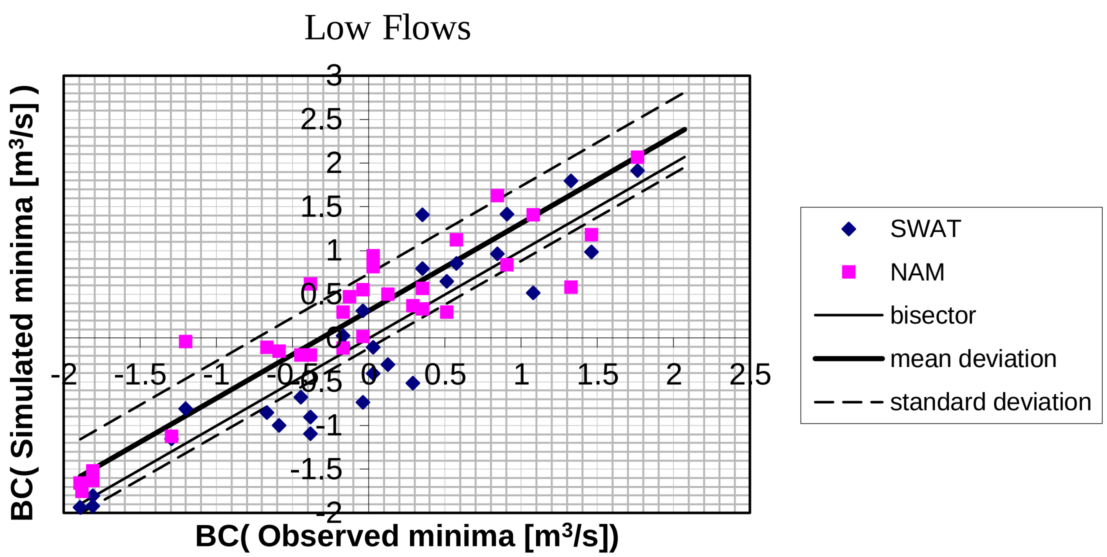
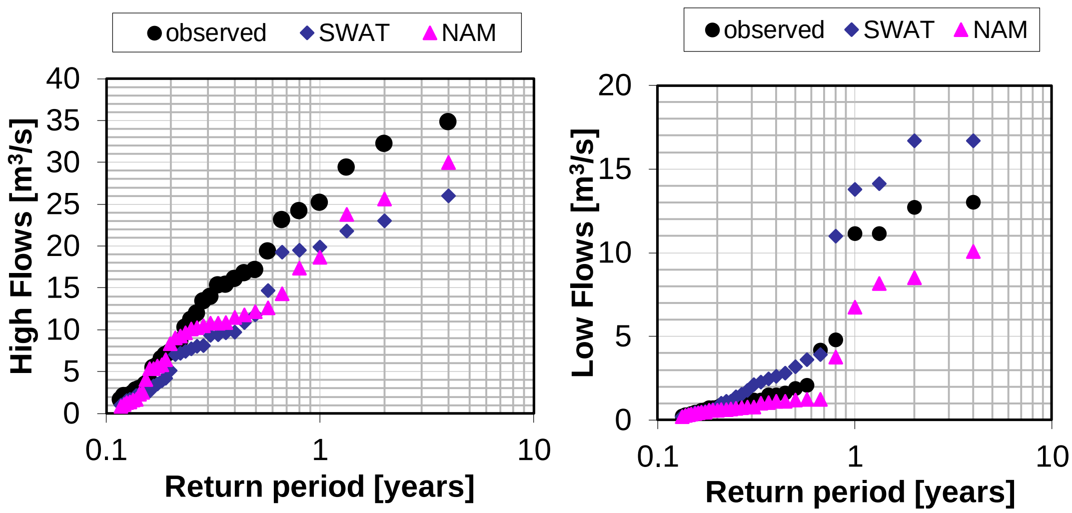


Figure 5.16 Model Residual plot (Box Cox Transformation) Low flows

The Figure 5.15 shows that for the high flows, both model residuals are better clustered within the band between the standard deviation plots which represent the model prediction confidence interval. The position of the mean deviation line indicates that both the SWAT and NAM models underestimate the peak flows and have a systemic negative bias. Figure 5.16 representing the low flow residuals transformation, shows less cluster between the standard deviation bands. The mean deviation line shows a positive bias and thus a systemic over prediction or overestimation of the low flows by both models.These results indicate that although the model prediction confidence interval bands were relatively narrow in both the high and low flow cases, both models are not highly accurate in capturing extreme flows.

5.6 Extreme value analysis

The output of both models were subjected to extreme value analysis. This was done to examine the suitability of the calibrated models in flood frequency prediction. Both models underestimated high flow values. The Figure 5.17 (a) shows an increasing underestimation for larger values. On the other hand, extreme value analysis on low flows show that the SWAT model output increasingly underestimates these flow values while the NAM model overestimates them as shown by Figure 5.17 (b). This results implies the model output as calibrated exhibits a wrong tail of the extreme value distribution and may not be appropriate for extrapolation purposes.



(a) (b)

Figure 5.17 Extreme value analysis on peak flows (a) and low flows (b)

Given the results presented both models can be said to be well calibrated as the model evaluation statistics show that:

1. The relative magnitude of the residual variance is highly correlated to the measured or observed data variance as NSE values are greater or equal to 65%.
2. The proportion of variability in the observed stream flows that is accounted for by the model is high as R^2 values are greater than 65%.
3. The simulated volumes are within acceptable ranges of observed flow volumes (PBIAS ± 15%).

Graphical methods applied show a good visual representation of a reasonable agreement between the simulated and observed flows. The models can therefore be applied to the Sergoit basin to determine its water yield as the performance of both models, SWAT and NAM are considered to have attained a “Good” to “Very Good” performance rating respectively as shown in Table 3.3.

5.7 SWAT and NAM model comparative assessment

A comparative analysis of the SWAT and the NAM model is necessary to further give insight into each model’s performance. In terms of the model structure, the NAM model is a lumped conceptual model meaning it conceders the whole catchment as a single unit with singular inputs for each time step. While these assumptions may be more applicable to inputs like potential evapotranspiration in meso scale or micro scale catchments the same cannot be applied to other inputs like rainfall or basin characteristics which are highlyvariable both temporally and spatially. The averaging of rainfall over the whole watershed has merits especially areas with low rain gauge density as the NAM model will be able to make use of all the available information. Demeritsof the approach is that rainfall events that were highly localized will be misrepresented as if they occurred throughout the catchment leading to simulated peaks that aren't in the observed discharge.

The answer to this problem is to have a discretized catchment and have a semi distributed model structure with sub basins as implemented in the SWAT model. This is carried out by having a sub basin's rainfall input from the rain gauge closest to its centroid. This however does not solve the problem in catchments with unevenly distributed rain gauges like the Sergoit catchment, since the simulated hydrographs from the SWAT model show that it wasn't able to capture a number of peaks present in the observed discharge data.

The generation of runoff is a key difference between the models. Since the NAM model is a conceptual model it generates runoff based on a given fraction (coefficient of overland flow-CQOF) that is determined during calibration or from prior knowledge of the catchment processes. The physically based SWAT model on the other hand generates runoff based on the empirical curve number method which relies on the physical characteristics of the catchment like land use soil properties and slope. Another key difference between the models is that the NAM model does not include a routing component while the SWAT model routes the HRU output through the basin streams channels.

In terms of data requirements the SWAT model has higher data requirements that need a lot of preprocessing before it can be used as input. The number of model parameters are high thus complicating the calibration processas also noted by Borah and Bera, (2004). To undertake calibration it was necessary to carry out sensitivity analysis in order to isolate and use the most sensitive model parameters in calibration. The SWAT user also has to have an intermediate to advanced skill level GIS processing as there is a large number of input files needed to run the model that are generated through the ArcGIS interface. The NAM model however has lower data requirements and fewer parameters which makes it easier to set up and calibrate. These differences are summarized in Table 5.10.

Table 5.10 Characteristics of the SWAT and NAM models

Model Characteristics	SWAT	NAM
Structure	Two divisions i. Land phase ii. Routing phase	Four interrelated storages i. snow storage, ii. surface storage, iii. root zone storage (subsurface) iv. groundwater storage
Temporal scale	Continuous (daily/monthly/annual)	Continuous (daily)
Climate data requirements	i. Rainfall ii. Temperature (Max and Min) iii. Solar radiation iv. Relative humidity v. Wind speed	i. Rainfall ii. Potential Evapotranspiration
Other data sets	i. Land cover map ii. Soils map	i. Catchment Area
Model parameterization	i. GIS processing ii. Calibration	i. Calibration
Calibration	i. Manual calibration ii. Automatic calibration	i. Manual calibration ii. Automatic calibration
Availability	Open source/public domain	Commercial

Based on these differences,the two modelling approaches yielded the results summarized in Table 5.11.

Table 5.11 Results summary

Model	SWAT	NAM
Model performance rating	"Good"	"Very Good"
NSE	0.697 (0.87)*	0.81 (0.95)*
R^2	0.704 (0.902)*	0.81 (0.94)*
IA	0.89 (0.96)*	0.94 (0.95)*
PBIAS	15.11 (15.21)*	1.80 (0.95)*
RSR	0.6 (0.37)*	0.43 (0.24)*
r	0.81 (0.93)*	0.90 (0.97)*

(* monthly time step evaluation statistics)

5.8 Estimation of catchment yield

Rainfall-Runoff modelling is the first step in water resources management since it is the only way to simulate the hydrological behavior of a basin so as to have a good evaluation of its potential in terms of water production. In this study the SWAT and the NAM models were both calibrated and validated. Table 5.12 shows the Sergoit catchment's annual water yields from the observed data and model simulations for the calibration and validation periods.

Table 5.12 Observed and model simulated catchment water yields

Period	Year	Observed Yield [MCM]	SWAT simulated yield [MCM]	NAM simulated yield [MCM]
Calibration period	1976	30.46	31.42	37.41
	1977	201.16	153.02	173.79
Validation period	1982	61.04	79.21	61.09
	1983	90.51	75.35	95.57
	1984	7.02	22.60	10.24

Given that both models attained satisfactory performance on evaluation, they were applied by preparing the necessary inputs to obtain the synthetic daily discharge hydrographs as shown in Figure 5.18.

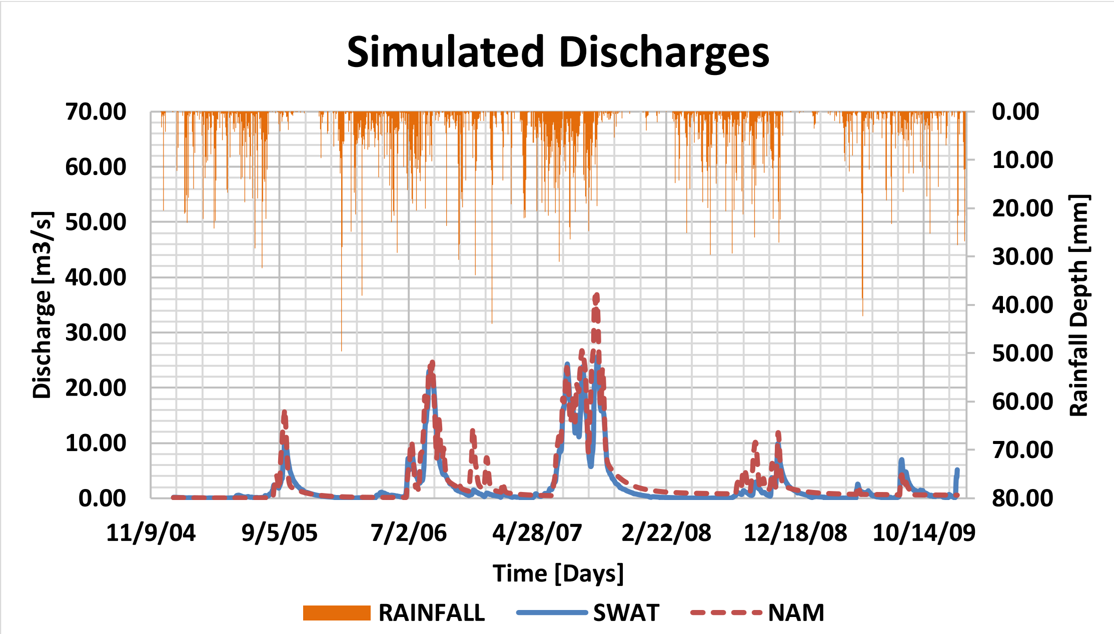


Figure 5.18 Simulated rainfall and flow hydrographs for 2005-2009.

From the hydrograph plots (Figure 5.18) both models seem to capture a similar trend in response to rainfall input. The SWAT model however fails to represent some peaks that are captured by the NAM model. The SWAT model also generates lower baseflow values thatn the MIKE11-NAM model. This is responsible for the low yields generated by the SWAT model for some years especially in the year 2008. From the estimation of the basin yields generated by the models and a plot of total annual rainfall for the study period(Figure 5.19), it can be observed that in the dry years, 1976, 1984, 2005 and 2009 the water yields are closer while a greater variation is observed in the wet years. The SWAT model however underestimates the catchment yields especially in the wet years. A similar observation was noted by Borah and Bera, (2004)where the SWAT model didn’t perform well in the wet months with big or extreeme storm events.

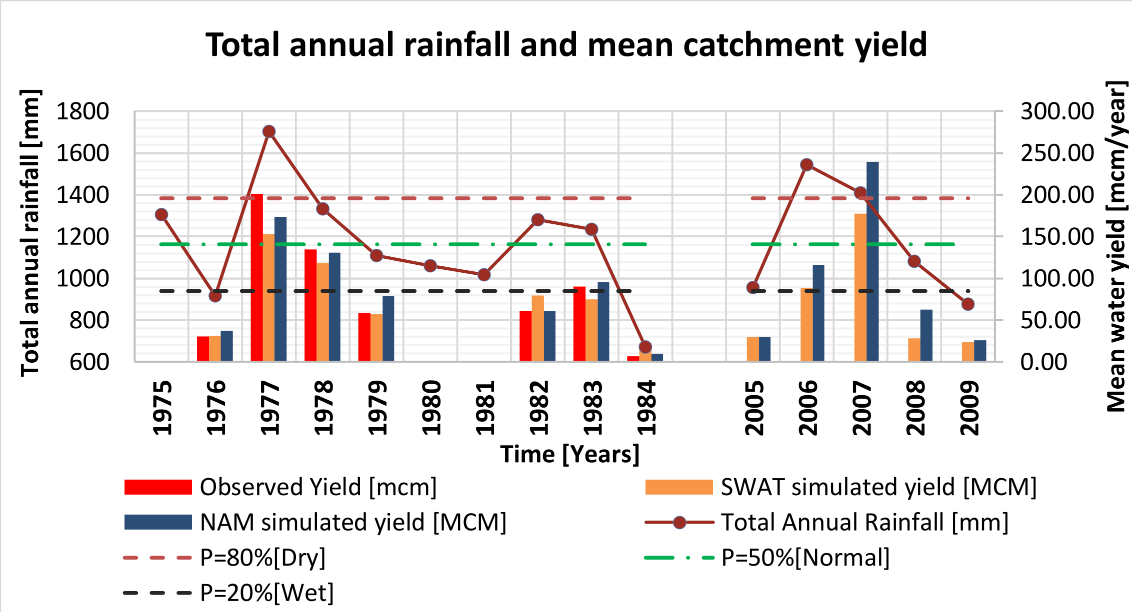


Figure 5.19 Total annual rainfall and mean catchment yield

The annual catchment yields for the years 2005 to 2009 is given in Table 5.13 as simulated form the SWAT and NAM models. The mean annual yield for this period as generated by the SWAT and the NAM models are 69.62 and 94.8 million cubic meters (MCM) respectively, a difference of 26%.

Table 5.13 Sergoit basin Mean Annual water yields

Period	Year	SWAT simulated yield [MCM]	NAM simulated yield [MCM]
Application Period	2005	29.50	29.60
	2006	88.91	116.37
	2007	177.48	239.31
	2008	28.49	62.48
	2009	23.74	26.25
Mean annual yield		69.62	94.80

The model application period had a number of data gaps and of the six rainfall stations used in the calibration and validation periods, half of them had no data for this period. Investigating further into why the SWAT model simulates lower yields than the NAM model reveals that the SWAT model does not select station number 2, (Table 5.14) due to its distance from any of the sub-basin centroids since rainfall input is at the sub-basin level from the nearest station(Neitsch et al.,2004).

Table 5.14 Completeness of Rainfall records

No	Station ID\Year	2005	2006	2007	2008	2009	% Complete
1	8935133	67	100	100	67	0	66.7
2	8935181	41	100	100	100	100	88.2
3	8935170	33	100	100	67	0	59.9
	% Ave. complete/yr	47	100	100	78	33	72

This demonstrates the SWAT models sensitivity to the quality of data in terms of how representative it is over the whole catchment. The reduced spatial detail in the input of rainfall in the SWAT model led to underestimation of the catchment rainfall shown in Table 5.15. The spatial averaging of rainfall input in the NAM model on the other hand was an advantage in this instance as all the available information was used to generate runoff.

Table 5.15 Annual mean water balancecomponents 2005-2009

Model	Rainfall (mm)	AET (mm)	PET (mm)	Gw Recharge (mm)	Runoff (mm)
NAM	1173.62	962.32	1505.1	73.1	135.42
SWAT	1113.96	933.35	1506.9	82.28	100.71

A concern encountered in the application of SWAT model in this study was the unavailability of required data in the necessary spatial detail. The coverage of rain gauge stations in the basin is not evenly distributed as only two gauges were located within the basin boundaries.Additionally, only one rainfall station had a complete record within the study period, while only one station is a climate station having temperature, wind, precipitation, and humidity data. This rendered the ability of the SWAT model to capture the spatial variation of other climatic variables other than rainfall quite weak. This situation was mentioned by Arnold, et al., (2012) where it was noted that there is in general, insufficient observed data to enable a fullspatial calibration and validation at the watershed scale. They further attributed the inadequate spatial coverage of precipitation input due to an inadequate number of rain gaugesthatfailed to capture the spatial detail of available rainfall data in simulatedwatersheds to poorsumulation results (Arnold, et al., 2012). The user in such a case, has to make use of a combination of data sets from different sources, this involves combining locally gathered data from local agencies and global data sets from global databases to overcome the data challenges. Lack of detailed physical data like soils and land use in high resolutions is another challenge to overcome. The soils and land use maps that are availablehave a coarse resolution of 1:1,000,000, which is not optimal for use on a meso scale catchment where smaller land use or soils classes may not be adequately represented. It has to be appreciated that the unavailability of these data sets could have an effect on the modelling results. Extra effort is required to ensure that the input weather, land use and soil data sets are of high quality while spatial data should be of high resolution for better hydrological prediction. A possible reason for both models underestimating peak flow values is the temporal detail of the input rainfall data as average daily rainfall values omit details that occur during storm events.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The understanding of hydrological processes and the development of suitable models for a watershed is the most essential aspect in water resource development and management programmes. These watershed based hydrologic simulation models are likely to be used for the assessment of the quantity and quality of water. The assessment of performance and applicability of these models is thus important in this respect.

The main objective of this study was to set up and evaluate comparatively the performance of a lumped conceptual model MIKE 11-NAM and a semi distributed physically based model SWAT, in estimating the catchment water yield of the Sergoit catchment given by the two models.The models were successfully calibrated and applied. The following conclusions were therefore arrived at;

a) The SWAT and NAM models were successfully calibrated, validated and applied to determine the Catchment water yield for the Sergoit catchment.The MIKE 11-NAM model was calibrated with data from 1975 to 1977 and validated using 1982 to 1984 data. On the other hand the SWAT model was calibrated with 1975 to 1979 data with 1975 used as the warm up period. Validation was done using data from 1981 to 1984.

b) The performance evaluation of each model was done using both goodness of fit statistics and graphical methods. The overall results from the goodness-of-fit statistics shows differences in performance and overall behaviour of the two models. MIKE 11-NAM model performed better than SWAT model during the calibration period with an NSE, R^2, IA, and PBIAS of 0.81, 0.81, 0.94 and 1.80

for the NAM model and 0.69, 0.70, 0.89, and 15.11for the SWAT model. The validation period marked a slight performance drop with an NSE, R, IA, and PBIAS of 0.78, 0.80, 0.95and 0.65 for the MIKE 11-NAM and 0.65, 0.65, 0.90 and -11.82 for the SWAT model respectively.

c) The graphical evaluation plots revealed a general tendency to underestimate the peak values in both models. On the basis of an extreme value analysis MIKE 11-NAM model performs better than the SWAT model as it is closer to the extreme value distribution of the observed flows. The general underestimation however increases for larger values, indicating poor extrapolation capabilities in both models. The cumulative plots show that both models underestimate flow volumes although the NAM model is closer to the observed. The B.C transformations show that despite the model prediction confidence interval bands being relatively narrow in both the high and low flow, there is a systemic negative bias (under prediction) for the extreme high flows and a systemic positive bias (over prediction) of extreme low flows in both model simulations. Both models therefore are not highly accurate in capturing extreme flows.

d) The semi-distributed nature of the SWAT model and the large number of model parameters and inputs, results in difficult calibration, whereas the lumped nature of NAM model and limited number of model inputs and parameters makes it easier to calibrate and allows for a better overall goodness-of-fit.

e) Despite its better performance, theNAM model has the disadvantage that its model structure has really simplified the hydrological system in the catchment with the main aim of capturing the discharge at the outlet. Important effects of vegetation on evapotranspiration which a major component in the hydrologic cycle affecting the water balance and the effect of channel routing arenot captured in the model's conceptual structure.

f) The SWAT model is sensitive to the quality and quantity of data, thus missing data greatly impacts the results of the simulated values.

g) The ability to simulate the dominant hydrological processes of the system in a physical sense is the more appealing characteristic of the SWAT model. It can serve as a research tool to investigate both the interactions and best management practices in the study area.

h) The mean catchment water yields for the calibration period, from the observed data, NAM and SWAT model simulations are 106.2 mcm/year, 90.16 mcm/year and 105.1 mcm/year, while for the validation period, the yields were, 86.2 mcm/year, 78.49 mcm/year and 86.56 mcm/year respectively.For the years 2005 to 2009, the mean annual catchment yield of the Sergoit basinas given by the SWAT and NAM models are 69.62 mcm/year and 94.8mcm/year.

i) Given the results of the model performance evaluation the NAM model is preferred based on the better performance as shown by the statistical and graphical evaluation criteria as well as the generated yields during the calibration and validation periods.

6.2 Recommendations

Based on this study that represented the hydrology of the Sergoit catchment using two different hydrological modelling approaches, it is recommended that:

a. A Further comparative evaluation of the performance of the NAM modelwith other hydrological modelling approaches including stochastic, parametric and non-parametric models.

b. Installation of additionalclimate stations within the Sergoit basin to improve the representation of rainfall within the catchment as the current distribution is not even.

c. Installation of a properly sited river gauging station near or at the catchment outlet.

d. A detailed land use study in the catchment is recommended toasses changes in land use that may affect the basin water yields.

e. A study on the effects of climate change is recommended as changes in rainfall and temperature affects the hydrological system in the catchment and thus has an impact on the basin's water yield.

References

Adeniyi, G., Bolaji, F., Adebayo, W., and Michael, O. (2014). Validation of SWAT Model for Prediction of Water Yield and Water Balance: Case Study of Upstream Catchment of Jebba Dam in Nigeria. *International Journal of Mathematical, Computational, Physical and Quantum Engineering, Vol:8*(No:2), 264-270.

Akivaga, M., Otieno, F. A., O, Kipkorir, E. C., Kibiiy, J., and Shitote, S. (2010). Impact of introducing reserve flows on abstractive uses in water stressed Catchment in Kenya: Application of WEAP21 model. *International Journal of the Physical Sciences Vol. 5(16),,* 2441-2449.

Alansi, A. W., Amin, M. S., Abdul Halim, G., Shafri, H. Z., and Aimrun, W. (2009). Validation of SWAT model for stream flow simulation and forecasting in Upper Bernam humid tropical river basin,Malaysia. *Hydrology and Earth System Sciences, 6*, 7581–7609.

Almendinger J. E., J. U. (2010). *Constructing a SWAT model of the Sunrise River watershed, eastern Minnesota.* Minnesota: St. Croix Watershed Research Station, Science Museum of Minnesota.

Amir, M. S., Ibne, S. I., Khan, M. M., Rasul, M., Sharma, R. H., and Akram, F. (2013). Automatic Multi-Objective Calibration of a Rainfall Runoff Model for the Fitzroy Basin, Queensland, Australia. *International Journal of Environmental Science and Development,, Vol. 4*(No. 3), 311-315.

Anh, N. L., Boxall, J. B., Saul, A. J., and Willems, P. (2008). *An evaluation of three lumped conceptual rainfall-runoff models at catchment scale.* Sheffield, UK: The 13th World Water Congress.

Arnold J.G. et. al. (1995). Automated Base Flow Separation and Recession Analysis Techniques. *Ground Water Vol 33; No 6*, 1010-1018.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., . . . Jha, M. K. (2012, May). SWAT: Model use, Calibration and Validation. *Transactions of the ASABE, 55*(1), 1491-1508.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., and Williams, J. R. (1998). Large area hydrologic modelling and assessment Part 1: Model development. *Journal of American Water Resources Association*, 73-89.

Bahremand, A. (2006). *Simulating the effects of reforestation on floods using spatially distributed hydrologic modeling and GIS.* Brussels: Department of Hydrology and Hydraulic Engineering,Vrije Universitiet Brussels.

Bengtson, M., and Padmanabhan, G. (1999). *A review of models for investigating the influence of wetlands on flooding.* Fargo, North Dakota: North Dakota Water Resources Research Institute,North Dakota State University.

Borah, D. K., and Bera, M. (2004). Watershed Scale Hydrologic and Non Point Source Pollution Models : Review of Applications. *Transactions of the ASAE, 47*(3), 789−803.

Célleri, R., Willems, P., and Feyen, J. (2010). Evaluation of a data-based hydrological model for simulating the runoff of medium sized Andean basins. *MASKANA, Vol. 1, No. 1,* 61-77.

Chow, V., Maidment, D., and Mays, L. (1988). *Applied Hydrology.* New York.: McGraw-Hill.

Climatemps.com. (2013, 3 2). *http://www.eldoret.climatemps.com/.* Retrieved 3 7, 2014, from CLIMATEMPS.COM: http://www.climatemps.com/

County Govt U.G. (2013). *County Integrated Development Plan,Uasin Gishu 2013-2018.* Eldoret,Kenya: The County government of Uasin Gishu.

De Silva, R. P., Dayawansa, N. D., and Ratnasiri, M. D. (2007). A comparison of methods used in estimating missing rainfall data. *Journal of Agricultural Science, 3*, 101-108.

DHI. (2009). *A Modelling System for Rivers and Channels reference manual.* Copenhagen: Danich Hydraulic Institute.

El-Nasr, A., Willems, P., Timbe, L., Christianes, K., and Feyen, J. (2011). *Comparative Analysis of the Runoff-Generation Using Lumped and Distributed Approaches, with Application to the Jeker Catchment in Belgium.* Leuven: Laboratory of Hydraulics, K.U.Leuven.

Gassman, P. W., Jha, M., Secchi, S., and Arnold, J. (2003). Initial calibration and validation of the SWAT model for the Upper Mississippi River Basin. *In Proceedings of the 7th International Water Association Conference on Diffuse Pollution* (pp. 10-35). Dublin: Diffuse Pollution Conference.

Gautam, R. (2004). *Development and evaluation of water quantity model in NAN watershed Thailand.* Ottawa, Canada: ASAE.

Githui, F. (2008). *Assessing the impacts of environmental change on the hydrology of the Nzoia catchment, in the Lake Victoria Basin.Phd Thesis.* Brussels, Belgium.: Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel,.

Griensven, A. v. (2008). *Sensitivity, auto-calibration , uncertainty and model evaluation in SWAT2005.* Delft: unesco-ihe.org.

GWP. (2000). *Integrated Water Resources Management. TAC Background Papers No. 4 .p67.* Stockholm.: Global Water Partnership.

Karani, P. W. (2005). *National Nile Basin Water Quality Monitoring Baseline Report.* Nairobi: Nile Basin Initiative (NBI),Water and Environment Management Consultants.

Kenya Soil Survey (KSS). (1997). *Soil Physical and Chemical Properties of Kenya.* Nairobi, Kenya: GOK,JICA.

KMD. (2005). Kenya Rainfall Station Index. Nairobi, Kenya: Kenya Meteorological Department.

Korir, L. K. (2010). *Farm households' livelihood diversification and its implications for young people's.* Egerton,Njoro,Nakuru-Kenya: Department of Agricultural Economics, Egerton University 20115 Kenya.

Kovacs, A., Simonffy, Z., and Batelaan, O. (2005). A Comparative study of two distributed rainfall-runoff models. *European Geosciences Union*, 12-15.

Krause, P., Boyle, D. P., and Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences European Geosciences Union, 5*, 89-97.

Krysanova, V., Bronstert, A., and Müller-Wohlfeil, D. I. (1999). Modelling river discharge for large drainage basins: from lumped to distributed approach. *Hydrological Sciences Journal, 44)*(2 (1999), 313-331.

Kundzewicz, Z., Mata, L., Arnell, N., Döll, P., Kabat, P., Jiménez, B., . . . Z. Sen and I.A. Shiklomanov. (2007). *Freshwater resources and their management. Climate Change 2007: Impacts, Adaptation and Vulnerability.* Cambridge, UK,: Cambridge University Press.

Linde, A. H., Aerts, J. C., Hurkmans, R. T., and Eberle, M. (2007). Comparing model performance of the HBV and VIC models in the Rhine Basin. *Hydrology and Earth System Sciences*, 4325–4360.

Lu, J., Sun, G., McNulty, S. G., and Amatya, D. M. (2005). A comparison of six potential evapotranspiration methods for regional use in the southeastern United States1. *Journal of the American Water Resources Association (JAWRA), 41*(3), 621-633.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., and Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *guidelines for systematic quantification of accuracy in watershed simulations. Trans. Asabe, 50*(3), 885-900.

MWI, and UN-Water. (2006). *Kenya National Water Development Report.* Nairobi: Ministry of Water and Irrigation.

Neistch, S. A. (2011). *Texas Water Resource Institute Technical Report No-406 Soil and Water Assessment Tool, Theoretical Documentation Version 2009.* Texas: Grassland Soil and Water Research Laboratory-ARS,Backland Research Center,TAMU.

Neitsch, S., Arnold, J., Kiniry, J., Srinivasan, R., and Williams, J. (2004). *Soil and water assessment tool; Input/output file documentation. Version 2005.* Texas: Grassland soil and water research laboratory;Agricultural Research Service.

Nietsch, S., Arnold, J., Kiniry, J., and Williams, J. (2005). *Soil and Water Assesment Tool Theoretical Documentation Version 2005.* Temple , Texas: Agricultural Research Service.

NOAA. (2014, FEBRUARY 25). *NOAA SATELITE AND INFORMATION SERVICE*. Retrieved from NNDC CLIMATE DATA ONLINE: http://www7.ncdc.noaa.gov/CDO/cdodata.cmd

Nossent, J. (2010). *Sensitivity and uncertainity analysis in view of the parameter estimation of a SWAT model for the River Kleine Nete, Belgium PHD Study Report.* Brussels,Belgium: Vrije Universiteit Brussels.

Pechlivanidis, I. G., Jackson, B. M., McIntyre, N. R., and Wheater, H. S. (2011). Catchment scale hydrological modelling: a review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. *Global NEST Journal,, Vol 13,* (No 3,), 193-214.

Quan, N. H. (2006). *Rainfall Runoff Modelling of the ungauged Can Le Catchment, Saigon River Basin.* Enschede, Netherlands: International institute of Geo informationscience and earth observation.

Raes, D. W. (2006). RAINBOW – a software package for analyzing data and testing the homogeneity of historical data sets. Proceedings of the 4th. *Proceedings of the 4th International Workshop on 'Sustainable management of marginal drylands'.* Islamabad: Pakistan.

Rubarenzya, M. H., Willems, P., and Berlamont, J. (2007). Identification of uncertainty sources in distributed hydrological modelling: Case study of the Grote Nete catchment in Belgium. *Water SA, 33* (No. 5), 633-642.

Ruelland, D., Ardoin-Bardin, S., Billen, G., and Servat, E. (2008). Sensitivity of a lumped and semi-distributed hydrological model to several methods of rainfall interpolation on a large basin in West Africa. *Journal of Hydrology 361, 361*(1), 96– 117.

Saleh, A. A. (2008). *Uncertainity Analysis of hydrological Models; Nzoia River Case Study.* Delft: UNESCO-IHE.

Setegn, S., R. Srinivasan, and Dargahi, B. (2008). Hydrological Modelling in the Lake Tana Basin, Ethiopia Using SWAT Model. *The Open Hydrology Journal*, 49-62.

Shawul, A. A., Alamirew, T., and Dinka, M. O. (2013, November 15). Calibration and validation of SWAT model and estimation of water balance components of Shaya mountainous watershed, Southeastern Ethiopia. *Hydrology and Earth System Sciences Discussions.*, 13955-13978. doi:10.5194/hessd-10-13955-2013

Shrestha, N., Shakti, P., and Gurung, P. (2010). Calibration and Validation of SWAT Model for Low Lying Watersheds: A Case Study on the Kliene Nete Watershed, Belgium. *HYDRO NEPAL*, 47-51.

Shultz, M. (2007). *Comparison of distributed versus lumped hydrologic simulation models using stationary and moving storm events applied to small synthetic rectangular basins and an actual watershed basin.* Arlington, Texas: Faculty of the Graduate School of The University of Texas at Arlington.

Shultz, M., Crosby, C., and McEnery, A. (2007). *Comparisson of distributed versus lumped hydrologic simulation models using stationary and moving storm events applied to small synthetic rectangular basins and an actual watershed basin.* ARLINGTON: THE UNIVERSITY OF TEXAS AT ARLINGTON.

Staes, J., Willems, P., Marbaix, P., and Vrebos, D. (2011). *Impact of climate change on river hydrology and ecology: a case study for interdisciplinary policy oriented research. Final report.* Brussels: Belgian Science Policy.

Tanner, J. L., and Hughes, D. A. (2013). *Validating hydrological models in a data scarce country – getting the right results for the right reasons.* Grahamstown, South Africa: Institute for Water Research, Rhodes University,.

Tessema, S. M. (2011). *Hydrological Modeling as a Tool for Sustainable Water Resources Management: A Case Study of the Awash River Basin.* STOCKHOLM, SWEDEN: Environmental Management and Assessment Research Group Department of Land and Water Resources Engineering Royal Institute of Technology (KTH).

Thomas, B. C. (2010). *Comparison of two physically-based spatially distributed hydrology models in contrasting geo-climatic settings MSc Thesis.* Twente: University of Twente (The Netherlands).

UNEP. (2008). *vital water graphics An Overview of the State of the World's Fresh and Marine Waters - 2nd Edition - 2008*. Retrieved 1 24, 2014, from www.unep.org: http://www.unep.org/dewa/vitalwater/article24.html

UNEP. (2012). *Status Report on The Application of Integrated Approaches to Water Resources Management.* Nairobi, Kenya: UNEP, Division of Communications and Public Information.

Vansteenkiste, T., Steenbergen, V., Ntegeka, N., and Willems, P. (2012). Intercomparison of runoff predictions by lumped and distributed models before and after climate change. *In EGU General Assembly Conference Abstracts, 14*, 2738.

Verma, A. K. (2010). Evaluation of HEC-HMS and WEPP for simulating watershed runoff using remote sensing and geographical information system. *Paddy and Water Environment Volume 8, Issue 2*, 131-144.

Wang, X., Shang, S., Yang, W., Clary, C. R., and Yang, D. (2010). Simulation of land use–soil interactive effects on water and sediment yields at watershed scale. (W. J. Mitsch, Ed.) *Ecological Engineering, The Jornal of Ecosystem Restoration, 36*(3), 328-344.

Willems, P. (2005). *Guidance document for calibration and verification of rainfall-runoff models.Internal report.* Leuven, Belgium: Hydraulics Laboratory, Katholieke Universiteit Leuven.

Willems, P. (2008). A time series tool to support the multi-criteria performance evaluation of rainfall-runoff models,. *Environmental Modeling Software*, 45-56.

Willems, P. (2009). A time series tool to support the multi-criteria performance evaluation of rainfall-runoff models. *Environmental Modelling and Software Vol: 24,Elsevier*, 311–321.

Willems, P. (2012). Model uncertainty analysis based on variance decomposition. *Physics and Chemistry of the Earth, Parts A/B/C 42 (2012)*, 21-30.

Willems, P., Mora, D., Vansteenkiste, T., Taye, M. T., and Van Steenbergen, N. (2014). Parsimonious rainfall-runoff model construction supported by time series processing and validation of hydrological extremes – Part 2: Intercomparison of models and calibration approaches. *Journal of Hydrology, 510*, 591-609.

Winchell M. et al., R. S. (2007). *ArcSWAT interface for SWAT 2005 User's guide.* Temple-Texas: Backland Research Center USDA-ARS.

Winchell, M., Srinivasan, R., Di Luzio, M., and Arnold, J. (2007). *Arc SWAT interface for SWAT 2005 User's Giude.* Temple,Texas: Grassland Soil and Water Research Laboratory, USDA ARS.

WMO. (2012). *Technical Material for Water Resources Assessment.* Geneva, Switzerland: Chair, Publications Board, World Meteorological Organization (WMO).

WRMA. (2000). River discharge for River sergoit 1CA02. Rift Valley, Kenya.

WRMA. (2009). *Integrated Water Resources Management and Water Efficiency Plan.* Nairobi: G.O.K.

Ximing C., C. R. (2006). *Modeling Water Resources Management at the Basin Level Methodology and Application to the Maipo River Basin.* Washington, D.C. U.S.A: International Food Policy Research Institute.

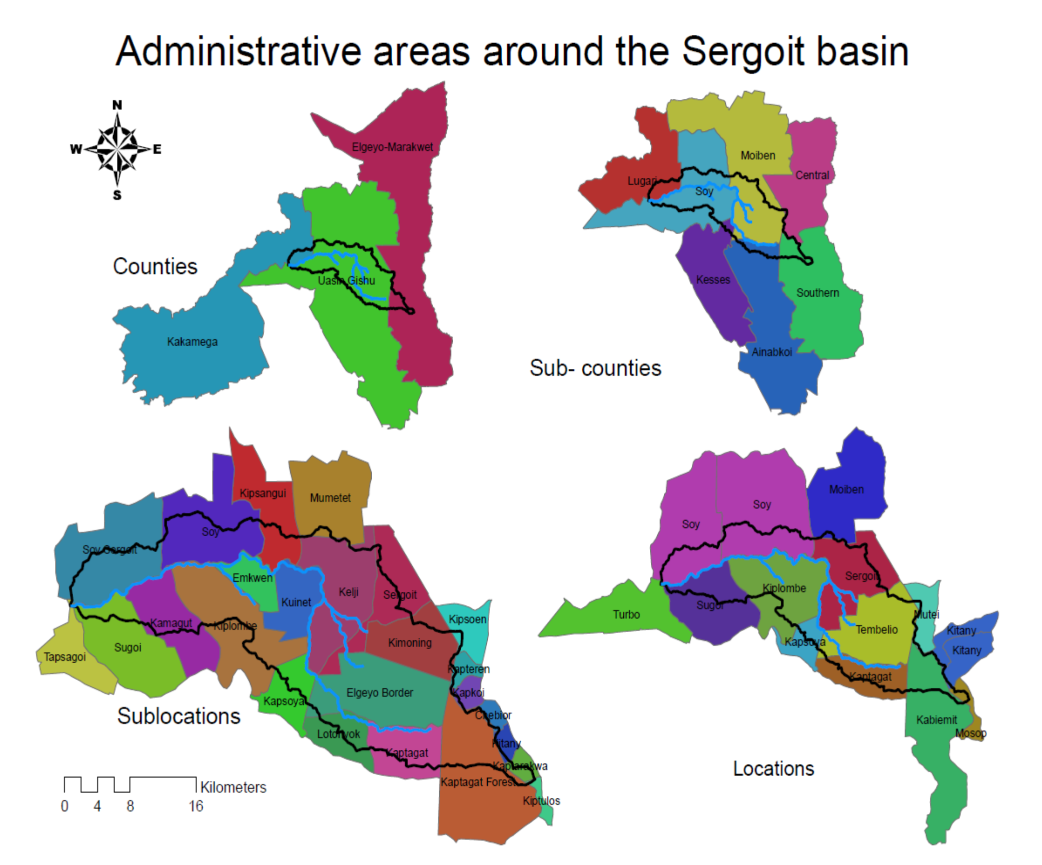
Xingqi, C., Wenchao, S., Jianbiao, T., Hao, S., and Xiaolei, Y. (2014). Effect of length of the observed dataset on the calibration of a distributed hydrological model. *Remote Sensing and GIS for Hydrology and Water Resources* (pp. 305-311). Guangzhou,: IAHS Press. doi:10.5194/piahs-368-305-2015

Xu, C. Y. (2002). *Text Book of Hydrologic Models.* Uppsala, Sweden: Uppsala University Department of Earth Sciences Hydrology.

Zakayo, S. (2009). *Multi-objective Calibration of SWAT model for pesticide simulation.* Delft: UNESCO-IHE.

Appendices

Appendix A: Administrative regions about Sergoit Basin



Appendix B : Thiessen weights of rain gauge stations used

No	Station ID	Latitude	Longitude	Altitude (m)	Thiessen weight
1	8935133	0.567	35.3	2156	0.441943
2	8935181	0.533	35.283	2137	0.022445
3	8935170	0.633	35.05	1817	0.127711
4	8935134	0.65	35.517	2151	0.048288
5	8935164	0.5	35.483	2438	0.22421
6	8935016	0.766667	35.18333	1969	0.135403

Appendix C : Homogeneity tests of rainfall data for the stations used

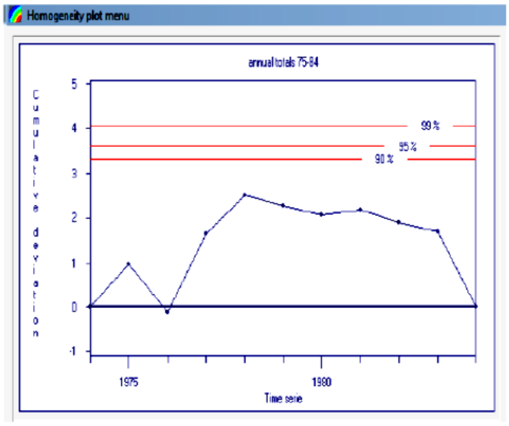


Figure 1: 8935016

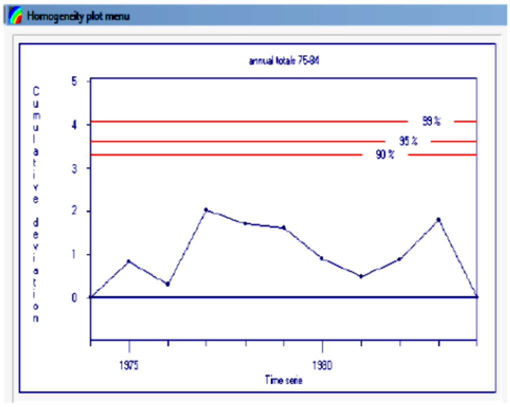


Figure 2: 8935181

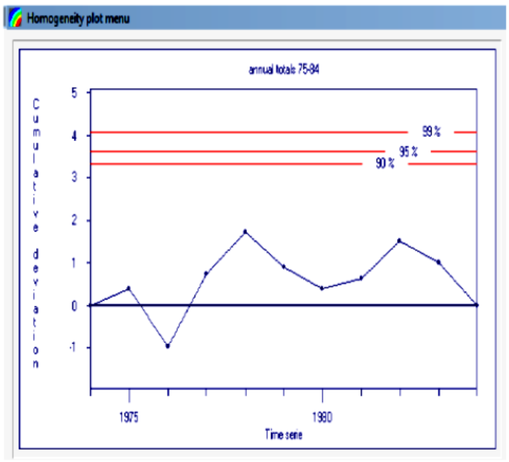


Figure 3: 8935170

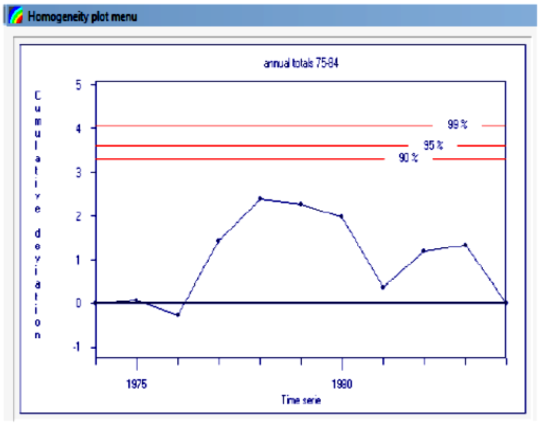


Figure 4: 8935164

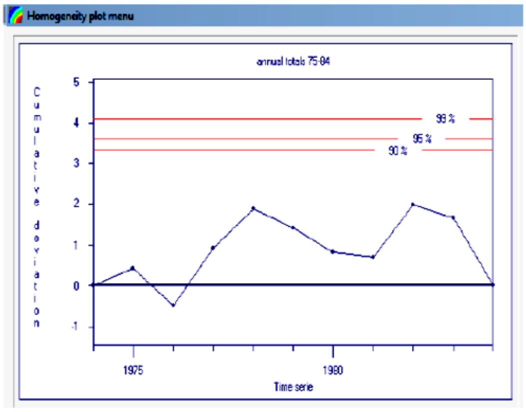


Figure 5: 8935134

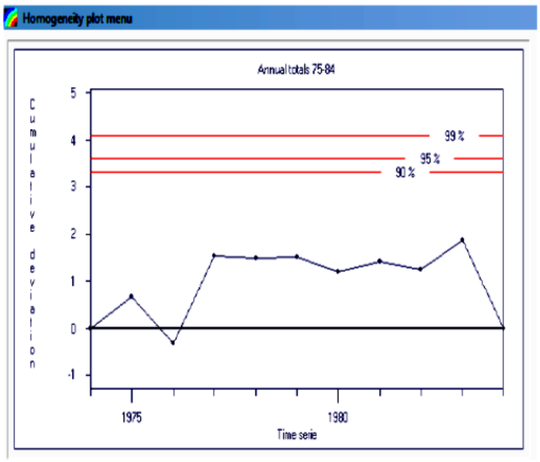


Figure 6: 8935133