ASSESSMENT OF THE TRANSFERABILITY OF SWAT MODEL PARAMETERS FROM GAUGED TO UNGAUGED SUB-WATERSHEDS FOR STREAMFLOW SIMULATION IN THE UPPER TANA WATERSHED, KENYA

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Assessment of the Transferability of SWAT Model Parameters from Gauged to Ungauged Sub-Watersheds for Streamflow Simulation in the Upper Tana Watershed, Kenya

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other university.

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DEDICATION

To my parents Charles and Rose Nkonge for all the guidance, love and sacrifices.

To my sisters Muthoni, Makena and Mwendwa for your support and prayers.

To my husband Kiptoo for supporting, encouraging and believing in me.

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ACRONYMS

AMSR	Advanced Microwave Scanning Radiometer
AMSU	Advanced Microwave Sounding Unit
ARS	Agricultural Research Service
ASCE	American Society of Civil Engineers
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellites Program
FEWS	Famine Early Warning System
FEWSNET	Famine Early Warning Systems Network
FEWS RFE	Famine Early Warning System Rainfall Estimates
GIS	Geographical Information System
GOES	Geostationary Operational Environmental Satellites
GTS	Global Telecommunication System
HBV	Hydrologiska Byrans Vattenbalansavdelning
HRUs	Hydrologic Response Units
IAHS	International Association of Hydrological Sciences
IDWI	Inverse Distance Weighted Interpolation

ISRIC	International Soil Reference and Information Centre
KMD	Kenya Meteorological Department
LH-OAT	Latin Hypercube One factor At a Time analysis
MAE	Mean Absolute Error
MCMC	Markov Chain Monte Carlo
MODIS	Moderate Resolution Imaging Spectro-radiometer
NOAA	National Oceanic and Atmospheric Administration
NSE	Nash-Sutcliffe Efficiency
NCWSC	Nairobi City Water and Sewerage Company
PBIAS	Percent Bias
PCCs	Physical Catchment Characteristics
PUB	Predictions in Ungauged Watersheds
$\mathbf{R^2}$	Coefficient of determination
RFE	Rainfall Estimate
RMSE	Root Mean Square Error
SHE	Système Hydrologique Europèen

SRTM Shuttle Radar Topography Mission

SSM/I Special Sensor Microwave/Imager

SWAT Soil and Water Assessment Tool

SWAT-CUP Soil and Water Assessment Tool-Calibration Uncertainty Program

TRMM Tropical Rainfall Measuring Mission

UNESCO Unitedhttp://www.unesco.org/ Nations Educational, Scientific and Cultural Organization

USDA United States Department of Agriculture

WRMA Water Resources Management Authority

ABSTRACT

Predictions in ungauged watersheds are regarded as some of the most challenging tasks in surface hydrology. A large amount of parameters and input data are required for the application of most hydrological models. Calibration of these models require high quality, sufficiently long term observation of streamflow and other variables, but observed data on both temporal and spatial scales of interest are always very limited. Due to the difficulty in direct implementation of hydrologic models in ungauged watersheds, alternative strategies for prediction are required. Prediction of streamflow in ungauged watersheds is performed through the transfer of hydrologic information (e.g., streamflow values, hydrologic indices, model parameters) from gauged to ungauged watersheds.

The objective of this study was to assess the transferability of the Soil and Water Assessment Tool (SWAT) model parameters from gauged sub-watersheds for streamflow simulation in "ungauged" sub-watersheds of the Upper Tana Watershed. Three methods namely: spatial proximity, global averages and regression were evaluated as approaches for developing SWAT parameters values to enable estimation of daily streamflow for ungauged sub-watersheds with a certain degree of accuracy. In Upper Tana watershed, water is used for electricity generation by five main hydropower stations in Tana River, municipal water supply and for irrigation schemes. With increased demand of water to meet agricultural, domestic, municipal and industrial needs, there is an urgent need to manage water resources in the Upper Tana Watershed in a sustainable and integrated way.

SWAT was calibrated at a daily time step in four sub-watersheds of the Upper Tana Watershed. Model calibration was first done manually and then automatically using the Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm in the SWAT CUP software. The spatial proximity method was used to transfer parameters between neighbouring sub-watersheds. Global average parameters were determined by

computing the mean of each of the parameters used in calibration. For the regression based transfer method, physical sub-watershed characteristics were derived from spatial data using GIS. Stepwise regression was used to develop equations which relate the sub-watershed characteristics to model parameters therefore enabling estimation of model parameters from sub watershed characteristics.

The SWAT model performed well in simulating daily streamflow, attaining a coefficient of determination (R^2) ranging from 0.57 to 0.69 and Nash-Sutcliffe efficiency (NSE) ranging from 0.51 to 0.67. The spatial proximity method yielded R^2 ranging from 0.5 to 0.69. Global average parameters method attained R^2 ranging from 0.54 to 0.67. For the regression based transfer method, R^2 obtained ranged from 0.5 to 0.73.

The spatial proximity method performed better than the global average and regression method. This was evident through the performance statistics and the simulation of the high and low flows. However, there is need to compare results from a different hydrological model in order to evaluate how the transfer approaches perform. The results of this study indicated that transfer of SWAT model parameters can be used to generate streamflow data in ungauged sub-watersheds for the purposes of water resources planning and management.

CHAPTER ONE

INTRODUCTION

1.1 Background information

A variety of predictive tools that can generate predictions of hydrologic responses over a range of space/time scales and climates are required for wise management of water and the environment, and integrating economic, social and environmental perspectives (Tessema, 2011). Accurate and reliable predictions of hydrologic responses are becoming extremely important to civic society due to their help in planning and managing water resources (Bao *et al*., 2012). Local and regional communities are increasingly making independent judgments about actions required to prevent and manage natural disasters, and manage the natural environment around them and their water resources in a sustainable manner (Lindenschmidt *et al*., 2007; Shakti *et al*., 2010). These decisions can only be made with the widest possible information being made available based on accurate and reliable predictions (Mango *et al*., 2011). Long-term measurements of river streamflow are necessary for a number of applications in water resources, such as planning of irrigation projects and water supply, delineation of river floodplains and day-to-day management of dams and canals e.t.c (Patil, 2011 & Mongelos, 2012).

However, many watersheds in the world are scarcely gauged (Goswami *et al*., 2007; Sellami et al., 2014). The few measurements that are available are often uncertain, scarce, intermittent or non-concomitant. Only in extremely rare cases will hydrological data be available at the exact location of the proposed site (Loukas & Vasiliades, 2014). This jeopardises the application of hydrological models that in the short term are needed to predict droughts, floods and availability of water, and in the long term the effects of changes in the land cover or climate on streamflow (Jotish *et al*., 2011; Winsemius et al., 2009).

Predictions in ungauged watersheds (PUB) are regarded as some of the most challenging tasks in surface hydrology. The International Association of Hydrological Sciences (IAHS) launched an initiative, the IAHS Decade on PUB (2003-2012). Its focus was on "formulating and implementing appropriate science programmes to engage and energize the scientific community, in a coordinated manner, towards achieving major advances in the capacity to make reliable predictions in ungauged watersheds" (Sivapalan *et al*., 2003). Developing practical predictions in ungauged watersheds is important for assessing water resources in ungauged or poorly gauged watersheds which are usually located in headwater regions (Zhang *et al*., 2009).

In such circumstances, the hydrologist has to generate streamflow records from rainfall and other meteorological data or synthesize flows from time series analyses carried out in nearby gauged watersheds (Gitau & Chaubey, 2010). Transferring hydrologic information (e.g. model parameters, hydrologic indices, streamflow values) from a gauged watershed to the target ungauged watershed is typically used for water quantity studies in PUB (Oudin *et al*., 2008; Sellami *et al*., 2014; Zhang *et al*., 2009). In order to successfully transfer the hydrologic information among watersheds, it is important to ensure that the donor (gauged) and receiver (ungauged) watersheds are similar to each other in terms of hydrologic behavior (Patil, 2011).

In most cases, runoff–rainfall relationships are developed for gauged watersheds in the region using regression analyses and the regression coefficients are then regionalized by relating them to watershed physical characteristics so that suitable coefficients may be derived for ungauged watersheds (Bao *et al*., 2012). Attempts to improve such regression approaches have been made by including additional variables such as temperature, antecedent wetness indices and time of the year among other variables. The accuracy with which streamflow can be estimated will improve as more variables are included, but the increased data requirement will prevent the widespread use of such relationships (Nandagiri, 2007).

1.2 Statement of the problem

Proper management and utilization of the available water resources is essential in order to meet the increasing water demand caused by rapid urbanization, extensive agricultural practices, and the growing population (Tessema, 2011). Hydrologic modeling, especially modeling streamflow generation processes, is vital for management and utilization of available water resources (Jotish *et al*., 2011). Reliable streamflow data is needed for the design and operation of water resource management structures. Such data can be obtained from watersheds which are gauged (Mutua *et al*., 2007).

However, majority of rivers in many watersheds in Kenya are poorly gauged or ungauged, and in some cases there is a decline of the existing measurement networks (Mutua *et al*., 2007). The high cost of maintaining flow measuring equipment is hindering long-term continuous monitoring. Due to the scarcity or absence of hydrological data, the efficiency of hydrological models in assessing flood and drought risk, water resources and man-made and climatic change effects in watersheds is jeopardized (Winsemius *et al*., 2009).

Kenya suffers from water crisis due to various causes, including floods, forest degradation, drought, lack of water supply management, contamination of water, and continued population growth (Marshall, 2011). Management of water resources in terms of quantity and quality requires access to daily streamflow data at the watershed scale. Construction of hydrologic structures such as a dam or bridge may require a prediction to be made of the hydrologic response of a watershed at an ungauged point. Therefore, an alternative tool that is capable of predicting the daily streamflow is needed (Jotish *et al*., 2011).

1.3 Justification of the study

Hydrological modeling is an important decision support system. The models have aided several management decisions in evaluating the impacts of variables like precipitation,

soil types and land use changes on natural resources like water (Alaba, 2010). These models have become increasingly sophisticated and useful and there is a need to extend their applicability to areas where they cannot be calibrated or validated. It is only natural that as hydrological models, computer technology and hydrometeorology data sources continue to evolve, there will be an ever increasing need to apply them in ungauged watersheds. Hydrological models cannot be calibrated or validated without streamflow data, hence regionalization methods are needed which easily relate measured watershed characteristics to model parameters (Zelewlew & Alfredsen, 2014).

Accurate estimates of hydrologic variables at ungauged sites are not only important for water resources planning and management issues, but are increasingly germane to ecological studies across a wide range of temporal and spatial scales. In fact, the limited availability of gauged data causes ill-quantifiable uncertainty in model outputs. Water resource managers are often restrained from further investigation by this problem while there is a great need for hydrological models in these ungauged watersheds. Therefore, this research seeks to analyze the transferability of model parameters from gauged to ungauged watersheds which will facilitate hydrological modeling and thus proper management of water resources. The Upper Tana was chosen for the study because it had a good amount of temporal and spatial datasets.

1.4 Research objectives

The broad objective of this research was to assess the transferability of Soil and Water Assessment Tool (SWAT) parameters from gauged sub-watersheds for streamflow simulation in “ungauged” sub-watersheds of the Upper Tana watershed.

The specific objectives were:

1. To calibrate and validate the Soil and Water Assessment Tool (SWAT) model for the selected sub-watersheds in the Upper Tana watershed.

2. To determine the parameter set to be transferred from the donor (gauged) sub-watersheds to the recipient ("ungauged") sub-watersheds using spatial proximity, global averages and regression approaches.
3. To estimate streamflow in the "ungauged" sub-watersheds using the transferred parameters and evaluate the model performance.

1.5 Scope of the study

Transferring hydrologic information from gauged to ungauged watersheds is a widely used approach for predictions in ungauged watersheds (Gitau & Chaubey, 2010; Oudin et al., 2008). The transfer of information is recommended among watersheds that are perceived to be similar in terms of hydrologic response (Patil, 2011). The model was calibrated and validated using data from chosen sub-watersheds in the Upper Tana Watershed. The optimized parameters were then transferred to the "ungauged" watersheds for streamflow prediction. In this study, an "ungauged" sub-watershed actually has data but it is assumed that it has no data for the purpose of this research. This is important because the simulated data has to be compared to the gauged data in order to assess how the transfer methods perform.

1.6 Description of the study area

1.6.1 Location

The Upper Tana watershed, covering an area of 7,366 km^2, includes the whole of Murang'a county and parts of Nyeri, Embu, Kiambu, Kirinyaga, Laikipia, Nyandarua and Machakos counties (Figure 0.1).It is located between Aberdare Ranges to the west, Nyambene hills to the east, Mt. Kenya to the north and Kikuyu escarpment to the south. It lies between longitudes 36.55°E and 37.60°E and between latitudes 0.15°S and 1.15°S. The main drainage channel is River Tana which rises from the Aberdare Ranges and runs into the Masinga dam.

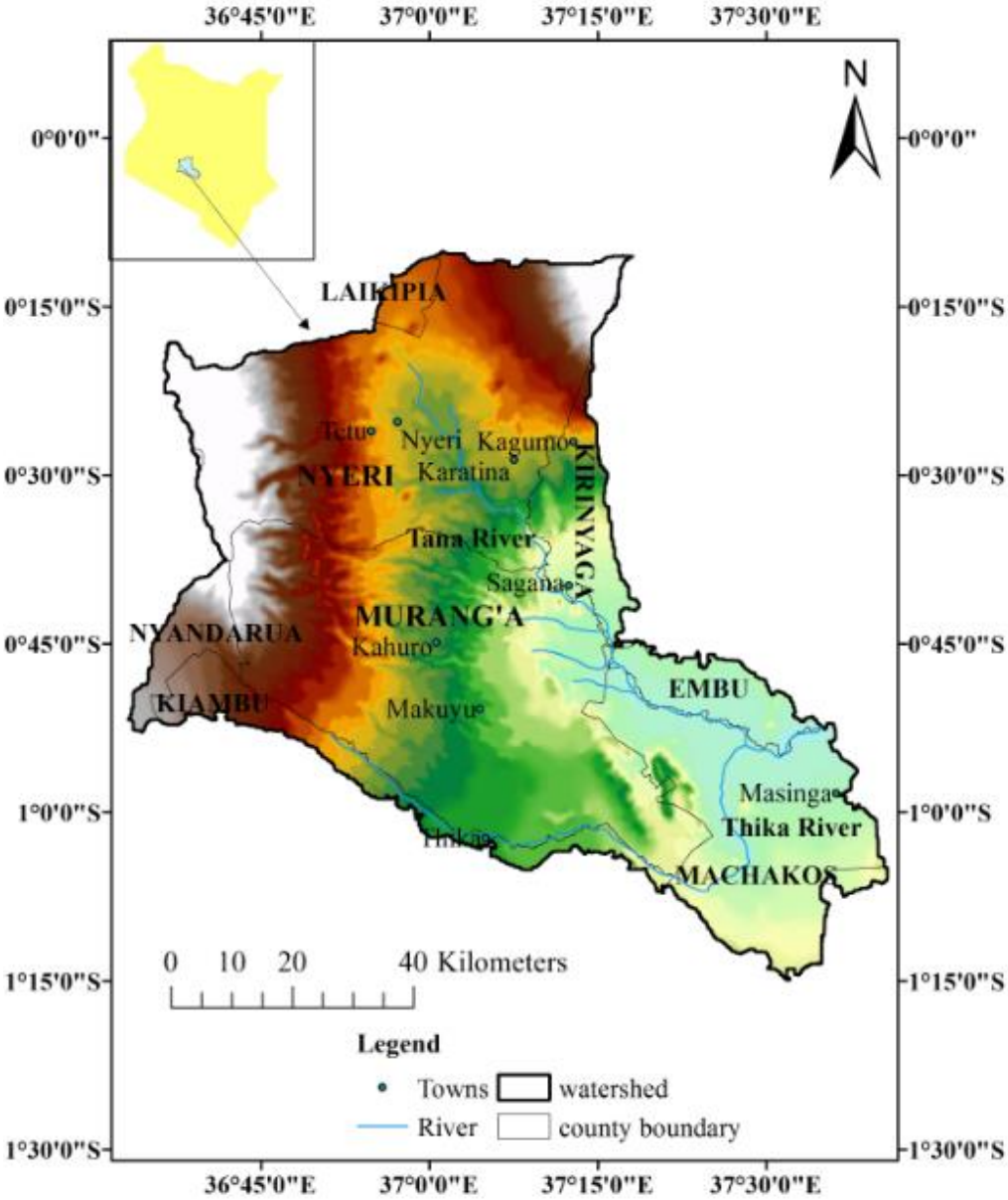


Figure 0.1: Location of the study area

1.6.2 Climate

The Upper Tana watershed experiences a bimodal rainfall pattern as a result of the Intertropical Convergence Zone; the long rains starts from March to May and the short rains starts from October to December. The driest period is between December and mid-March (Hunink *et al*., 2009). The rainy seasons vary considerably from year to year in their duration and rainfall totals. The mountainous watersheds have very heterogeneous rainfall patterns which are hard to capture due to the few meteorological stations.

Rainfall in the watershed area decreases with decreasing altitude. The windward south-eastern side of Mt. Kenya receives annual precipitation of 2,300 mm while those in the summit region and savannah receive 800 mm per annum and 400 mm per annum, respectively (Geertsma *et al*., 2011; Njogu & Kitheka, 2017). (Figure 0.2) shows the rainfall distribution in the Upper Tana watershed. Annual Potential evapotranspiration ranges from less than 500 mm in the summit region to around 1,700 mm in the low elevation savannah zone. Areas below the forest zone have a rainfall evapotranspiration deficit thus the discharge of the rivers in the dry periods is provided by moorland zones and high elevation forests. The mean annual minimum and maximum temperatures are 10°C and 22°C, respectively (Jaeztold *et al*., 2006).

1.6.3 Soils and geology

The higher parts of the watershed such as the slopes of Mt. Kenya and Aberdare Ranges are dominated by volcanic ash soils (Andosols), histosols and lithic leptosols. The middle foot slopes mainly have Nitisols which are deep well-structured nutrient rich clay soils. The lower foot slopes are dominated by very deep strongly leached poor clay soils (Ferralsols) and by less leached soils (Cambisols and Luvisols). Cambisols and sodic-alkaline soils (Solonetz) are the dominant soils at elevations lower than 1,000m (Hunink & Droogers, 2011)

The surface geology of the watershed comprises two main geologic structures: the volcanic rocks and metamorphic rocks. The volcanic rocks such as trachytes, basalt and phonolites; of the Cenozoic era are found in the west. The volcanic rocks mainly originate from the Mt Kenya. The east contains metamorphic rocks of the Mozambique belt (Wilschut, 2010). The entire flood plain in the Upper Tana consists of recent alluvial sediments overlying the Mozambique belts and metamorphic rocks (Hughes, 1984).

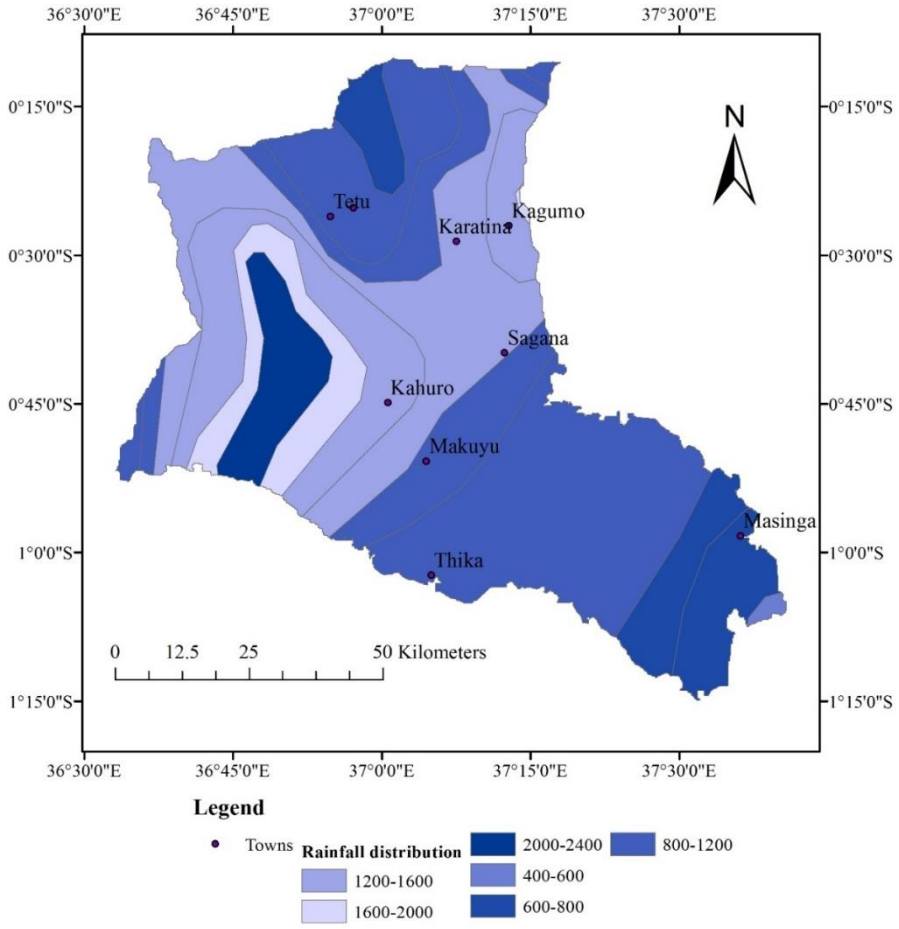


Figure 0.2: Rainfall distribution in the Upper Tana watershed

1.6.4 Hydrology

Tana River is the main river in the watershed and it supplies water to 17 million people. The Tana River receives its water from Mt. Kenya and the Aberdare Ranges. The rivers which drain from Mt. Kenya are Nyamindi, Mutonga, Nithi, etc while those that drain from the Aberdare Ranges are Mathioya, Sagana and Maragua (Wilschut, 2010). The flow of the Tana ranges between 60 and 750 m^3/s. The peak river discharges occur from March to June and October to December and low discharges during months of January and February (Geertsema, 2009).

CHAPTER TWO

LITERATURE REVIEW

1.7 Hydrological modeling

A model is an elucidated representation of the real world (Devi *et al*., 2015). A hydrological model can be defined as a set of equations that aid in the simulation of streamflow as a function parameters that describe the characteristics of the watershed. The best model is the one which closely simulates the reality. Hydrological processes simulation is fundamental in addressing water and environmental issues. (AghaKouchak & Habib, 2010). Water resources managers use hydrological models to help in assessing the impact of management practices on water supplies and non-point source pollution in watersheds and river watersheds (Mongelos, 2012). Hydrologic model have evolved over time into complex decision support tools ((Tang *et al*., 2007).

1.7.1 Classification of hydrological models

Hydrological models can be grouped into various categories depending on their modelling approaches. These are physically-based, empirical or conceptual depending on the nature of the algorithm that has been used (Daniel *et al*., 2011). They can also be classified according to the model input and parameters. A model can either be distributed or lumped based on model parameters as a function of time and space (Devi *et al*., 2015).

A wide range of spatially distributed hydrologic models have been developed in the past decade due to advances in hydrologic sciences, remote-sensing and Geographical Information System (GIS). The SWAT model which is among the many hydrologic models in the past decade, developed by (Arnold *et al*., 1998), has been extensively used by researchers worldwide (Jamshidi *et al*., 2010; Tong *et al*., 2009; Van Liew *et al*., 2012). This is because SWAT uses readily available inputs for weather, topography, land and soil and allows considerable spatial detail for watershed scale modeling

(Narishmhan, 2004). It is also freely available in the internet, computationally efficient and enables users to study long term impacts (Neitsch *et al*., 2005).

SWAT model performance has been widely compared to other models. Nazirappoya *et al*. (2015), compared the IHACRES and SWAT models for streamflow simulation at two watersheds, Sulan and Yalfan, in West of Iran. It was found that SWAT performed better in streamflow simulation. SWAT was also compared to the GWLF model and the results showed that SWAT is suitable where data measured is scarce and when high accuracy is required (Qi *et al*., 2017). SWAT was chosen for this study because surface-groundwater are represented better through base flow and recharge, it can rum with minimal data, it combines strength of both fully distributed and lumped models and it is computationally efficient (Abbaspour *et al*., 2010; Mango *et al*., 2011; Orellana *et al*., 2008). SWAT has also been successfully used in Kenya (Hunink *et al*., 2009; Hunink *et al*., 2012; Mango *et al*., 2011; Mwangi *et al*., 2016).

1.7.2 The SWAT model

SWAT is a watershed scale model whose design makes it reliable in modeling ungauged watersheds and, more importantly, simulating the impact of alternative input data such as changes inland management practices, land use and climate (Arnold *et al*., 1998; Neitsch *et al.*, 2005). Major input datasets include weather, topography, hydrography, land use/land cover data, soils and management practices (Jha *et al*., 2007). SWAT divides a watershed into sub-watersheds connected by a stream network and further delineates each sub-watershed into hydrologic response units (HRUs), which consist of unique combinations of soil type, slope and land cover (Stehr *et al*., 2008) .HRU delineation can minimize a simulation's computational costs by lumping similar soil and land use areas into a single unit (Neitsch *et al*., 2005).

1.8 Baseflow separation

Baseflow is one of the important components of streamflow. In hydrological modelling, it is essential to know groundwater contribution to streamflow. This can be done by assessing the base flow component of streamflow (Gonzales *et al*., 2009). Baseflow separation is important because the quick flow and baseflow generation processes in the watershed are dis-similar (Stewart, 2015). Various methods have been used previously for separation of the base flow component from streamflow as discussed below.

1.8.1 Separation using tracers

In order to use tracers in base flow separation, the isotopic and/or hydro-chemical composition of the water is determined in order to identify the water characteristics coming from different sources and having different ages. An end member mixing analysis is carried out to define the hydro chemical component of the different components. If the chemical composition of the components are significantly different and constant, the mass balance method is used in calculating the separation by solving the following linear mixing equations:

$\boldsymbol{c_i, 1q1 + c_i, 2q2 + \cdots + c_i, jqj + \cdots + c_i, nqn = c_i TqT}$ **Equation 0.1**

$\boldsymbol{q1 + q2 + \cdots + qj + \cdots + qn = qT}$ **Equation 0.2**

Where c_i, j (ppm) is the solute concentration i in the flow component j, c_i, r (ppm) is the solute concentration i in the total discharge qT (m^3/s) measured at the outlet, and qj (m^3/s) is the contribution of the flow component j to the total discharge. The sum of all qj equals qT. To separate n different flow components, $(n-1)$tracers are needed for solving the mixing equations (Gonzales *et al*., 2009).

1.8.2 Graphical approach

In order to determine the runoff contribution, the hydrograph is plotted on a semi-logarithmic scale and the groundwater recession curve is identified as an approximately straight line. It is assumed that the linear reservoir concept can be used to determined groundwater flow and that the point where the line deviates from the hydrograph is the end of surface flow. From then on, the hydrograph is controlled by groundwater discharge. A straight line of this point at the beginning of a flood event, when surface runoff has not occurred, is used for base flow separation. Another assumption is that surface runoff is significantly faster than base flow, which is not normally the case as shown by several case studies in mountainous regions (McDonnell & Tanaka, 2001; Uhlenbrook & Hoeg, 2003).

1.8.3 Filtering approach

This method takes the minimum values of the hydrograph within an interval and connect them. A recursive digital filter is used which takes into consideration the sequential nature of the observation making up the original storm hydrograph. The discharge under the constructed line is base flow (Gonzales *et al*., 2009; Luo *et al*., 2012). It is assumed that the initial hydrograph is made up of a number of frequency components. The hydrograph is a sum of these components and each frequency component has a particular amplitude and phase. Quick flow is a set of short wavelength (high frequency) while baseflow is a set of long wavelength (short frequency) components. The advantage of this method is that it's systematic and standardized and can therefore be easily translated into a computer code and hence reduce the time required for computation. It also eliminates inconsistencies that occur while using manual methods (Rouhani & Malekian, 2012; Vasconcelos *et al*., 2013). These advantages are what led to the use of baseflow filter program for baseflow separation in this study.

1.9 Sensitivity analysis

Sensitivity analysis is the process of determining the rate of change in model output with respect to changes in model inputs (Pechlivanidis *et al*., 2011). It is a necessary process to identify key parameters and the parameter precision required for calibration (Moriasi *et al.*, 2007). Distributed watershed models involve too many parameters. Dealing with all these parameters at the calibration stage is not feasible. Hence, parameter reduction by filtering out the less influential ones is essential (Fadil *et al*., 2011). So, to ensure efficient calibration, an appropriate sensitivity analysis has to be carried out.

Sensitivity analysis methods can be classified in a variety of ways which are: mathematical, statistical and graphical (Saltelli *et al*., 2000). Mathematical methods assess sensitivity of a model output to the range of variation of an input. These methods typically involve calculating the output for a few values of an input that represent the possible range of the input. These methods do not address the variance in the output due to the variance in the inputs, but they can assess the impact of range of variation in the input values on the output (Salehi *et al*., 2000). Statistical methods involve running simulations in which inputs are assigned probability distributions and assessing the effect of variance in inputs on the output distribution. Statistical methods allow one to identify the effect of interactions among multiple inputs. The range and relative likelihood of inputs can be propagated using a variety of techniques such as Monte Carlo simulation, Latin hypercube sampling, and other methods (Andersson *et al*., 2000). Graphical methods give representation of sensitivity in the form of graphs, charts, or surfaces. Generally, graphical methods are used to give visual indication of how an output is affected by variation in inputs. Graphical methods can be used for screening before further analysis of a model or to represent complex dependencies between inputs and outputs (Frey *et al*., 2002).

1.10 Model calibration and validation

Hydrological models which are distributed and physically based should be calibrated before they are used for simulation of hydrologic processes. Model calibration is the process of selecting suitable values of model parameters such that the hydrological behaviour of the watershed can be simulated closely (Pechlivanidis *et al*., 2011). This is done in order to reduce the uncertainty associated with the model prediction.

The SWAT model contains both manual and auto-calibration tools. Manual calibration is a process that mainly depends on the modeler adjusting "by hand" model parameter values until the output of the model closely matches the observed data (Wheater, 2002). Automatic calibration involves the use of a search algorithm to determine best-fit parameters. The development of computer-based methods for automatic calibration of hydrological models has been partly motivated by the need to speed up the process of calibration. Another aim has been to develop an objective strategy for parameter estimation that provides consistent performance by eliminating the subjective human judgment involved in the manual approach (Boyle *et al*., 2000). The automatic process can provide more objectivity and reduce the need for expertise with the particular model (Sorooshian & Gupta, 1995).

Validation takes place after calibration to test if the model performs well on a portion of data, which was not used in calibration. It aims to verify the model's robustness and ability to describe the watershed's hydrological response, and further detect any biases in the calibrated parameters (Gupta *et al*., 2005). Split sample tests have commonly been tried (Perrin *et al*., 2001), where one period of observations is used in model calibration and one or more separate periods are used to check that the model predictions are satisfactory.

1.11 Uncertainty analysis

Differences between observed values and model output values can result from either natural variability, caused by evapotranspiration, unpredictable rainfall, water consumption and the like, and/or by both known and unknown errors in the model itself, the model parameters and input data (UNESCO, 2005). Uncertainty analysis attempts to describe the entire set of possible outcomes, together with their associated probabilities of occurrence. It also provides information and insight on the sources of uncertainty in results from a predictive model, such as errors in inputs, outputs and parameters (Abbaspour, 2007). On a wider scope, uncertainty analysis also includes parameter optimization, sensitivity analysis, characterization of subjective data and linguistic imprecision and lack of knowledge and context (Alaba, 2010).

Natural resource management decisions are being made based on complex models of hydrological systems. There is need for decision-makers to know the confidence level of the models' results (Benke, 2006). Various different approaches have been used for analyzing the impact of parameters and inputs uncertainty on predictions of streamflow and other important variables. Very common methods are the Markov Chain Monte Carlo (MCMC) or the Taylor's Series Error Propagation method (Alaba, 2010).

1.12 Model parameter transfer

Researchers have suggested that developing regionalized parameter values can be used to improve the accuracy of models in making predictions in ungauged watersheds (Gitau *et al.*, 2010).The term regionalization was derived from the process of watershed grouping and regime classification. It was later extended in the rainfall-runoff modeling context to refer to the transfer of model parameters from neighboring gauged watersheds to an ungauged watershed (Wang & Kalin, 2010). Nowadays, the term regionalization refers to all the methods aimed at estimating model parameter values on any ungauged watershed in a definable region of uniform hydrological response (Merz & Blöschl,

2004). There are three widely used regionalization approaches that have been used to choose the donor gauged watershed whose optimized parameter values are used to model runoff for the target ungauged watershed: regression; spatial proximity; and global averages (Gitau *et al*., 2010; Merz & Blöschl, 2004; Oudin *et al*., 2008; Parajka *et al*., 2005; Zhang & Viney, 2011).

Various researchers have over the past few decades tried to identify the best regionalization approach suitable for different hydrological models. For example, the Hydrologiska Byrans Vattenbalansavdelning model (HBV) was used to simulate the water balance dynamics of 308 catchments in Austria. Spatial proximity and regression regionalization methods for estimating the model parameters in ungauged catchments were compared in terms of the model performance. It was found that the best regionalization method is spatial proximity. Regression performed significantly poorer (Merz & Bloschl, 2004). SWAT was calibrated for 25 catchments which are part of eight larger sub-watersheds in the Scheldt river watersheds, Belgium. Two approaches were used to group the units into zones: a single parameter approach and a parameter set approach. SWAT was run with the local parameter optima, with the average parameter values for the study region of Flanders, with the zone delineated with the single parameter approach and with the zone obtained by the parameter set approach. Comparison of the model performance for the two parameterization approaches showed that both single parameter approach and parameter set approach lead to streamflow predictions that are more accurate than if the entire study region was treated as a single zone. Clustering of the parameters gives a better result than single parameter approach (Heuvelnus *et al.*, 2004).

1.12.1 Regression approach

Regionalization based on regression is the most popular method (Kim & Kaluarachchi, 2008). This approach links parameter values to watershed physical characteristics and climate, such as annual rainfall, temperature, slope, area, and land use/cover in a gauged

watershed (Yadav *et al*., 2007; Zhang & Chiew, 2009). Once the relationships have been established, the physical and climatic attributes are used to determine parameters for the ungauged watershed. There are two assumptions underlying this method. First is that it considers that there is a good relationship between model parameters and watershed characteristics but, most models don't have a unique set of parameters to define the best model fit to the flow response of a watershed. The model parameter are more or less dependent on the calibration period condition and input data quality (Perrin *et al*., 2007). The second assumption is that the watershed descriptors chosen for regression provide relevant information on the ungauged watersheds. However, there is spatial variability in watershed characteristics which hinders identification of watershed descriptors that are hydrologically relevant. This method has been strongly criticized by a number of researchers in the recent past (Bardossy, 2007; Oudin *et al*., 2008). The main argument against the regression approach is that the cross-correlation between parameters are rarely taken into account and because model calibrations can produce vastly different sets of parameter values that give similar model performance i.e. the equifinality problem.

1.12.2 Global averaging

Regionalization based on global averaging approach estimates the mean of all the calibrated parameter values available (Merz & Blöschl, 2004). It gives one set of values for the receiver watersheds. Global averaging has been commonly used in streamflow predictions (Kokkonen *et al*., 2003 & Merz & Blöschl, 2004).Various studies such as (McIntyre *et al*., 2005; Oudin *et al*., 2008) show that the global averaging method can reduce uncertainty in streamflow predictions. However, this method ignores the heterogeneity among watersheds and has been found to give unsatisfactory results (Merz & Blöschl, 2004).

1.12.3 Spatial proximity

Regionalization based on spatial proximity approach uses the calibrated parameter values from the geographically closest gauged watershed. The underlying assumption here is that neighboring watersheds should behave similarly because of similar climatic and physical characteristics. The physical similarity method transfers the whole set of parameter values from a physically similar watershed whose characteristics (climatic and physical) are similar to those of the target ungauged watershed (Vaze *et al*., 2011).So the supposition is made that watersheds are highly uniform with respect to climatic and topographic properties. Therefore, calibrated model parameter values from gauged watersheds can be derived and applied at the ungauged watersheds in order to predict the discharge regime. Initial studies have shown that choosing the donor watersheds based on spatial proximity to the ungauged watershed alone is by far the most credible approach (Merz & Blöschl, 2004; Zhang & Chiew, 2009).

1.12.4 Kriging

An interpolation method in which the neighboring measured values are weighted to derive a simulated value for an ungauged location. Weights are based on the distance between the gauged points, the ungauged locations, and the general spatial arrangement between the gauged points. It considers the geometric structure and organization of the hydrographic network, the watershed area and the nested nature of watersheds. However, kriging success depends on the the availability of spatially refined datasets (Gitau & Chaubey, 2010; Oudin *et al*., 2008).

These first three methods were selected because they are among the commonly used approaches, and available data were sufficient for the required analyses. The use of kriging was not explored as these would require more spatially refined model parameter datasets than were available.

1.13 Satellite precipitation data

Where meteorological data is not available, remotely sensed data can be used to run a model during a timeframe of interest. In this study, very few meteorological station data was available and therefore satellite rainfall estimates were used to counter the problem. Recent improvements in satellite based remote sensing have made it possible for scientists to develop precipitation estimates having near global coverage, thereby providing data for areas where Ground based networks are scarce or unavailable. Presently, there is an abundance of satellite missions dedicated exclusively to observe variables germane for land surface hydrology at a global scale. Precipitation, for instance, has been the main focus of a number of satellite missions during the last four decades, among them: Defense Meteorological Satellites Program (DMSP), National Oceanic and Atmospheric Administration (NOAA), Advanced Microwave Scanning Radiometer (AMSR), Moderate Resolution Imaging Spectro-radiometer (MODIS)-Aqua, Geostationary Operational Environmental Satellites (GOES) and Tropical Rainfall Measuring Mission (TRMM) Yilmaz *et al*., 2005. The major advantage of satellite products with respect to meteorological stations is their spatia-temporal coverage. Thus, satellite data may be the only available products to study the weather, climate and hydrology in most regions with sparse networks. However, the quality of these satellite products for hydrologic applications is still in dispute because of its coarseness and intrinsic bias (Samaniego *et al*., 2011; Yilmaz *et al*., 2005).

Famine Early Warning System Rainfall Estimates (FEWS RFE) Asadullah *et al*., (2008) and Hunink *et al*., (2009) was used in this research to run the SWAT model. There are two versions of RFE i.e. RFE version 1.0 that was operational from 1995 through 2000 and RFE version 2.0, created by Ping-Ping Xie that has been implemented by NOAA's Climate Prediction Center. RFE 2.0 uses additional techniques to better estimate precipitation while continuing the use of cloud top temperature and station rainfall data that formed the basis of RFE 1.0. RFE 1.0 used an interpolation method to combine Meteosat and Global Telecommunication System (GTS) data for daily precipitation

estimates, and warm cloud information was included to obtain dekadal estimates. The two new satellite rainfall estimation instruments that are incorporated into RFE 2.0 are the Special Sensor Microwave/Imager (SSM/I) on board Defense Meteorological Satellite Program satellites, and the Advanced Microwave Sounding Unit (AMSU). Both estimates are acquired at 6-hour intervals and have a resolution of 0.25 degrees. RFE 2.0 obtains the final daily rainfall estimation using a two part merging process, then sums daily totals to produce dekadal estimates (Maidment *et al*., 2013).

CHAPTER THREE

MATERIALS AND METHODS

1.14 Data used in the study

The following were the data sources in this study for the Upper Tana watershed. Streamflow data was obtained from the Water Resource Management Authority (WRMA) for eight river gauging stations, covering the period 1945-2013.The data was evaluated for consistency and five river gauging stations with continuous discharge records were chosen for further analysis. The evaluation carried out for selecting the five river gauging stations for further analysis was based on the length of available records, quality of data, and spatial distribution of the stations in the watershed. The years between 2001 and 2008 were chosen because they had the least number in missing streamflow values and the data included the dry, average and wet years. Table 0.1 gives the discharge data for the five gauging stations used in the study, whereas Figure 0.1 shows the location of the river gauging stations.

Table 0.1: Streamflow gauging stations used in the study

Station ID	Name of River	Longitude	Latitude	Start Year	End Year	% missing

		(Deg)	**(Deg)**			**data**
4AD01	Gura	37.07	-0.52	2001	2008	13
4BC02	TanaSagana	37.20	-0.67	2001	2008	29
4BE01	Maragua	37.15	-0.75	2001	2008	8
4CB04	Thika	37.07	-1.02	2001	2008	22

The climatic conditions of a watershed regulate the moisture and energy inputs that control the water balance and determine the relative importance of the different components of the hydrologic cycle. The climatic variables required by SWAT in daily time steps are: rainfall, temperature, relative humidity, solar radiation and wind speed which consist of inputs that could be records of observed data or generated during the simulation. Rainfall data which was obtained from Kenya Meteorological Department (KMD) was available for two stations covering the period 1970 to 2013. Daily maximum and minimum temperature, solar radiation, humidity and wind speed were obtained from National Aeronautics and Space Administration (NASA), Prediction Of Worldwide Energy Resource (POWER). Satellite based daily rainfall was obtained from the United States Geological Survey (USGS) Famine Early Warning Systems Network (FEWSNET) for the period 2001 to 2008.

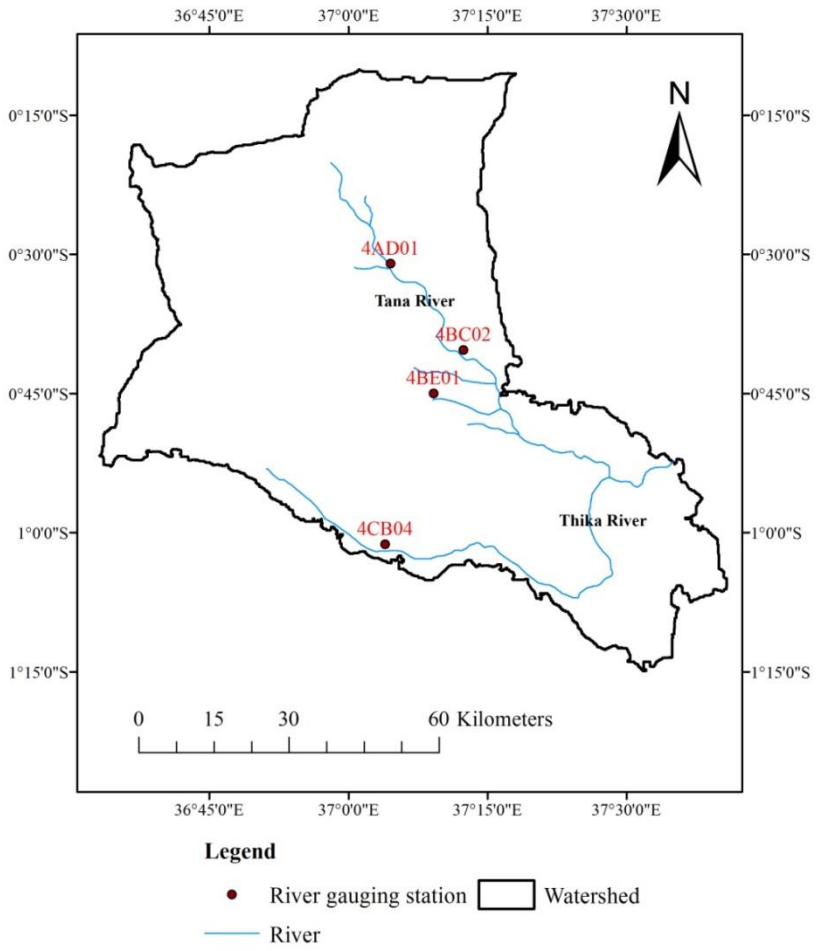


Figure 0.1: Location of the river gauging stations in the Upper Tana Watershed

1.14.1 Digital Elevation Model

A 3 arc-second resolution, hydrologicaly conditioned DEM, derived from elevation data of the Shuttle Radar Topography Mission (SRTM) was obtained from USGS. Methods such as void-filling, filtering, stream burning, and up scaling techniques were used to improve the DEM. The DEM was then clipped and projected before use. The DEM was used in delineating the watersheds and deriving terrain and topographic parameters, such as slope and elevation that are useful in streamflow modelling.

1.14.2 Soils data and map

The soil data was obtained from Kenya Soil and terrain database (KENSOTER) at a scale of 1:1,000,000. The soil data that describes hydraulic properties of the soil are required to predict streamflow in SWAT. The soil map provides the baseline definition of the soil classes (Figure 0.2).The soils names are in the appendices.

1.14.3 Land use/land cover map

The land use /land cover map (Figure 0.3) was obtained from Food and Agriculture Organization (FAO) and it was reclassified into SWAT land use/land cover classes. In order for the SWAT model to simulate the hydrology for the landscape, it needs to track plant growth. The land use /land cover map gives the classification of the various land use and land cover classes in the study area and there spatial extent. The land use /land cover map is combined with the soils data to give the hydrologic characteristics of a watershed which determines the amount of excess precipitation, groundwater recharge and soil layer storage. The land use/land cover classes are defined in table

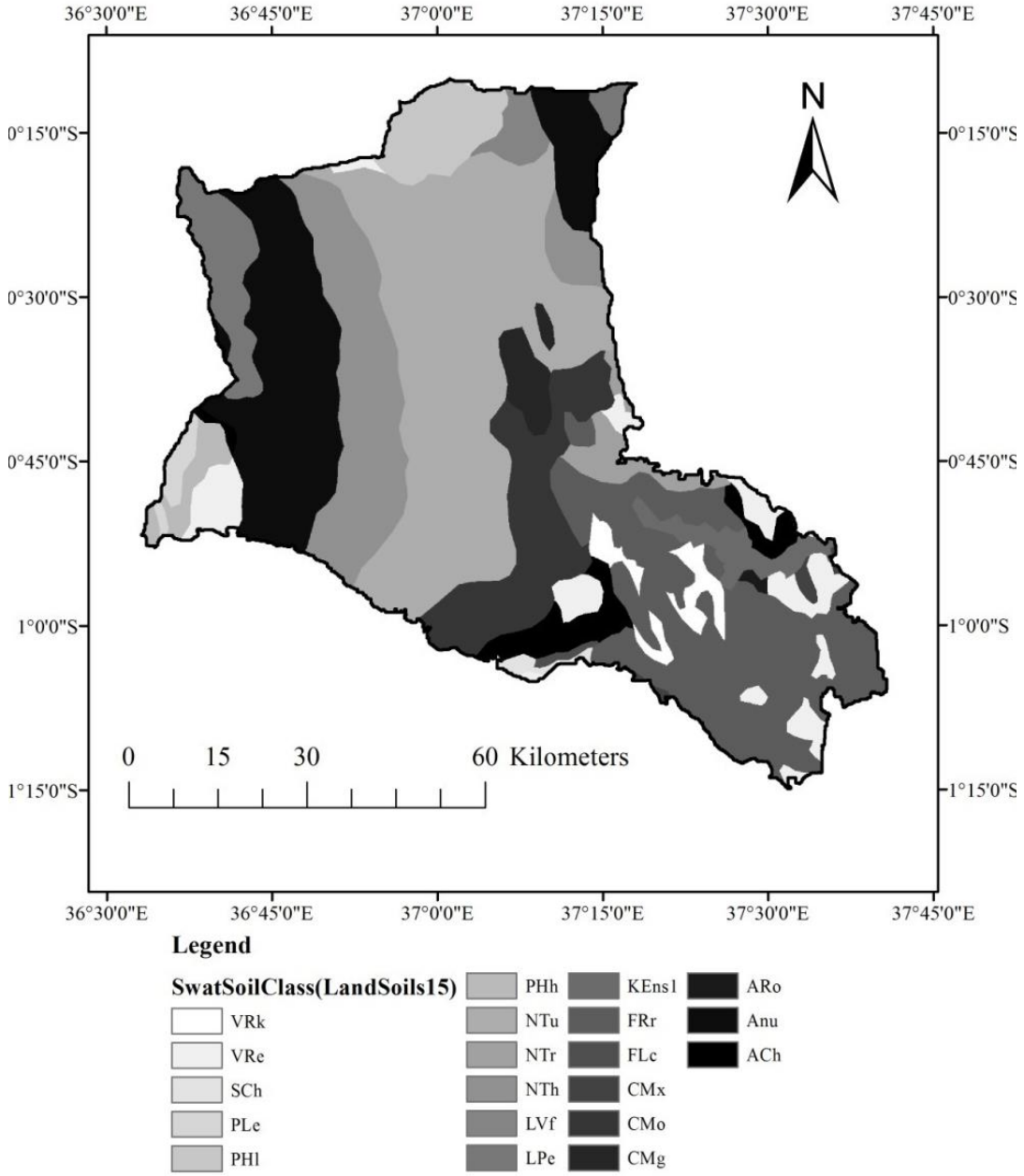


Figure 0.2: Soils of the Upper Tana Watershed

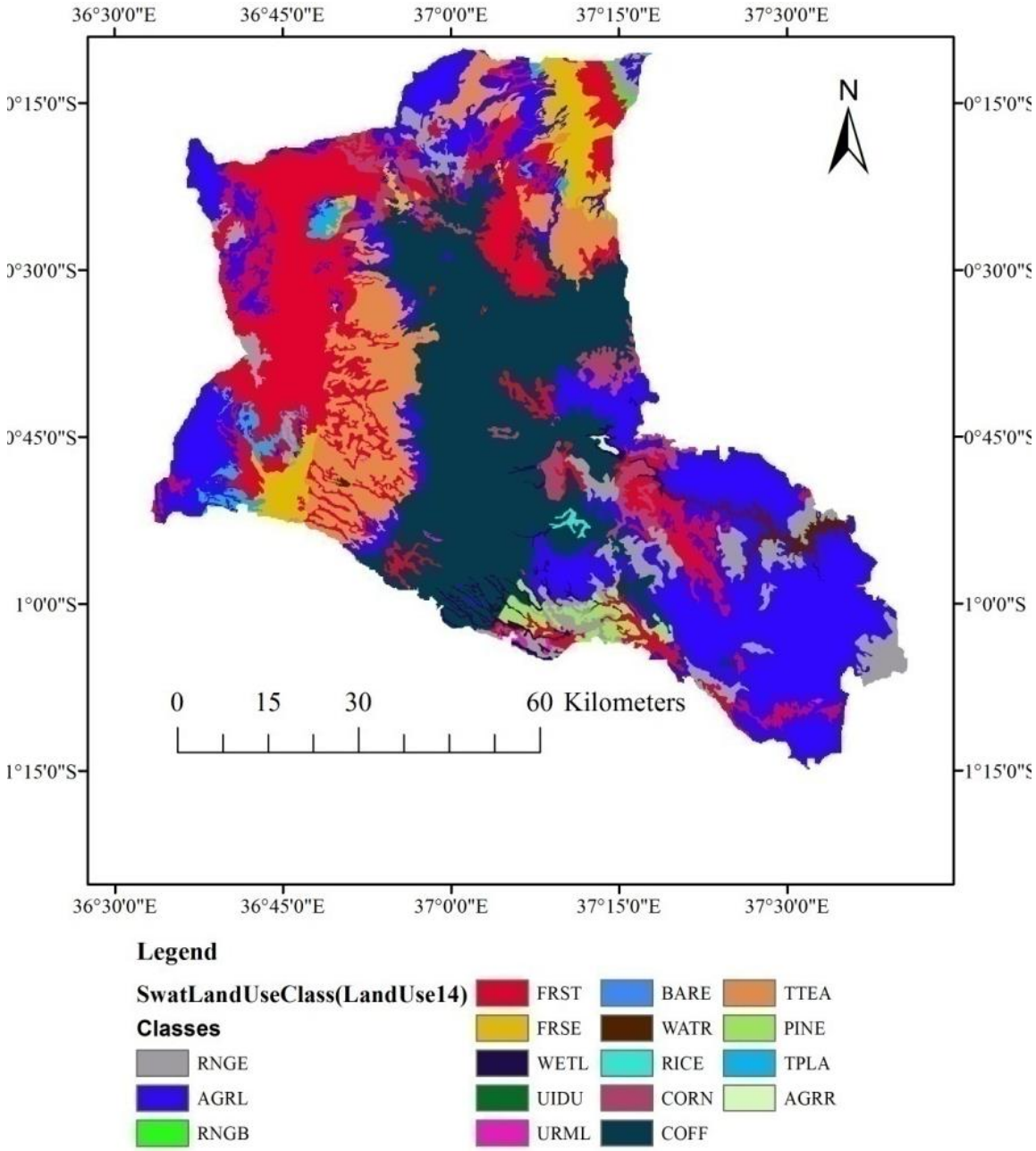


Figure 0.3: Land use/land cover map of the Upper Tana Watershed

Table 0.2: SWAT land use classes

SWAT land use class	Description
AGRL	Rain-fed Shrub Crop, Large Fields
WATR	water
BARE	Bare soils
RICE	Cereals, Rice - Small Fields
WETL	wetland
FRSE	Forest Plantation, Broad Leaved Evergreen, Rainfed permanent
RNGB	Closed shrubs with sparse trees
FRST	Open trees (broadleaved deciduous) with closed to open shrubs
CORN	Herbaceous - Medium Fields -Maize, Rainfed
AGRI	Herbaceous - Large to Medium Fields, Irrigated Surface permanent
UIDU	Industrial area - general
RNGE	Very open shrubs with closed to open herbaceous
COFF	Rainfed Shrub Crop, Large Fields - Coffee
PINE	Rainfed Shrub Crop, Large Fields - Pineapple
TEA	Rainfed Shrub Crop, Large Fields - Tea
AGRR	Rainfed Tree Crop, Clustered Small Fields
URML	Rural settlements/urban settlements
PLAN	Plantation

1.15 Calibration and validation of SWAT

Calibration was done both manually and automatically. It was carried out by adjusting parameters and producing simulated streamflow which was then compared to the observed streamflow. Validation involved comparison of simulated streamflow to observed streamflow from a different time frame with the one used in calibration but by sing the parameter values obtained during the calibration period. Input data preparation, model set up and sensitivity analysis was carried out before calibration and validation (Figure 0.4).

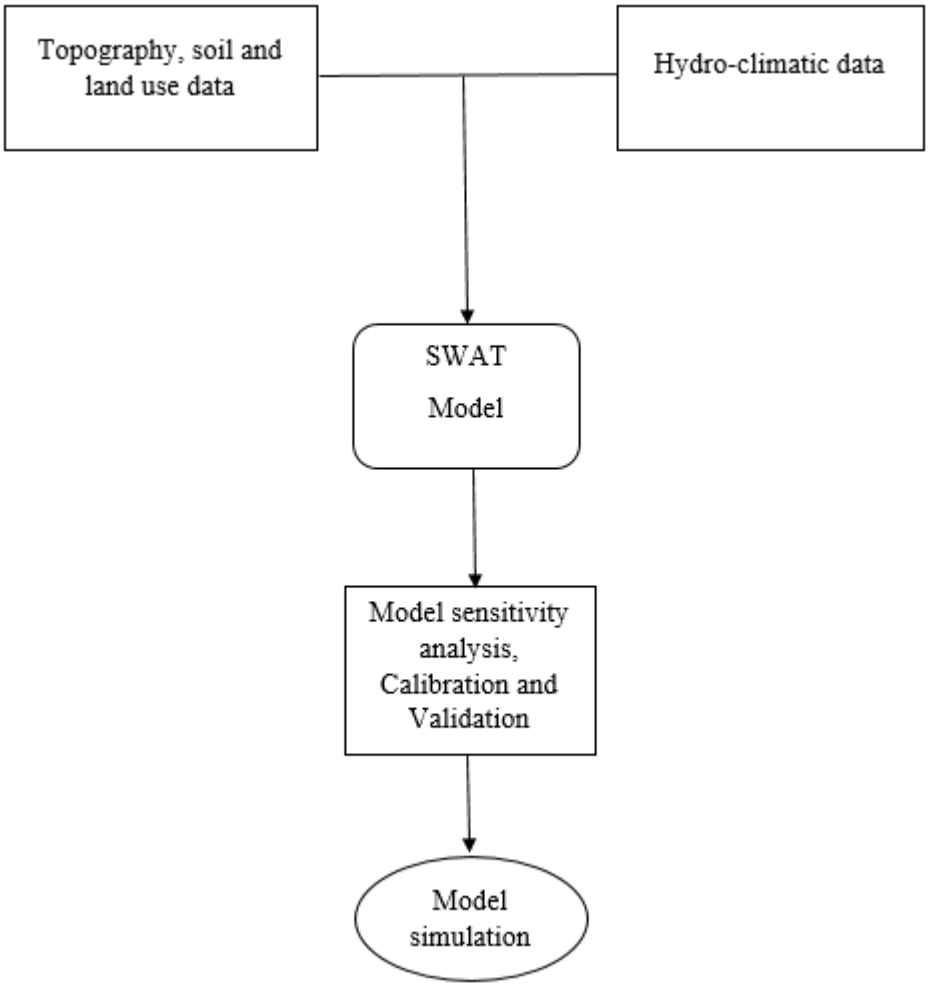


Figure 0.4: The process of calibration and validation of the SWAT model

1.15.1 Input data preparation

The quality of input data has an effect on model performance and may introduce uncertainties to model predictions. Validation of the satellite derived precipitation is required to establish the level of confidence and the probability of using the data in areas where ground observations are not available. Therefore, raw satellite rainfall data that was obtained was checked to identify and eliminate outlier data points. The satellite rainfall estimates were also compared to ground rainfall station data. Statistical analyses were done to compare the FEWS dataset with the ground observation data. The statistics

calculated were Coefficient of determination (R^2) and over or under estimation (Hunink *et al*., 2009).

Coefficient of determination (R^2)

$$R^2 = \left[\frac{\Sigma_{i=1}^{n} \left(o_i - \bar{o}\right)\left(s_i - \bar{s}\right)}{\sqrt{\Sigma_{i=1}^{n} \left(o_i - \bar{o}\right)^2} \sqrt{\Sigma_{i=1}^{n} \left(s_i - \bar{s}\right)^2}} \right]^2 \quad \textbf{Equation 0.1}$$

Where, R^2 is the coefficient of determination, o_i is ground observation data (mm), s_i is FEWS estimates (mm), $\bar{o}$ is mean ground observation data (mm) and $\bar{s}$ is mean FEWS estimates (mm).

Over or under estimation = $\frac{\Sigma_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})}{\Sigma_{i=1}^{n} Y_i^{obs}}$ **Equation 0.2**

Where n is the number of observations, Where Y_i^{obs} is the ith observed value of the constituent being evaluated and Y_i^{sim} is the ith simulated value of the constituent being evaluated.

1.15.2 Model setup

The various processes in the model set up were watershed delineation using the digital elevation model (DEM), creation of hydrological response units using the land use/land cover and soils data, writing of climatic data and editing the input files. The DEM was loaded onto the model interface during watershed delineation. The DEM was projected before loading. The Watershed was then delineated based on the DEM. Maps of flow direction and accumulation were computed by pre-processing the DEM through filling sinks, calculation of the flow direction and flow accumulation grids. The number and size of sub-watersheds were limited by a threshold area of 30,000ha that was set. A

small value of threshold area will lead to increases of drainage density but decreases the model computational time (Jha *et al*., 2004). The threshold area was also useful in the stream network definition where two layers grid were created: reach which is the synthetic drainage network and monitoring points which are the stream junction points. A database file containing the outlets was loaded onto the interface and the most downstream point was selected as the watershed outlet. The watershed delineation process was run and calculation of sub-watershed parameters was carried out.

In SWAT, the watershed is discretized into sub-watersheds and these sub-watersheds are further discretized into Hydrologic Response Unit (HRU). For this to be done, the model requires land use/land cover and soil data to determine the area and the hydrologic parameters of each HRU category simulated within each sub-watershed. Land use, soil and slope definition was performed using the commands from HRU Analysis Menu. The SWAT user has two options, either to use dominant land use/land cover and soil or multiple HRU in the sub-watersheds. The multiple HRU option was used in this study.

After creation of the HRUs, weather data was imported into the project. The weather stations locations were loaded and weather data was assigned to the sub-watersheds. For each type of weather data loaded, each sub-watershed was linked to one gage which was closest to the centroid of the sub-watershed. After loading the weather data, all files are then written into the project.

1.15.3 Sensitivity analysis

Initial coarse model calibration was carried out in order to know how the different parameters affect the hydrological processes. Sensitivity analysis was then carried out after this. Sensitivity analysis is essential especially in SWAT model which is a comprehensive conceptual model that relies heavily on several parameters varying widely in spatial and temporal scales while transforming input into output. Sensitivity analysis is the process of establishing the rate of change in model output with respect to

changes in model parameters values. It is important to identify the key parameters and parameter accuracy required for calibration (Mongelos, 2012). The relative ranking of parameters whose variability would produce more changes in the model output is ascertained through sensitivity analysis. The parameters used in sensitivity analysis are shown in Table 0.1.

The global sensitivity analysis method that is incorporated in SWAT-CUP was used in this study to identify the sensitive parameters. The global sensitivity analysis uses a multiple regression system, shown below, which regresses Latin hypercube generated parameters against the objective function values to determine parameter sensitivities.

$\boldsymbol{g} = \propto + \sum_{i=1}^{m} \boldsymbol{\beta_1 b_1}$ **Equation 0.3**

A t-test is then used to identify the relative significance of each parameter b_1. The sensitivities given are estimates of average changes in the objective function due to parameter change, whilst other parameter changes. The relative sensitivities are thus linear approximations, therefore only providing partial information about the sensitivity of objective function to model parameters. The parameter that has the largest absolute t-stat value is the most sensitive. The p-value determines the significance of the sensitivity with smaller values implying more significant (Abbaspour, 2007).

1.15.4 Calibration

Calibration of the model parameters was carried out using the available hydrological data for the years 2001 to 2004. This process was done using daily streamflow data. The results obtained from the sensitivity analysis were used in the calibration process to guide in changing of the parameter values. The calibration was first done manually by changing the values of the model parameters that affect streamflow and comparing the simulated streamflow to the observed streamflow to check if it is within a certain range of difference. The parameters were changed within a physically realistic range. The

manual calibration was then followed by automatic calibration which was carried out by Soil and Water Assessment Tool-Calibration Uncertainty Program (SWAT-CUP).

Table 0.3: Parameters used in sensitivity analysis

Stream flow parameter	Description
CN2.mgt	Curve Number
ALPHA_BF.gw	Base flow alpha factor
GW_DELAY.gw	Groundwater delay time
GWQMN.gw	Threshold depth of water in shallow aquifer required for return flow to occur
GW_REVAP.gw	Groundwater 'revaporation' coefficient
REVAPMN.gw	Threshold depth of water in the shallow aquifer for 'revaporation' to occur
SOL_AWC.sol	Available water capacity of the soil layer
ESCO.hru	Soil evaporation compensation factor
SOL_K.sol	Soil hydraulic conductivity
CH_K2.rte	Effective hydraulic conductivity in main channel
SURLAG.bsn	Surface runoff lagtime
OV_N.hru	Manning's "n" value for overland flow
EPCO.hru	Plant uptake compensation factor

1.15.5 Validation

Validation was done to determine if the calibrated model is able to make accurate predictions (Pechlivanidis *et al*., 2011). Model validation was done by running the model using the model parameters determined during the calibration process. The model was run to check predictive ability for the period that was not used for calibration of the model parameter. The data for the years 2005 to 2008 was used for this process. The simulated streamflow was then compared to the observed streamflow.

1.15.6 Parameter uncertainty

Parameter uncertainty in SUFI-2 accounts for all sources of uncertainty such as uncertainty in inputs, parameters and conceptual model. The model output uncertainties are expressed as the 95% probability distribution. They are calculated at the 2.5% and 97.5% of the cumulative distribution of every simulated output variable obtained through the sampled parameter sets using Latin hypercube sampling. It is referred to as 95% prediction uncertainty (95PPU) (Abbaspour *et al*., 2007).

Two statistical indicators are used to quantify the adjustment of the parameter values. These are: the p-factor and the *r*-factor. The *p*-factor which is the percentage of observed data bracketed by the 95PPU. The *r*-factor indicates the strength of the uncertainty analysis and is defined as the ratio of the average thickness of the 95PPU band to the standard deviation of the observed data as shown in the equation below (Franco & Bonumá, 2017).

$r = \frac{\bar{d}_x}{\sigma_x}$ **Equation 0.4**

Where $\bar{d}_x$ is the average distance between the upper and lower 95PPU and σ_x is the standard deviation of the measured variable x.

The main objective it to ensure majority of the observation is enclosed within the smallest possible uncertainty bound as this ensures that parameter uncertainty accounts for all other uncertainties. Theoretically, p-factor values range between 0% and 100% while R-factor values range between 0 and infinity. A p-factor of 1 and r-factor of zero shows that simulated data has a perfect correspondence with the observed data (Singh *et al*., 2014).

1.16 Transfer parameter set determination

Three methods namely spatial proximity, global averages and regression were used in determining the parameter sets to be transferred from the donor sub-watersheds to the test sub-watersheds. The results of these three methods were analyzed statistically and compared to determine the best method.

1.16.1 Spatial proximity

The whole set of calibrated parameter values were transferred between sub-watersheds that are near each other. The underlying assumption here is that neighboring sub-watersheds should behave similarly because of similar climatic and physical characteristics. The donor sub-watersheds were calibrated and the changes applied to the various parameters were applied to the receiver sub-watersheds. The model was then run and the simulated streamflow was then compared to the observed streamflow of the receiver sub-watershed.

1.16.2 Global averages

The global average parameters were determined by computing the average of the values of each of the parameters attained during calibration, across all the sub-watersheds, therefore obtaining a single value for each of the parameters. The values were then written in the input file of the test sub- watershed. The model was then run using the parameter values obtained through global average. The simulated streamflow was then compared to the observed streamflow of the test sub-watershed.

1.16.3 Regression method

A stepwise regression was used to determine functional relationships between sub-watershed characteristics and model calibration parameters. Where relationships obtained were significant, resulting equations were used to compute model parameters

for each of the ungauged sub-watersheds. Any values exceeding the reasonable range for the parameter in question were reset to the maximum for the range. A broad range of sub-watershed characteristics were defined. This was done to capture the range of topography, land use, soil, and climatic conditions that are present in the study sub-watersheds. To avoid problems associated with co-linearity between model parameters, sub-watershed characteristics were assessed for correlation. Co-linearity was considered to exist when bivariate correlations are large (>0.8). If co-linearity was found, only one of the characteristics concerned was included in the regression equation. For each parameter, the variables suggested by correlation analysis and stepwise regression were combined in a multiple regression model enabling the parameters to be described in terms of watershed characteristics as follows:

$$y(k) = \beta_o + \beta_1 x_1(k) + \beta_2 x_2(k) + ...\beta_p x_p(k) + \varepsilon(k)$$ **Equation 0.5**

With k =1,….., N

Where, $y(k)$ is model parameter; $x_1(k), x_2(k).....x_p(k)$ are watershed characteristics in kth model simulations; N is the total number of catchments; $\beta_0.....\beta_p$ are regression coefficients and p = number of watershed characteristics used in the regression model

1.17 Estimation of streamflow at the ungauged watersheds and model performance evaluation

The parameter sets that were derived from the three parameter transfer methods were used together with the daily rainfall and temperature data series to simulate streamflow at the "ungauged" sub- watershed. However, because the sub-watershed is in fact gauged, the simulated daily streamflow was compared with the observed streamflow to assess the accuracy of estimation. The ability of a model in simulating runoff from a watershed should be judged using multiple evaluation criteria (Moriasi *et al*., 2007). In this study, graphical and statistical evaluation techniques were used.

1.17.1 Graphical approach

Model performance can be addressed by means of qualitative criteria, which essentially relies on the graphical comparison between observed and simulated data. Visual representation is a fundamental step in model validation as it allows the study of temporal dynamics of model performance and facilitates the identification of patterns in error occurrence. The observed streamflow will be compared to the simulated streamflow using line graphs (Legates & McCabe, 1999).

1.17.2 Statistical approaches

Several statistical approaches were used to check the model performance, viz. coefficient of determination (R^2), Nash-Suttcliffe simulation efficiency (NSE) and percent bias (PBIAS). The R^2 value is an indicator of relationship strength between the observed and simulated values. NSE indicates how well the plot of observed versus simulated values fits the 1:1 line. PBIAS measures the average tendency of the simulated to over simulate or under simulate the observed data. Model prediction is considered unacceptable or poor if the R^2 and NSE values are less than or very close to zero while perfect if the values are one (Alansi *et al*., 2009).

The coefficient of determination

It describes the degree of co-linearity between simulated and measured data (Equation 3.6).The coefficient of determination describes the proportion of the variance in measured data explained by the model. It ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Moriasi *et al*., 2007)

$$R^2 = \left[\frac{\Sigma_{i=1}^{n} \left(o_i - \bar{o}\right)\left(s_i - \bar{s}\right)}{\sqrt{\Sigma_{i=1}^{n} \left(o_i - \bar{o}\right)^2} \sqrt{\Sigma_{i=1}^{n} \left(s_i - \bar{s}\right)^2}} \right]^2 \quad \textbf{Equation 0.6}$$

Where,

R^2 = coefficient of determination

o_i = observed streamflow (m^3/s)

s_i = simulated streamflow (m^3/s)

$\bar{o}$ = mean observed streamflow during evaluation period (m^3/s)

$\bar{s}$ = mean simulated streamflow.

Nash-Sutcliffe efficiency (NSE)

The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information"). NSE is computed as shown in Equation 3.7. NSE indicates how well the plot of observed versus simulated data fits the 1:1 line (Tesfahunegn *et al*., 2012).

$$\mathbf{NSE} = \mathbf{1} - \left[\frac{\sum_{i=1}^{n}(o_i - s_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o})^2}\right] \quad \textbf{Equation 0.7}$$

Where,

o_i= the ith observation for the constituent being evaluated

s_i= the ith simulated value for the constituent being evaluated

$\bar{o}$= the mean of observed data for the constituent being evaluated

n = the total number of observations

The values of NSE ranges between $-\infty$and 1.0 (1 inclusive), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance.

Percent bias (PBIAS)

The optimal value of PBIAS is 0, low absolute values indicate accurate model simulation. Underestimation bias is indicated by positive values while overestimation bias is indicated by negative values. PBIAS is calculated using the equation below (Moriasi et al., 2007).

$$\mathbf{PBIAS} = \left[\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim}) * 100}{\sum_{i=1}^{n} Y_i^{obs}}\right] \textbf{ Equation 0.8}$$

Where Y_i^{obs} is the ith observed value of the constituent being evaluated and Y_i^{sim} is the ith simulated value of the constituent being evaluated.

CHAPTER FOUR

RESULTS AND DISCUSSION

1.18 Calibration and validation of the SWAT model

1.18.1 Evaluation of daily, monthly and annual rainfall data from meteorological station and satellite data

The satellite rainfall data was compared to gauged data from Nyeri Prisons rainfall station (9036223) and Thika Meteorological station (9137048) in order to ascertain that it could be used for modelling purposes. In order to compare the satellite and ground rainfall data, time series were extracted from the daily FEWS grids for the location of the two meteorological weather stations. Figure 0.1 shows a comparison of the daily values during the wet months of March and April for the 9137048 station.

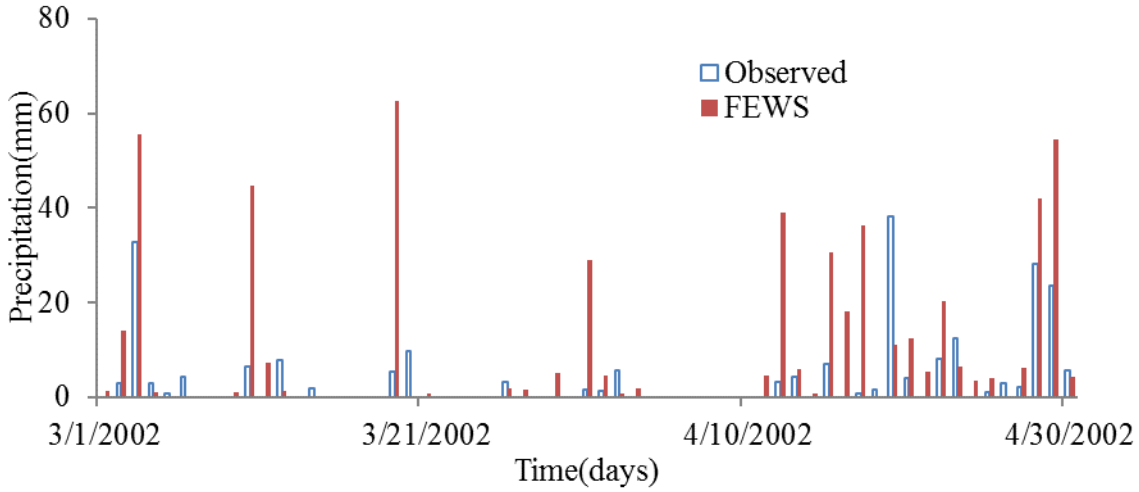


Figure 0.1: Comparison of daily rainfall for March and April at the 9137048 station for observation (gauged) and satellite estimates (FEWS)

From the figure it can be deduced that there is a high correspondence between the two datasets. Some strong rainfall events in either the estimated or measured precipitation are not represented in the other dataset. This can be caused by either outliers in the observed data due to measurement errors or erroneous estimates caused by resolution and scale issues. This is consistent with the findings of (Hunink *et al*., 2009).

The monthly rainfall totals of both datasets were calculated. Figure 0.2 shows a scatter plot and 1:1 line of the observed and FEWS estimates monthly totals. The correlation coefficients (R^2) for are 0.77 for station 9036223 and 0.74 for station 9137048. It is clear that the performance of the FEWS estimates compared to the observations is dependent on the weather stations. There is a good correlation between the two datasets as is shown by the fairly high correlation coefficient (R^2). However, discrepancies in large rainfall events can be found especially in the Nyeri Prisons rainfall station (9036223) dataset. These discrepancies strongly affect the correlation coefficient causing it to be relatively low for this station. The FEWS rainfall estimates are based on observation of cloud top temperatures, which are related to convection and vertical motion. The FEWS algorithm may fail to detect short rains that occur due to convection and orographic precipitation (Shrestha *et al*., 2008). Such rainfall events occur mostly during the wet season around the months of April and November. The discrepancies in FEWS dataset were shown especially during these months where heavy rainfall events were measured in the ground observation dataset.

The annual totals of the FEWS estimates and observation datasets were compared (Figure 0.3). The yearly total was obtained by summing the daily totals of the datasets. The years containing many missing data the gauged rainfall data were filtered out. The graphs show that there is an underestimation by the satellite rainfall.

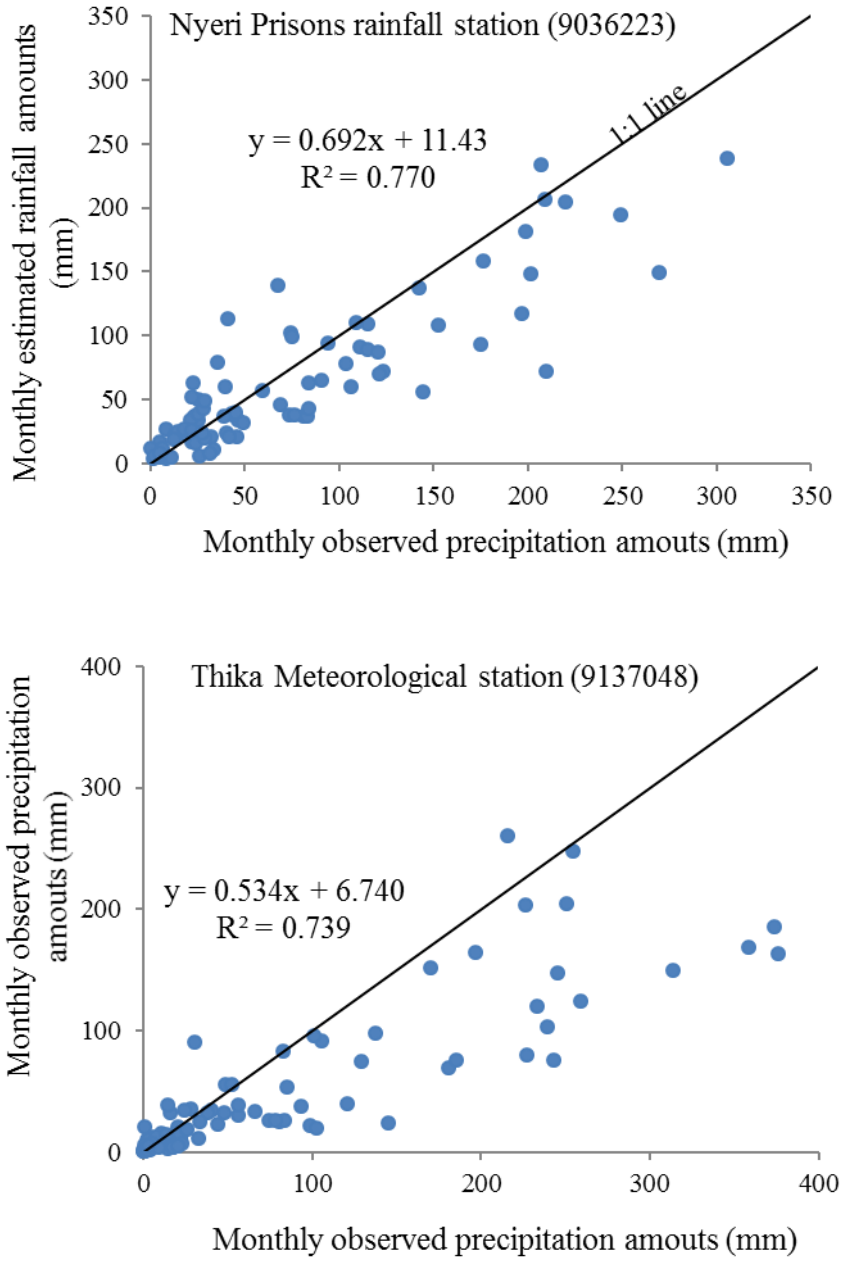
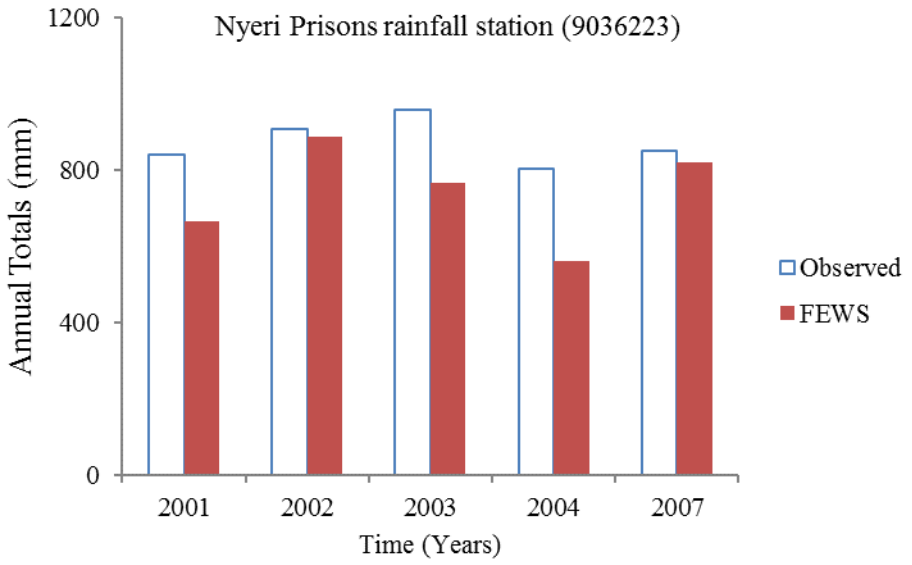


Figure 0.2: Scatter plot and 1:1 line of observed and FEWS satellite estimates monthly rainfall totals for stations 9036223 and 9137048



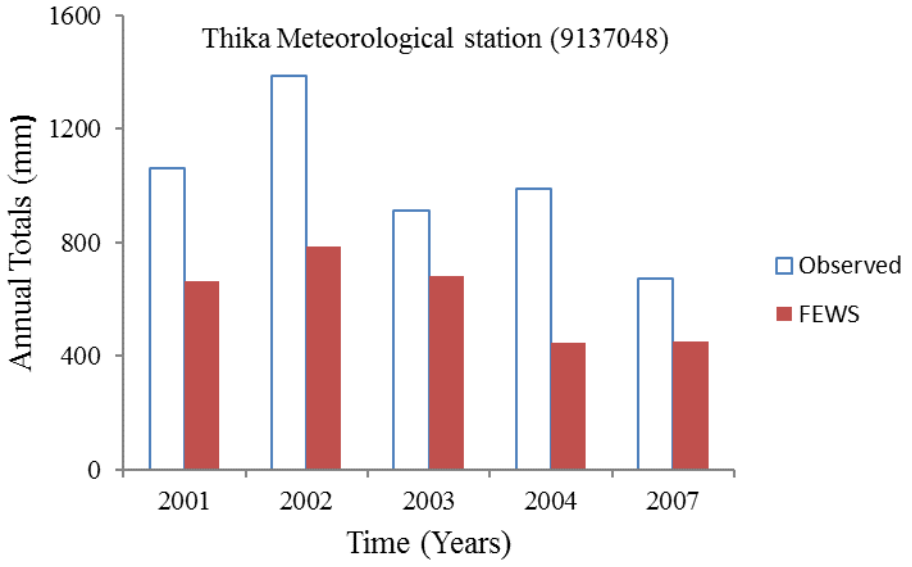


Figure 0.3: Annual totals for observed and satellite estimates (FEWS) rainfall

The analysis carried out showed that there is a good correlation between the satellite-derived and the observed precipitation. The correlation shows that the FEWS dataset can

be corrected by a factor in order for it to have a better correlation with the observed precipitation. The FEWS estimates can provide a reasonable water balance calculation and therefore were used at a daily time step to run the model. A similar conclusion was made comparing the FEWS dataset with gauged estimates by (Asadullah *et al*. 2008; Hunink *et al*. 2009).

The rainfall under estimation was calculated and it was 12.14% at the Nyeri Prisons rainfall station and 38% at the Thika Meteorological station. A correction factor was applied to the FEWS estimates in order to make the dataset in good correspondence with the observed station data. The FEWS daily estimates were multiplied by a factor of 1.25 over the entire record. This is because the average underestimation by the FEWS estimates was at 25%.

1.18.2 Baseflow separation

The baseflow filter program was used for baseflow separation. The program makes three passes of baseflow separation. The fraction of water yield contributed by baseflow should fall somewhere between the value for first and second pass (Arnold *et al*., 1995).In this study, the amount of streamflow contributed by baseflow was estimated by calculating the mean of the first and second pass.

A summary of the baseflow separation output is given in Table 0.1, whereas a sample hydrograph of baseflow separation is given in Figure 0.4. The daily streamflow data used for this sample hydrograph is from Maragua gauging station (4BE01) for the year 2001-2004. The alpha factor gives the baseflow recession constant. Baseflow days are the number of days for the baseflow recession to decline through one log cycle. Large alpha factors indicate steep recession which is due to minimal storage and rapid drainage. On the other hand, low alpha values signify very slow drainage (Arnold *et al*., 1995). These values were used as the initial estimates of the factor during the model

setup. The fractions of streamflow contributed by baseflow (mean of the first and second pass in Table 0.1 varied from 0.45 to 0.74.

Table 0.1: Summary of baseflow separation output

Gauging Station	Baseflow Pass1	Baseflow Pass2	Baseflow Pass3	Alpha factor	Baseflow Days
4AD01	0.62	0.41	0.29	0.07	31.47
4BC02	0.70	0.53	0.41	0.05	44.13
4BE01	0.80	0.68	0.61	0.03	76.79
4CB04	0.56	0.34	0.22	0.10	28.00

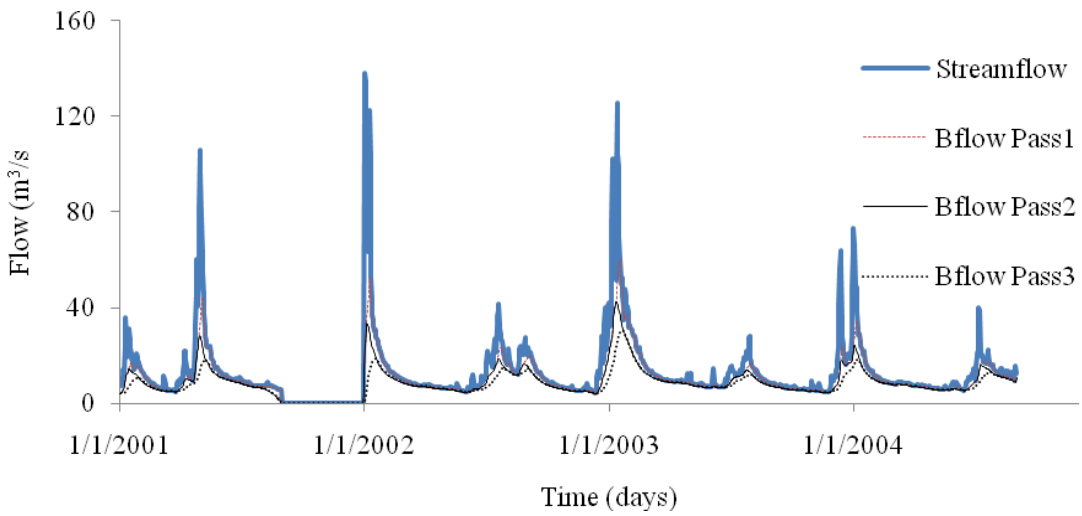


Figure 0.4: Hydrograph of baseflow separation at pass 1, 2 and 3 at 4BE01

1.18.3 Sensitivity analysis of SWAT parameters in Upper Tana

Parameter sensitivity analysis was done in order to determine the key parameters that are needed for calibration. 14 calibration parameters that affect flow were used in the sensitivity analysis Table 0.2. The description of the parameters is given in Table 0.3**.** These parameters were chosen based on the results of previous studies by (Faramarzi *et al.*, 2009; Levesque *et al*., 2008; Liu *et al*., 2008; Santhi *et al*., 2001; White & Chaubey, 2005). Global sensitivity analysis method was used and the parameters that were found

to be most sensitive were used in the calibration process. The t-stat is a measure of sensitivity where larger in absolute values are more sensitive. The p-value determines the significance of sensitivity where values close to zero are more significant (Abbaspour, 2007).

Table 0.2: Sensitivity analysis output

Parameter Name	t-Stat	P-Value
RCHRG_DP	-6.85	0.00
REVAPMN.	2.06	0.04
GW_REVAP	-0.27	0.78
ESCO	-0.31	0.76
EPCO	-1.81	0.07
GWQMN	-2.40	0.02
GW_DELAY	-0.35	0.72
ALPHA_BF	2.42	0.02
SURLAG	-51.78	0.00
SOL_K	-0.20	0.84
SOL_AWC	8.63	0.00
CH_K2	8.06	0.00
OV_N	27.94	0.00
CN2	-16.79	0.00

The most sensitive parameters governing the streamflow for the Upper Tana watershed were SURLAG, CN2, OV_N and SOL_AWC. This shows that the surface flow component is very significant in the streamflow of the watershed. SURLAG controls the fraction of the total available water that will be allowed to enter the reach on any one day (Arnold *et al*., 2011), OV_N affects overland flow, CN2 determines the partitioning of precipitation between surface runoff and infiltration as a function of land use, soil hydrologic group and antecedent moisture condition (Mishra & Singh 2003) and SOL_AWC is a soil parameter that affects groundwater recharge estimates (Arnold *et al*., 2011).

1.18.4 Calibration of the SWAT model

Calibration of the SWAT model to predict streamflow in Upper Tana watershed was done using weather and streamflow data for the period 2001-2008 based on daily values. The parameters were first manually calibrated by changing their values based on recommendations from previous literature such as Neitsch *et al*., (2005) and Van Griensven *et al*., (2006) and checking their effect on streamflow, and then automatically calibrated using SWAT-CUP by the SUFI-2 program (Abbaspour, 2007; Abbaspour *et al*., 2007).Table 0.3 shows the parameter values that were attained during calibration.

Table 0.3: SWAT calibration parameter values

	Parameter value/change					
Parameter	4AD01	4BC02	4BE01	4CB04	lower limit	upper limit
CN2	-9.65	-9.97	-1.35	-3.11	35.00	98.00
SOL_AWC	-0.04	-0.02	-0.02	-0.03	0.00	1.00
CH_K2	0.00	0.00	19.00	0.20	0.01	500.00
RCHRG_DP	0.28	0.55	0.34	0.01	0.00	1.00
REVAPMN	57.80	0.00	166.20	79.00	0.00	500.00
SURLAG	0.79	0.27	0.46	0.07	0.05	24.00
OV_N	12.76	3.82	10.00	0.10	0.01	30.00
ALPHA_BF	0.09	0.06	0.03	0.10	0.00	1.00
GWQMN	62.30	0.00	4.30	22.85	0.00	5000.00
GW_DELAY	31.47	30.27	81.00	28.00	0.00	500.00

Most of the parameter values were similar in proportion when compared among watersheds, but the effective channel hydraulic conductivity (CH_K2) values and revaporation (REVAPMN) values obtained for the 4BE01 sub-watershed, the GWQMN value obtained for the 4AD01 sub-watershed and GW_DELAY value obtained for the 4BE01 sub-watershed were out of proportion in comparison to the other sub-watersheds. The CH_K2 is a measure of the rate of water loss from the channel to ground water. Values of CH_K2 ranging between0.025–2.5 mm/hr indicate low rates of water loss to

ground water, while values between 6-25mm/hr indicate moderate water loss to the ground water (Arnold *et. al*., 2011; Lane, 1983). The 4BE01 sub-watershed has a CH_K2 value of 19mm/hr indicating moderate water loss to the groundwater. This could be due to the fact that sub-watershed 4BE01 is predominantly covered by Nitisol which is a well-drained soil (Gathenya *et al*., 2011; Tekleab *et al*., 2010).

The REVAPMN defines the threshold depth of water in the shallow aquifer for percolation to the deep aquifer to occur, and is particularly important in areas with deep-rooted crops or high water tables (Neitsch *et. al*., 2005).The high value of REVAPMN is sub-watershed 4BE01 and 4CB02 could be attributed to the Nitisol soils which are deep, porous and have a stable structure thus permit deep rooting. GWQMN refers to the threshold depth of water in the shallow aquifer required for return flow to occur (Neitsch *et al*., 2001).Base flow will occur when the GWQMN threshold is met or exceeded; thus, zero and/or low values of the parameter can cause base flow to be overestimated. The different values could be due to the different geological properties of the watersheds. The calibration results using daily streamflow values are presented in Figure 0.5 to Figure 0.8. Table 0.4 gives the R^2 and the Nash-Sutcliffe coefficient values of the observed and simulated obtained during calibration.

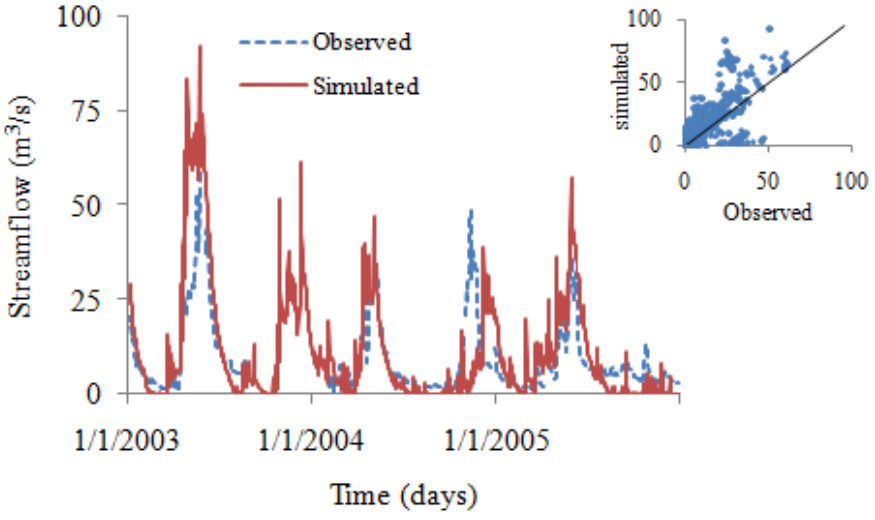


Figure 0.5: Calibration hydrograph and scatter plot for daily streamflow at sub-watershed 4AD01

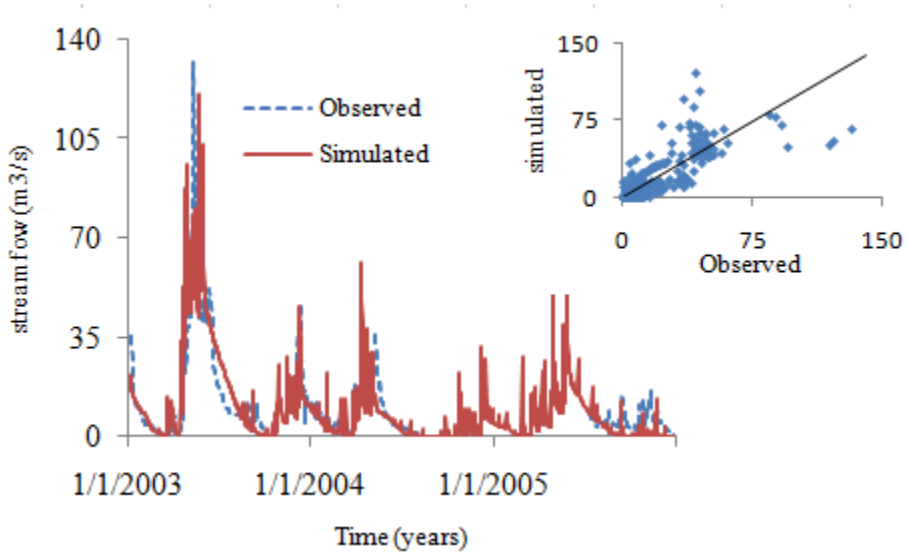


Figure 0.6: Calibration hydrograph and scatter plot for daily streamflow at sub-watershed4BC02

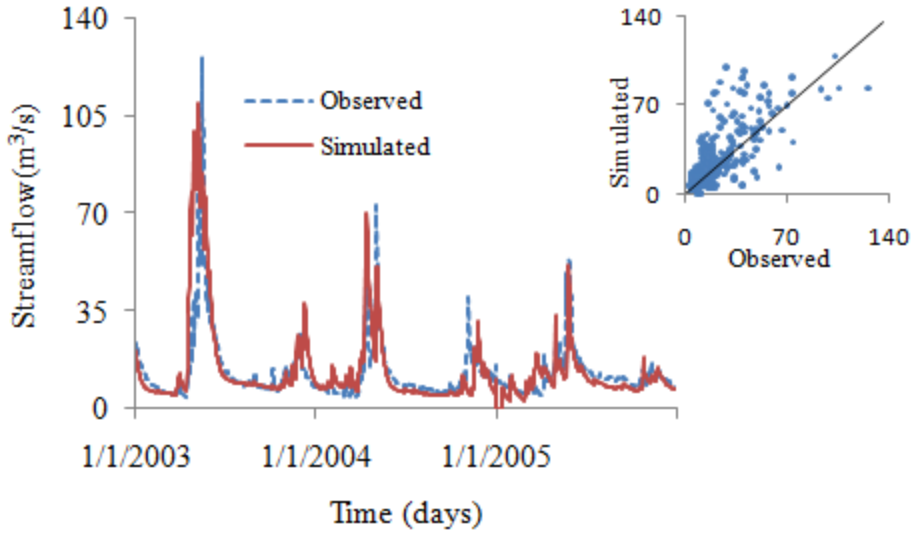


Figure 0.7: Calibration hydrograph and scatter plot for daily streamflow at sub-watershed 4BE01

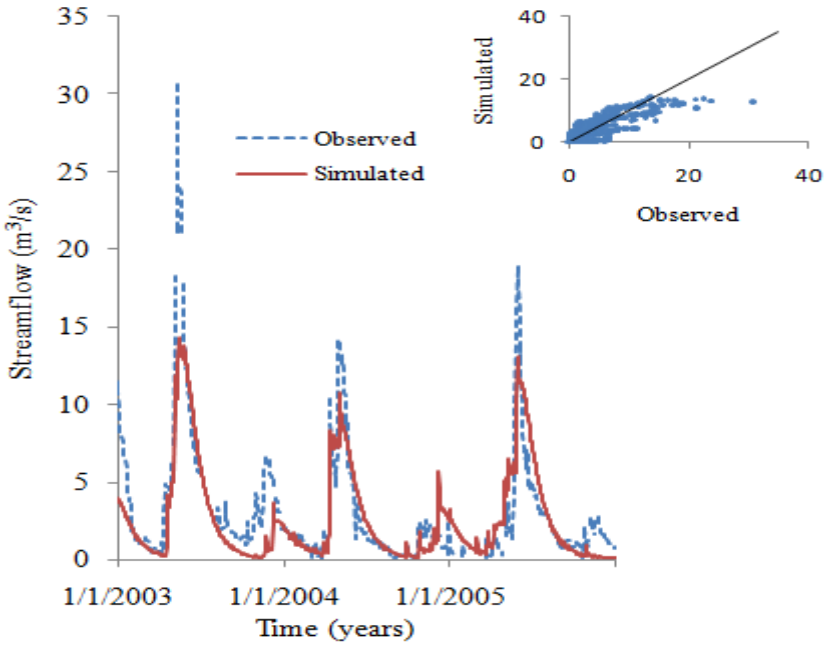


Figure 0.8: Calibration hydrograph and scatter plot for daily streamflow at sub-watershed 4CB04

Table 0.4: Calibration results

Sub-watershed	R^2	NSE	PBIAS
4AD01	0.57	0.52	4.80
4BC02	0.60	0.58	5.12
4BE01	0.68	0.54	5.75
4CB02	0.69	0.68	10.00

The goodness of fit between the observed and simulated streamflow was analyzed for each of the four streamflow gauging stations separately. Satisfactory model calibration results based on (Moriasi *et al*., 2007) were obtained as evaluated by the coefficient of determination and the Nash-Sutcliffe coefficient values. While there is no consensus on specific Nash-Sutcliffe coefficient values that must be obtained for SWAT predictions to be considered good, a value greater than 0.5 is considered acceptable (Engel *et al*., 2007; Gassman *et al*., 2007; Moriasi *et al*., 2007). A value that is greater than 0.5 for the

coefficient of determination is also considered acceptable (Santhi *et al*., 2001). The PBIAS values obtained during calibration range between 4.80 and 10 which is regarded as very good. The positive PBIAS values mean that the simulated data underestimated the observed data (Moriasi *et al*., 2007). In this study there was a fairly good simulation of the low flows as shown in Figure 0.5 to Figure 0.8. There was some slight under prediction of the high flows in the 4BE01 and 4BC04 sub-watersheds. This happened during the wet season in the months of April, May and November. As pointed earlier, under prediction can be attributed to the fact that the FEWS rainfall estimates may fail to detect short rains that occur due to convection and orographic precipitation (Hunink *et al*., 2009). The underestimation of the high flows by the SWAT model has also been observed in other studies (Qiu *et al*., 2012; Van Liew *et al*., 2007). This shortcoming in SWAT can be attributed to the model not being able to account for antecedent soil moisture conditions prior to events in the watershed, which affects partitioning of precipitation and streamflow with the SCS curve number method (Van Liew *et al*., 2007).

1.18.5 Validation of the SWAT model

In order to verify that the model could be used in the watershed, a model validation test was carried out. This was done by using independent datasets (2005-2008) from those used in the calibration period. Table 0.5 gives the R^2, NSE and PBIAS values. Results from the validation exercise are shown in Figure 0.9 to Figure 0.12.

Table 0.5: Performance statistics of validation

Sub-watershed	R^2	NSE	PBIAS
4AD01	0.59	0.51	19.83
4BC02	0.60	0.50	-20.00
4BE01	0.63	0.46	15.00
4CB04	0.59	0.51	20.00

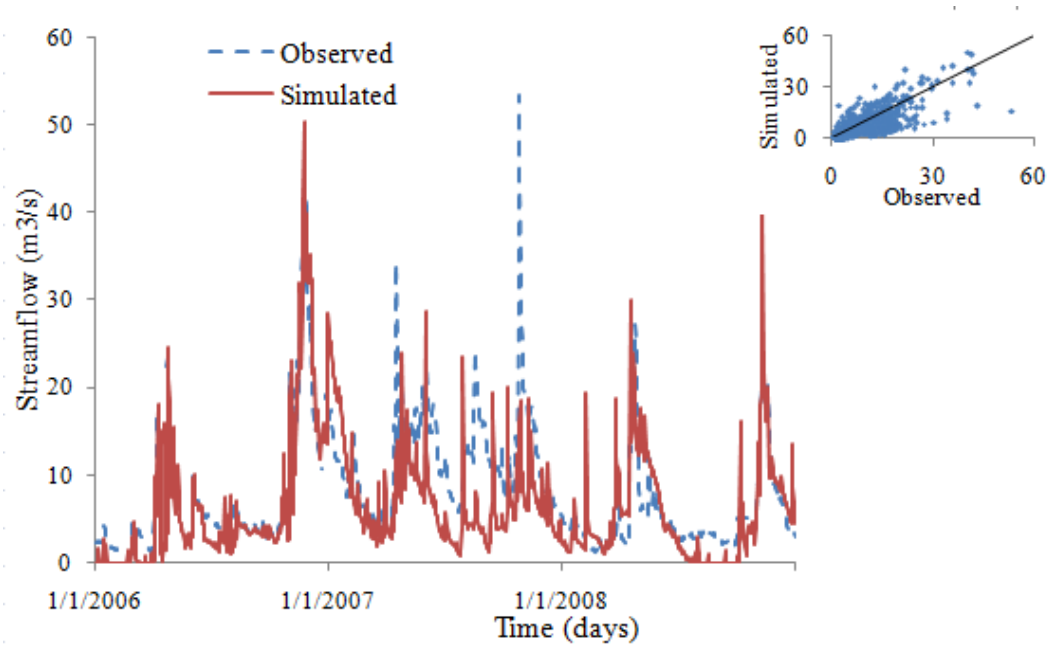


Figure 0.9: Validation hydrograph and scatter plot for daily streamflow at sub-watershed 4AD01

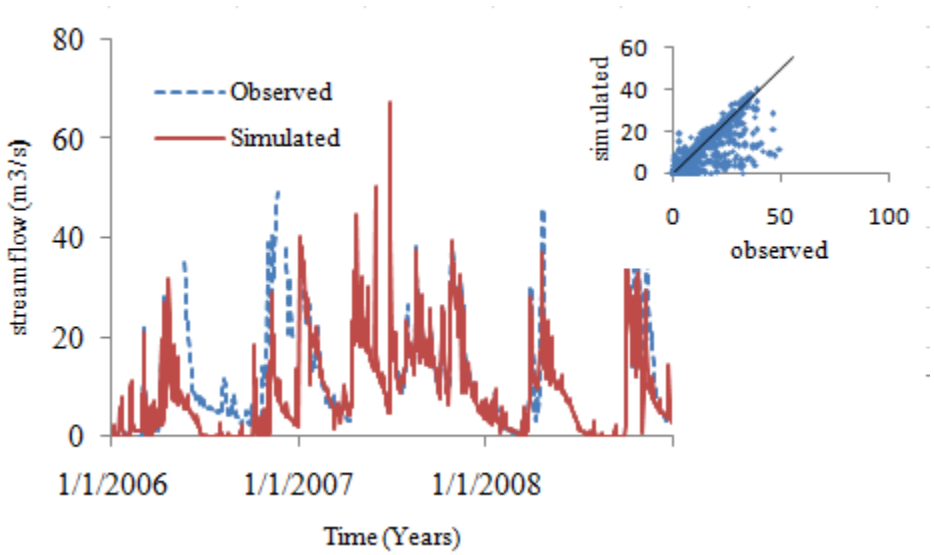


Figure 0.10: Validation hydrograph and scatter plot for daily streamflow at sub-watershed 4BC02

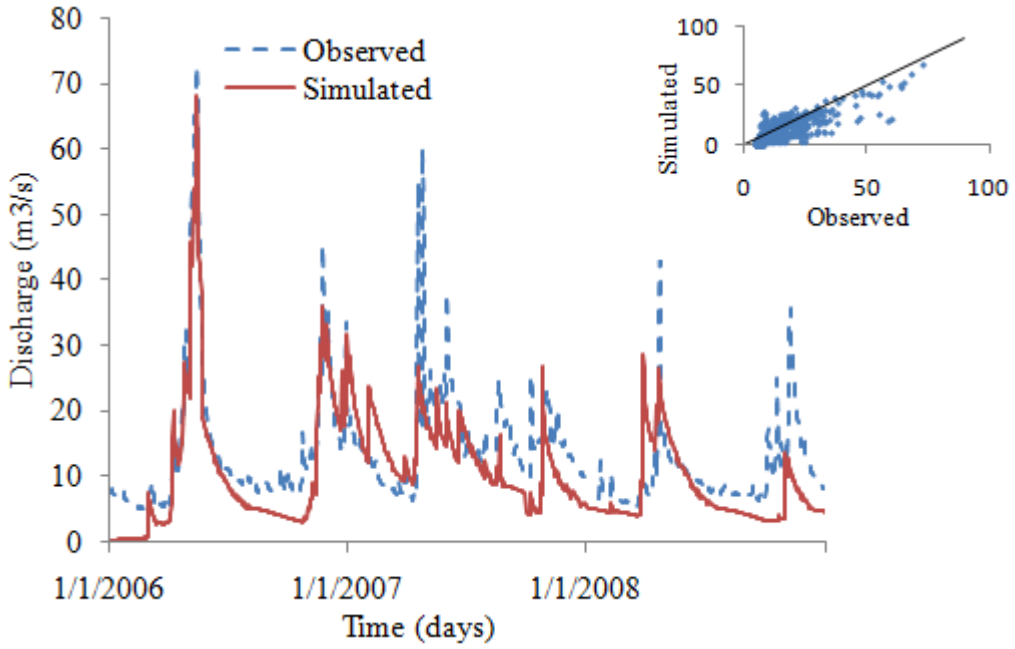


Figure 0.11: Validation hydrograph and scatter plot for daily streamflow at sub-watershed 4BE01

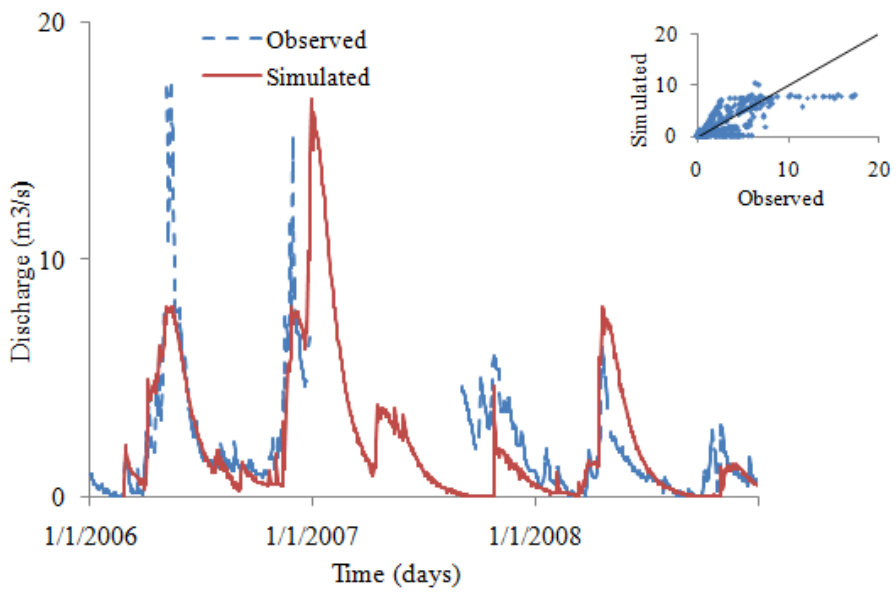


Figure 0.12: Validation hydrograph and scatter plot for daily streamflow at sub-watershed 4CB04

There was underestimation of the low flows especially at stations 4AD01 and 4BE01. This could be due to the fact that base flow may be composed of a number of components, such as subsurface flow, which may vary seasonally with different recession constants (Luo *et al*., 2012). Figure 0.9 shows that at 4AD01 the high flows were well captured. Station 4AD01 had R^2 and NSE values of 0.59 and 0.51, respectively as shown in Table 0.5. Figure 0.11 shows that high flows were fairly captured at station 4BE01. The R^2 and NSE values of 4BE01 are 0.63 and 0.46, respectively. The low NSE value attained is due to the under estimation of the low flows at the station. Figure 0.10 shows that flow was well captured at 4BC02 apart from a few months in 2006. The R^2 and NSE values are 0.6 and 0.5, respectively. Figure 0.12 shows that flow was well simulated for 4CB04 apart from two high flow peaks, which can be attributed to the model not being able to account for antecedent soil moisture conditions prior to events in the watershed (Van Liew *et al*., 2007). The R^2 and NSE values are 0.59 and 0.51, respectively.

The calibration and validation indicated that the model represented well the hydrologic characteristics of the Upper Tana watershed. The streamflow was well simulated by the model. The model performance was also acceptable with R^2 ranging between 0.57 and 0.69 and NSE ranging between 0.52 and 0.58. Therefore, the calibrated model was considered suitable for simulating streamflow in the assessment of transferability of SWAT model parameters from gauged to ungauged sub-watersheds.

1.18.6 Uncertainty analysis

Parameter uncertainty is shown in Figure 0.13. The figure shows the observed and simulated daily streamflow and the 95% uncertainty bound obtained by the SUFI-2 algorithm. Based on the results, the simulated flow underestimates the observation. Most of the observed high flows are not enveloped by the 95%PPU. The p-factor attained was 0.63 which indicates that only 63% of uncertainty was detected by the SUFI-2 algorithm. There is also increase of uncertainty with increase of streamflow and

this was observed during the high rainfall periods. The increase of uncertainty as streamflow increased was also observed by Shen *et al*., (2011) who accredited it to the parameters of the model.

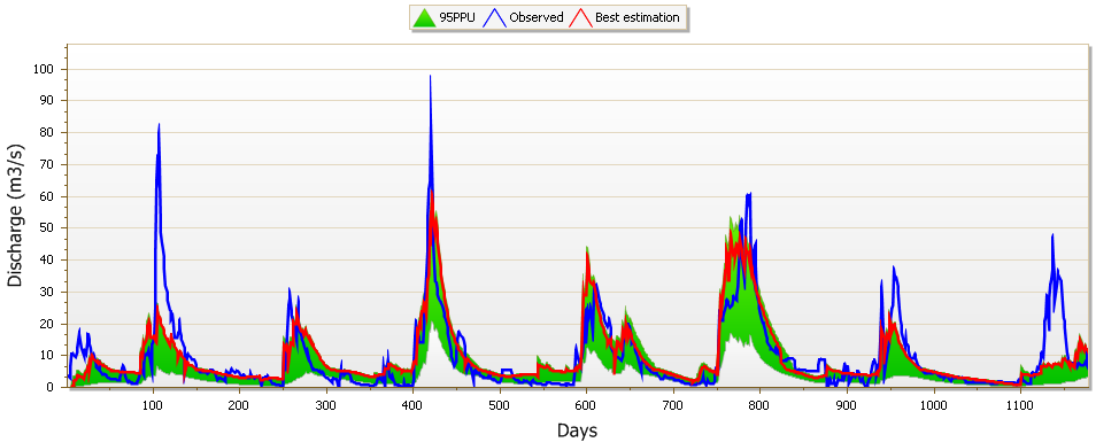


Figure 0.13: Uncertainty during calibration (2003-2005)

1.19 Parameter transfer for streamflow simulation at ungauged sub-watersheds

1.19.1 Spatial proximity

Spatial proximity approach was carried out by transferring parameters from a neighbouring donor sub-watershed to the receiver sub-watershed (Heuvelmans *et al*., 2004; Parajka *et al*., 2005; Patil, 2011; Wang & Kalin, 2010). The parameters in Table 0.3 were transferred between sub-watersheds 4BE01 and 4CB04; 4AD01 and 4BC02. The rationale was that because the sub-watersheds are near each other, they have similar behavioral characteristics. This is due to the fact that watershed and climatic conditions vary evenly in space (Oudin *et al*., 2008).

1.19.2 Global averages parameter estimation

Global average parameters were determined by computing the mean of each of the parameters of the four sub-watersheds used in calibration. These parameter values were then written into the input files of each of the sub-watersheds. The model was run and

the corresponding streamflow simulation values were obtained. Table 0.6 shows model parameter values as obtained through global averaging.

Table 0.6: Global average parameters

	Parameter value/ change from original				
Parameter	4AD01	4BC02	4BE01	4CB04	mean
CN2	-9.65	-9.97	-1.35	-3.11	-6.02
SOL_AWC	-0.04	-0.02	-0.02	-0.03	-0.03
CH_K2	0.00	0.00	19.00	0.20	4.80
RCHRG_DP	0.28	0.55	0.34	0.01	0.29
REVAPMN	57.80	0.00	166.20	79.00	75.75
SURLAG	0.79	0.27	0.46	0.07	0.40
OV_N	12.76	3.82	10.00	0.10	6.67
ALPHA_BF	0.09	0.06	0.03	0.10	0.08
GWQMN	62.30	0.00	4.30	22.85	22.36
GW_DELAY	31.47	30.27	81.00	28.00	42.69

For sub-watershed 4CB04, the value of soil available water capacity (SOL_AWC) and the threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN) obtained through global averages was close to that obtained during calibration. In some instances, global average values obtained differed substantially from calibrated values. For example, the calibrated value of REVAPMN for sub-watershed 4BC02 was 0 while that for global average was 75.75.

1.19.3 Regression based parameter estimation

Using data from available databases and Arc Map, a broad range of watershed characteristics were initially defined (Table 0.7). This was done to capture the range of land use, soil, topography and climatic conditions that were present in the study watersheds. Preliminary analysis was done to investigate the correlation within the model parameters and between the model parameters and the watershed characteristics as shown in (Table 0.8). The results shows that the correlations were fairly medium with parameter CH_K2 having a perfect negative correlation with GW_DELAY. REVAPMN

had very low correlation with all of the parameters. Table 0.9 shows that most of the parameters have a normal distribution although SOL_AWC, RCHRG_DP, OV_N and ALPHA_BF are negatively skewed. The distribution of CN2, REVAPMN and SURLAG is less than one.

Table 0.7: Watershed characteristics used in the study

Characteristic	4AD01	4BC02	4BE01	4CB02
Size,km^2	1653.00	2549.00	396.00	288.00
Mean elevation(m)	2210.17	2139.67	2114.40	2080.67
Annual precipitation (mm)	989.15	709.41	1711.85	1168.00
AGRL%	25.00	20.00	7.00	4.00
FRST%	34.95	29.18	12.46	16.75
Anu	19.51	17.77	20.69	31.10
slope (0-20)%	94.15	96.10	93.44	98.68
Ntu	37.43	41.55	46.70	27.82
RNGE%	4.47	2.93	0.61	3.22

Table 0.8: Correlation matrix for the calibrated parameters

	CN2	SOL_AWC	CH_K2	RCHRG_DP	REVAPMN	SURLAG	OV_N	ALPHA_BF	GWQMN	GW_DELAY
CN2	1									
SOL_AWC	0.34	1								
CH_K2	0.71	0.52	1							
RCHRG_DP	-0.53	0.49	0.13	1						
REVAPMN	0.87	0.16	0.88	-0.34	1					
SURLAG	-0.39	-0.53	0.12	0.28	0.11	1				
OV_N	-0.19	-0.34	0.38	0.32	0.32	0.96	1			
ALPHA_BF	-0.24	-0.75	-0.80	-0.68	-0.42	-0.16	-0.37	1		
GWQMN	-0.37	-0.98	-0.43	-0.38	-0.11	0.67	0.50	0.62	1	
GW_DELAY	0.66	0.51	1.00	0.17	0.86	0.18	0.43	-0.82	-0.40	1

Table 0.9: Summary of parameter descriptive statistics

	CN2	SOL_AWC	CH_K2	RCHRG_DP	REVAPMN	SURLAG	OV_N	ALPHA_BF	GWQMN	GW_DELAY
Mean	-6.02	-0.03	4.80	0.29	75.75	0.40	6.67	0.07	22.36	42.69
Standard Error	2.22	0.00	4.73	0.11	34.46	0.15	2.88	0.02	14.21	12.79
Median	-6.38	-0.03	0.10	0.31	68.40	0.36	6.91	0.07	13.58	30.87
Standard Deviation	4.44	0.01	9.47	0.22	68.93	0.30	5.76	0.03	28.41	25.58
Sample Variance	19.69	0.00	89.63	0.05	4750.68	0.09	33.15	0.00	807.19	654.53
Skewness	0.13	-0.85	2.00	-0.40	0.61	0.58	-0.15	-0.37	1.36	1.98
Range	8.62	0.02	19.00	0.54	166.20	0.72	12.66	0.07	62.30	53.00
Minimum	-9.97	-0.04	0.00	0.01	0.00	0.07	0.10	0.03	0.00	28.00
Maximum	-1.35	-0.02	19.00	0.55	166.20	0.79	12.76	0.10	62.30	81.00
Count	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00

Table 0.10: Correlation matrix for the watershed characteristics

	Size(km^2)	Mean elevation(m)	Annual precipitation (mm)	AGRL%	FRST%	Anu	slope (0-20)%	Ntu	RNGE%
Size,km2	1								
Mean elevation(m)	0.60	1							
Annual precipitation (mm)	-0.83	-0.38	1						
AGRL%	0.85	0.93	-0.67	1					
FRST%	0.82	0.86	-0.80	0.96	1				
Anu	-0.72	-0.68	0.22	-0.74	-0.52	1			
slope (0-20)%	-0.14	-0.59	-0.39	-0.40	-0.14	0.77	1		
Ntu	0.26	0.26	0.32	0.23	-0.05	-0.82	-0.85	1	
RNGE%	0.44	0.56	-0.76	0.62	0.81	0.07	0.32	-0.62	1

Table 0.11: Summary of parameter descriptive statistics

	Size(km2)	Mean elevation(m)	Annual precipitation (mm)	AGRL%	FRST%	Anu	Slope (0-20)%	Ntu	RNGE%
Mean	1221.50	2136.23	1144.60	14.00	23.34	22.27	95.59	38.38	2.81
Standard Error	540.16	27.45	211.32	5.05	5.25	3.00	1.17	4.00	0.81
Median	1024.50	2127.04	1078.58	13.50	22.97	20.10	95.13	39.49	3.08
Standard Deviation	1080.33	54.90	422.64	10.10	10.50	6.01	2.35	7.99	1.61
Sample Variance	1167107.00	3014.09	178624.09	102.00	110.23	36.11	5.50	63.90	2.59
Skewness	0.55	0.90	0.85	0.13	0.11	1.76	0.86	-0.74	-0.95
Range	2261.00	129.50	1002.44	21.00	22.49	13.33	5.24	18.88	3.86
Minimum	288.00	2080.67	709.41	4.00	12.46	17.77	93.44	27.82	0.61
Maximum	2549.00	2210.17	1711.85	25.00	34.95	31.10	98.68	46.70	4.47
Count	4	4	4	4	4	4	4	4	4

Table 0.12: Correlation between model parameters and watershed characteristics

	CN2	SOL_AWC	CH_K2	RCHRG_DP	REVAPMN	SURLAG	OV_N	ALPHA_BF	GWQMN	GW_DELAY
Size,km2	-0.93	0.02	-0.52	0.78	-0.83	0.26	0.12	-0.07	0.02	-0.47
Mean elevation(m)	-0.75	-0.59	-0.27	0.40	-0.33	0.90	0.77	0.05	0.69	-0.21
Annual precipitation (mm)	0.89	0.24	0.90	-0.32	1.00	0.05	0.28	-0.46	-0.19	0.88
AGRL%	-0.93	-0.41	-0.47	0.58	-0.63	0.69	0.53	0.06	0.50	-0.41
FRST%	-0.97	-0.55	-0.70	0.39	-0.76	0.55	0.34	0.34	0.59	-0.65
Anu	0.58	-0.19	-0.17	-0.92	0.22	-0.63	-0.65	0.62	0.05	-0.22
slope (0-20)%	0.07	-0.03	-0.60	-0.53	-0.41	-0.82	-0.93	0.69	-0.14	-0.66
Ntu	-0.01	0.54	0.69	0.79	0.30	0.43	0.60	-0.95	-0.39	0.73
RNGE%	-0.73	-0.81	-0.91	-0.20	-0.71	0.25	-0.01	0.82	0.75	-0.89

Table 0.11 shows that most variables are normally distributed although Anu is slightly skewed positively which means it has a relatively small coverage within the sub watersheds compared to other sub watershed characteristics. The sub-watershed characteristics that correlated well with the model parameters were considered to be the major drivers of watershed hydrological response. The watershed characteristics that had low correlation with the model parameters meant that their hydrological effects if any were hidden by overpowering drivers of the watershed hydrological response. In this respect parameter CN2 had a high correlation with almost all of the watershed characteristics except slope (0-20) % and Ntu soil. Parameter GWQMN had the lowest correlation with all the watershed characteristics. Within the Upper Tana Watershed, the main drivers of the watershed hydrologic response were therefore identified, annual precipitation and RNGE%.

1.19.3.1 Stepwise and multiple regression

In order to identify those watershed characteristics that had the strongest statistical relationship with the model parameters, stepwise regression was carried out. The best regression equation was built using the forward approach where the variables that explained the largest amount of unexplained variance were added one at a time at each time step. For each model parameter, the watershed characteristics suggested by correlation analysis and stepwise regression were combined in a multiple regression equation where the model parameters were expressed in terms of the watershed characteristics. The model parameters were recalculated using the resulting multiple regression equation (Table 0.13). R^2 is a multiple regression coefficient. Equations obtained were best for REVAPMN and ALPHA_BF, for which R^2 values obtained were 0.99.

Table 0.13: Multiple regression equations for estimating parameters

Parameter	Multiple regression equation of parameters in terms of watershed characteristics	R^2
CN2	3.278-0.379FRST%-0.032AGRL%	0.94
CH_K2	1.230+0.011Annual Precipitation-3.182RNGE%	0.93
RCHRG_DP	0.875-0.031ANu+0.003NTu	0.85
REVAPMN	110.377+0.163Annual precipitation	0.99
SURLAG	1.749+0.004mean elevation-0.057slope(0-20)%	0.94
OV_N	224.935-2.283slope(0-20)%	0.94
ALPHA_BF	0.154-0.002NTu+0.007RNGE%	0.99
GW_DELAY	33.487-8.463RNGE%+0.029Annual precipitation	0.89

1.20 Estimation of streamflow and evaluation of model performance

1.20.1 Spatial proximity

The hydrographs and scatter plots for daily streamflow estimation using the spatial proximity method are shown below in Figure 0.14 to Figure 0.17. The model performance statistics are shown in Table 0.14.

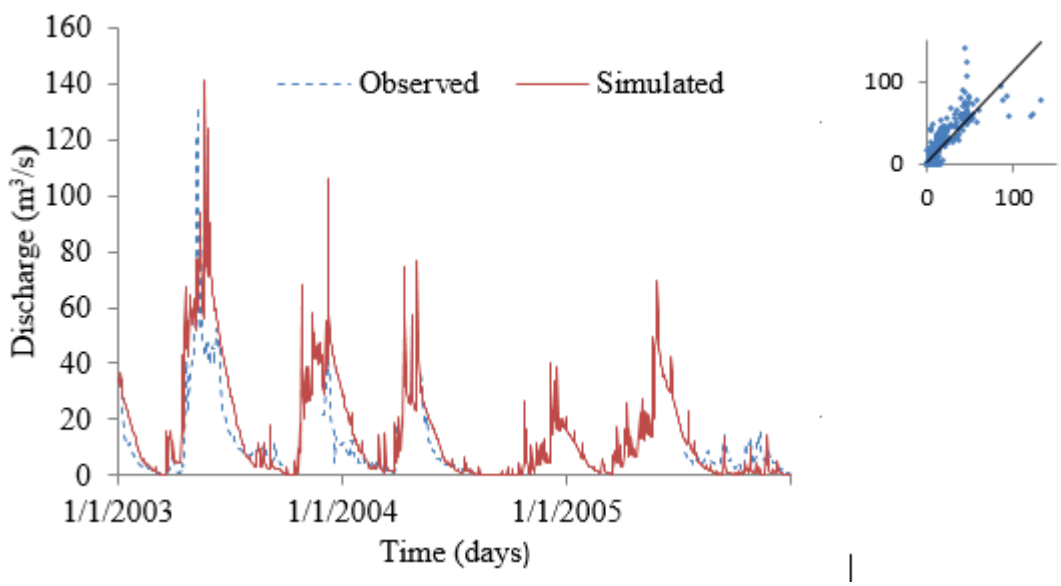


Figure 0.14: Hydrograph and scatter plot for daily streamflow simulation with parameters transferred from sub-watershed4AD01 to sub-watershed 4BC02

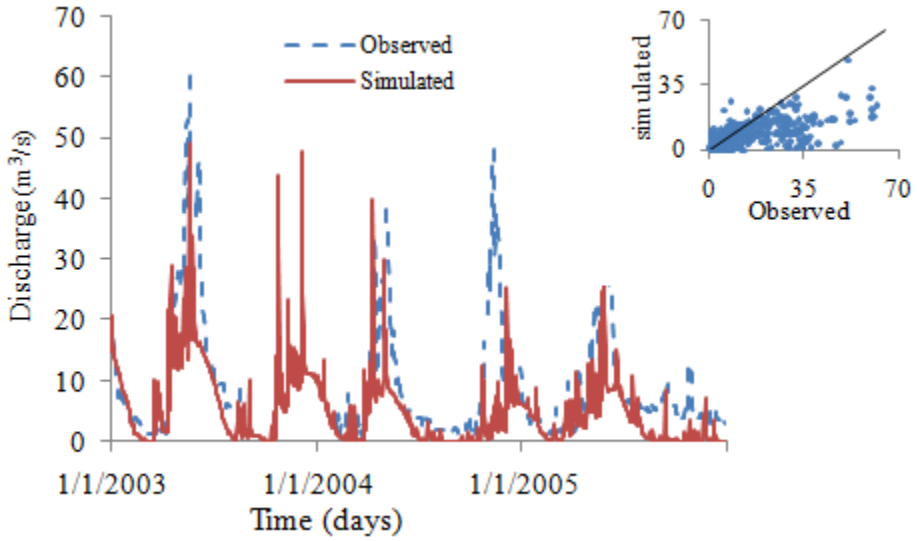


Figure 0.15: Hydrograph and scatter plot for daily streamflow simulation with parameters transferred from sub-watershed4BC02 to sub-watershed 4AD01

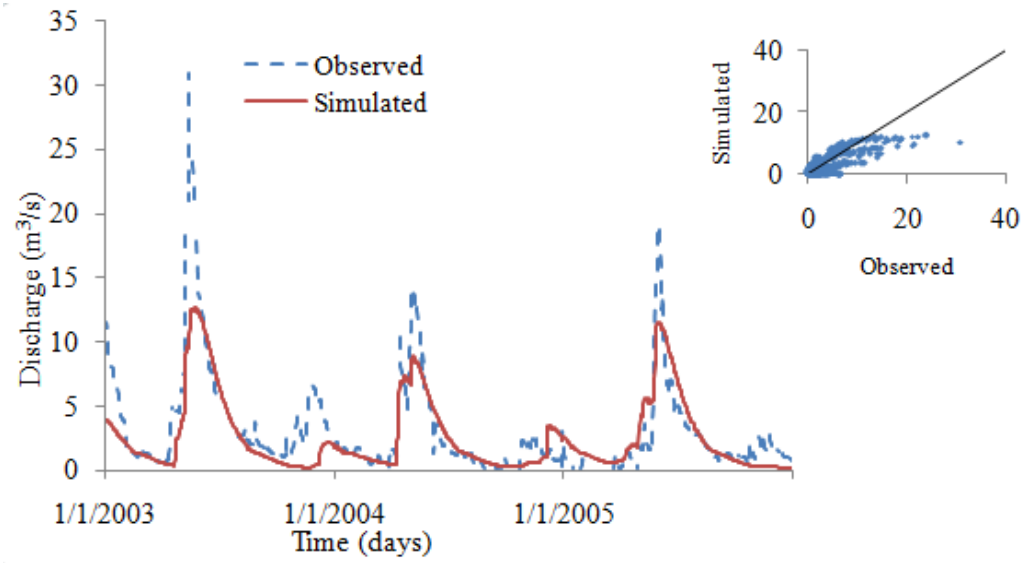


Figure 0.16: Hydrograph and scatter plot for daily streamflow simulation with parameters transferred from sub-watershed4BE01 tosub-watershed 4CB04

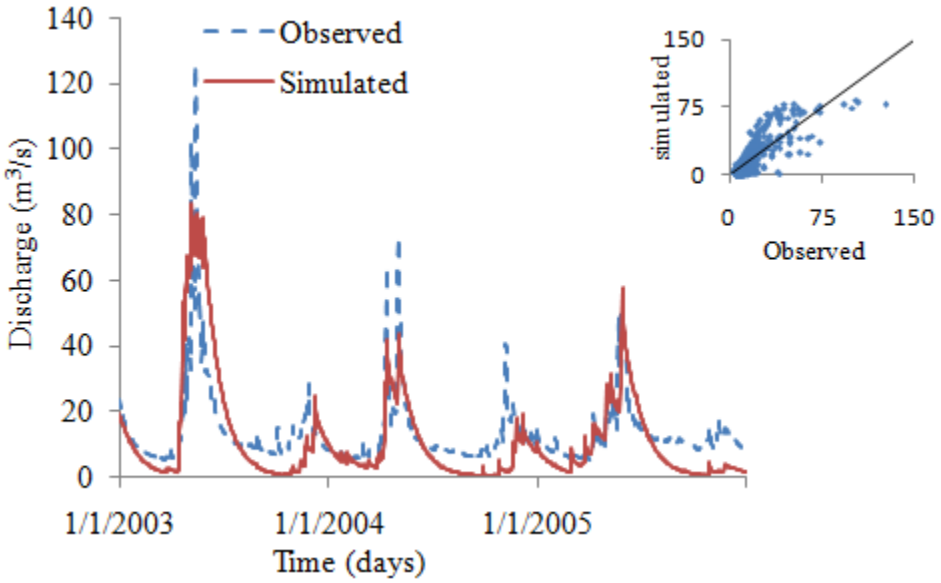


Figure 0.17: Hydrograph and scatter plot for daily streamflow simulation with parameters transferred from sub-watershed 4CB04 to sub-watershed 4BE01

Table 0.14: Performance statistics of spatial proximity

Transfer	R^2	NSE
4AD01 to 4BC02	0.69	0.50
4BC02 to 4AD01	0.50	0.48
4BE01 to 4CB04	0.66	0.46
4CB04 to 4BE01	0.68	0.51

Figure 0.14 shows that the model performance after transfer of parameters from 4AD01 to 4BC02 was good because both the high and low flows were well simulated. The R^2 and NSE were 0.69 and 0.5, respectively. However, the transfer of parameters from 4AD01 to 4BC02 did not give a good model performance as shown in Figure 0.15 because most of the low flows were under predicted. The R^2 and NSE were 0.5 and 0.48, respectively. Figure 0.17 shows that parameter transfer from 4BE01 to 4CB04 was successful because the low flows were well simulated while the high flows were moderately simulated. The low flows were not well captured in Figure 0.17.

4.3.2 Global averages

The global averages performance statistics are shown in Table 0.15 while the hydrographs and scatter plots for daily streamflow estimation are shown below Figure 0.18 to Figure 0.21 .

Table 0.15: Performance statistics of global averages

Sub-watershed	R^2	NSE
4AD01	0.54	0.53
4BC02	0.65	0.43
4BE01	0.65	0.46
4CB04	0.66	0.54

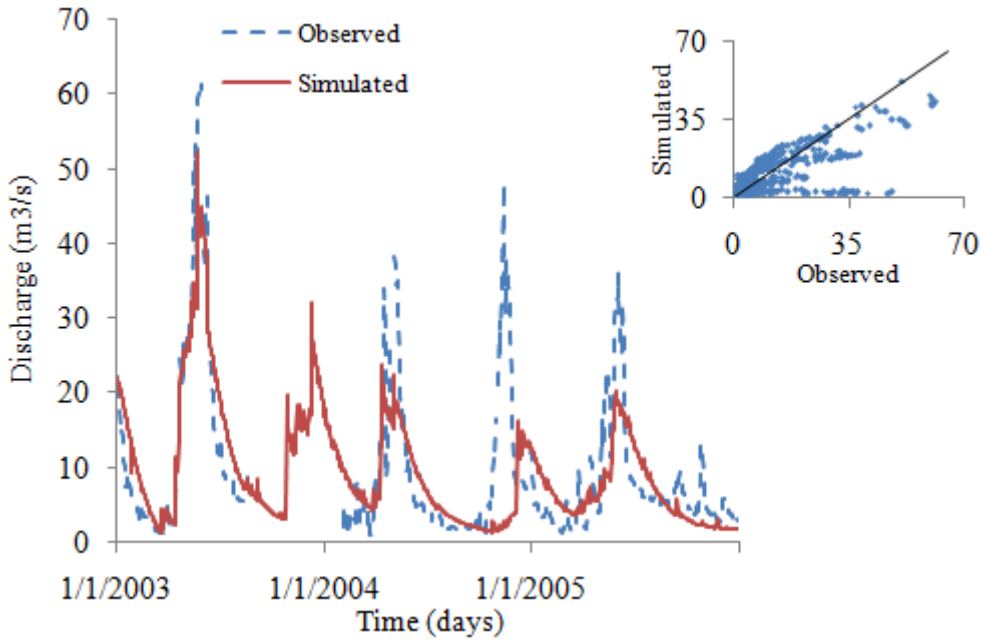


Figure 0.18: Global average hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4AD01

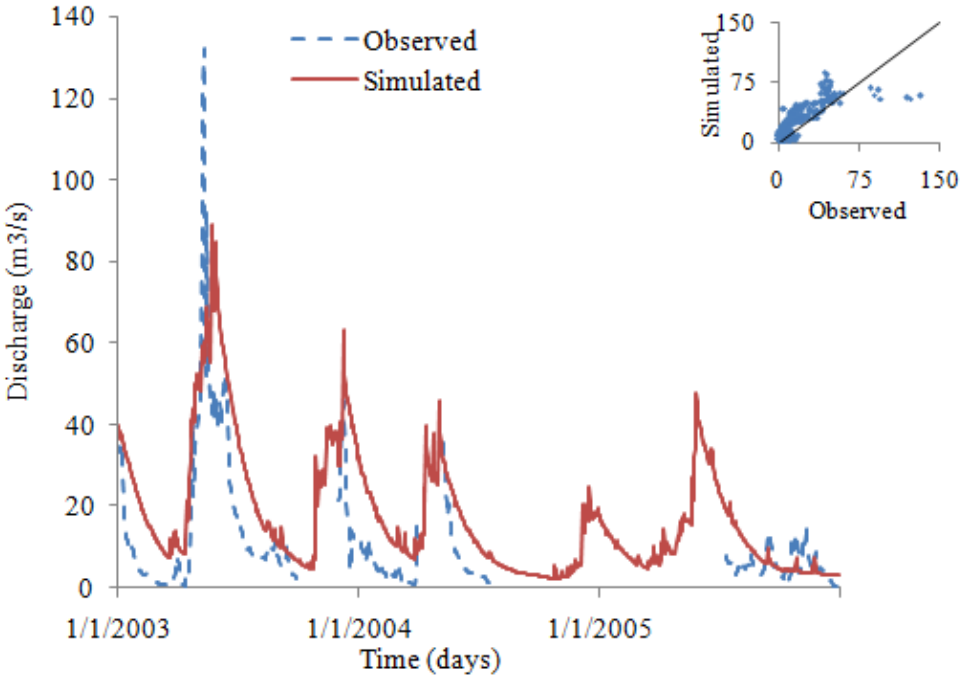


Figure 0.19: Global average hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4BC02

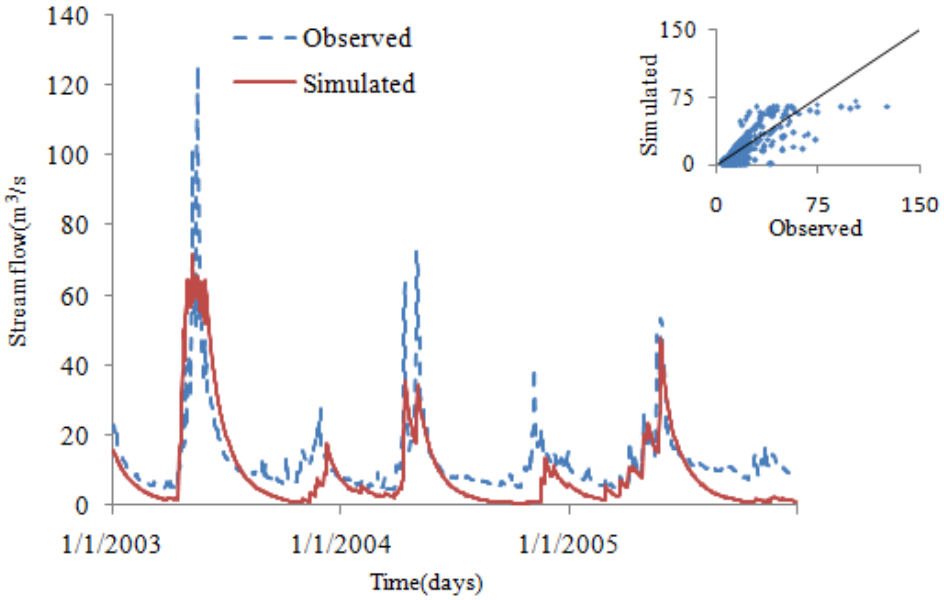


Figure 0.20: Global average hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4BE01

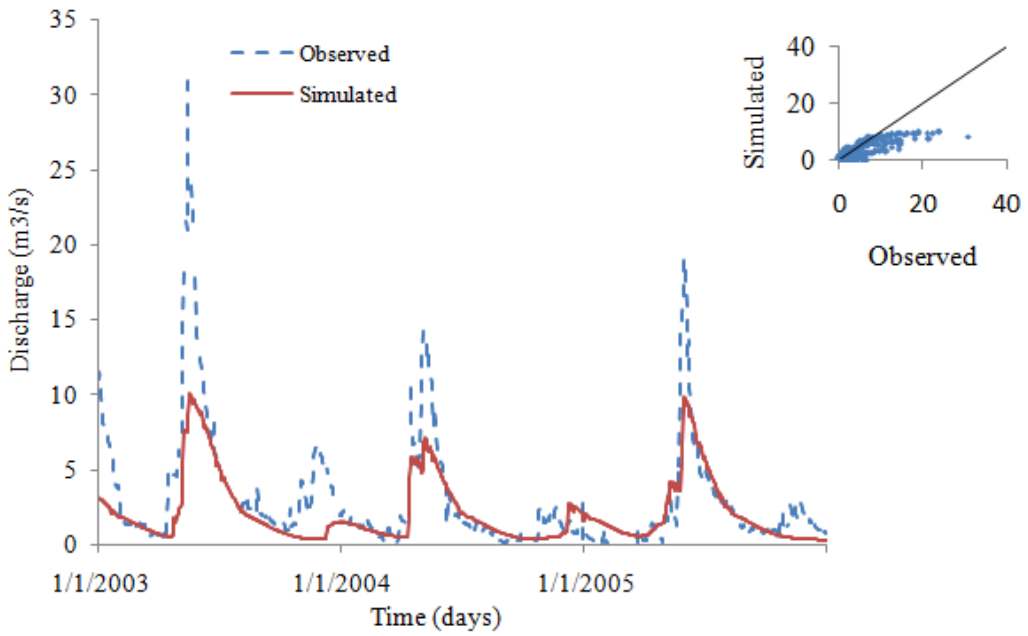


Figure 0.21: Global average hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4CB04

Figure 0.18 shows the flow hydrograph at 4AD01. The simulated streamflow obtained using global average parameters was similar to the observed streamflow except that it didn't capture one of the peaks well. Figure 0.19 showed that the simulated streamflow at 4BC02 matched the observed relatively well. Figure 0.20 shows that at 4BE01, some high flows and low flows were not well simulated. Figure 0.21 shows that the high flows were not captured by simulated streamflow at 4CB04, although the base flows were well simulated.

4.3.3 Regression

The simulated hydrograph and scatter plot obtained using the regression-based parameters are show in Figure 0.22 to Figure 0.25. The performance statistics are also shown in Table 0.16. R^2 values ranged from 0.5 in sub-watershed 4AD01 to 0.73 in sub-watershed 4CB02. Figure 0.22 shows that the simulated streamflow compared well to the observed streamflow at 4AD01. The best performance was at 4BC04 which had the

highest value of NSE at 0.64 and an R^2 of 0.66. Figure 0.25 shows that the high and low flows were fairly well simulated. Figure 0.23 shows that some of the low flows were overestimated at 4BC02. Figure 0.24 shows that the flow was fairly simulated at 4BE01 with a few underestimations of the high flows.

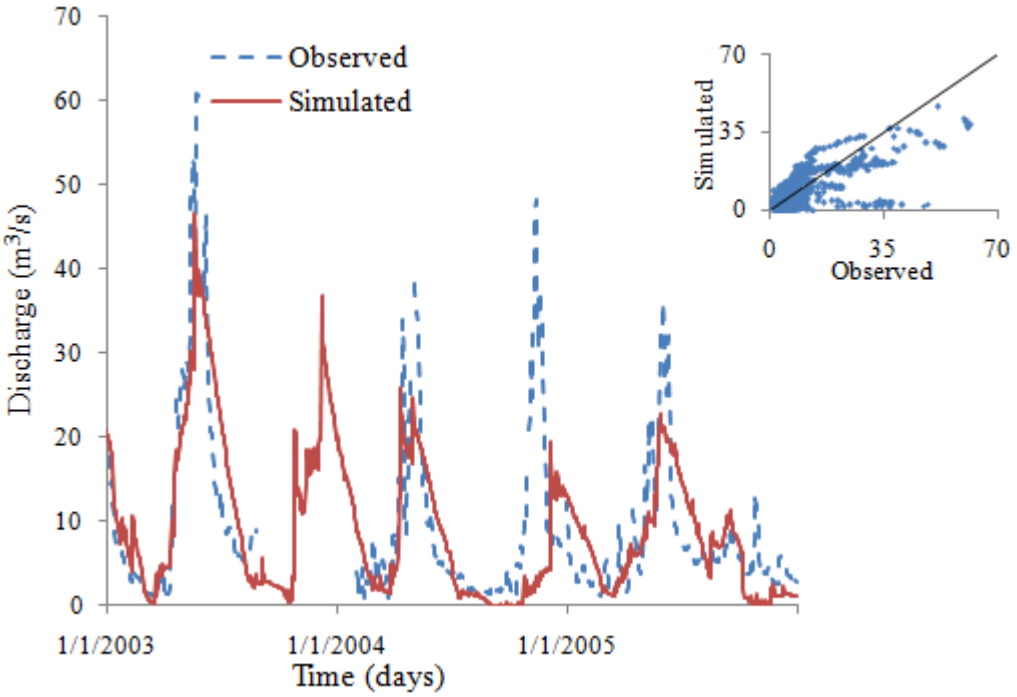


Figure 0.22: Regression-based hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4AD01

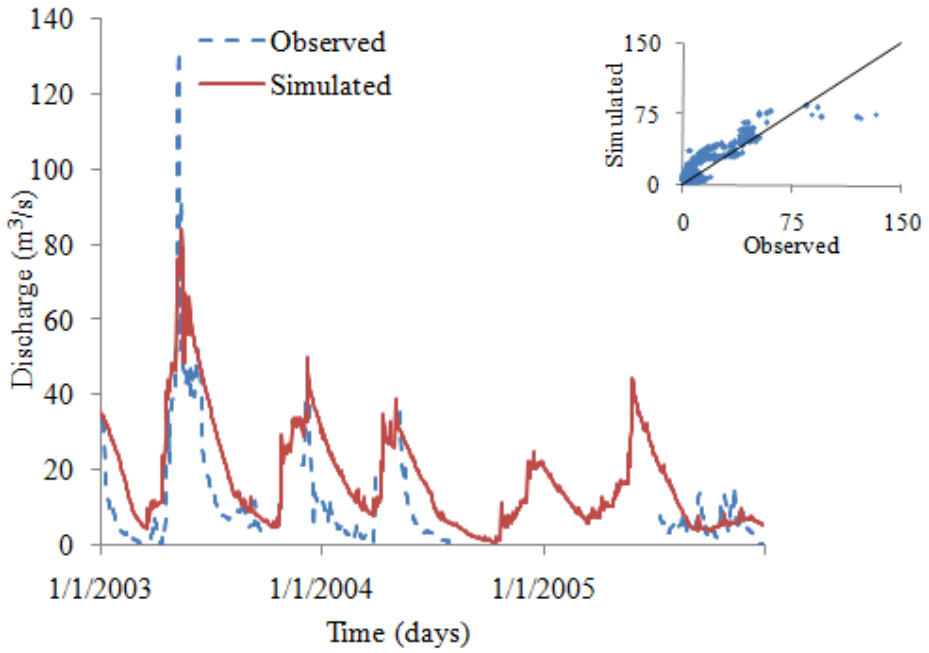


Figure 0.23: Regression-based hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4BC02

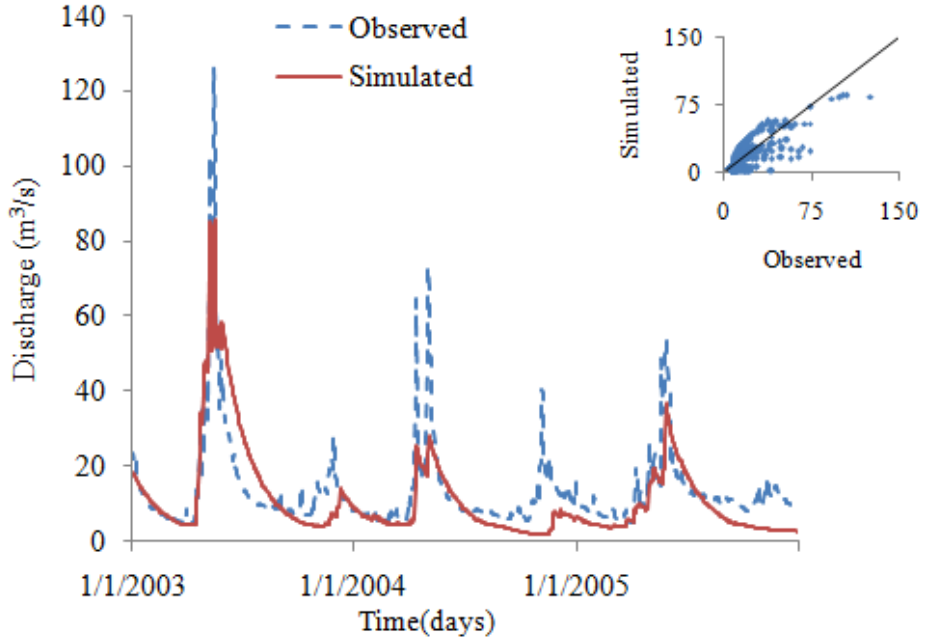


Figure 0.24: Regression-based hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4BE01

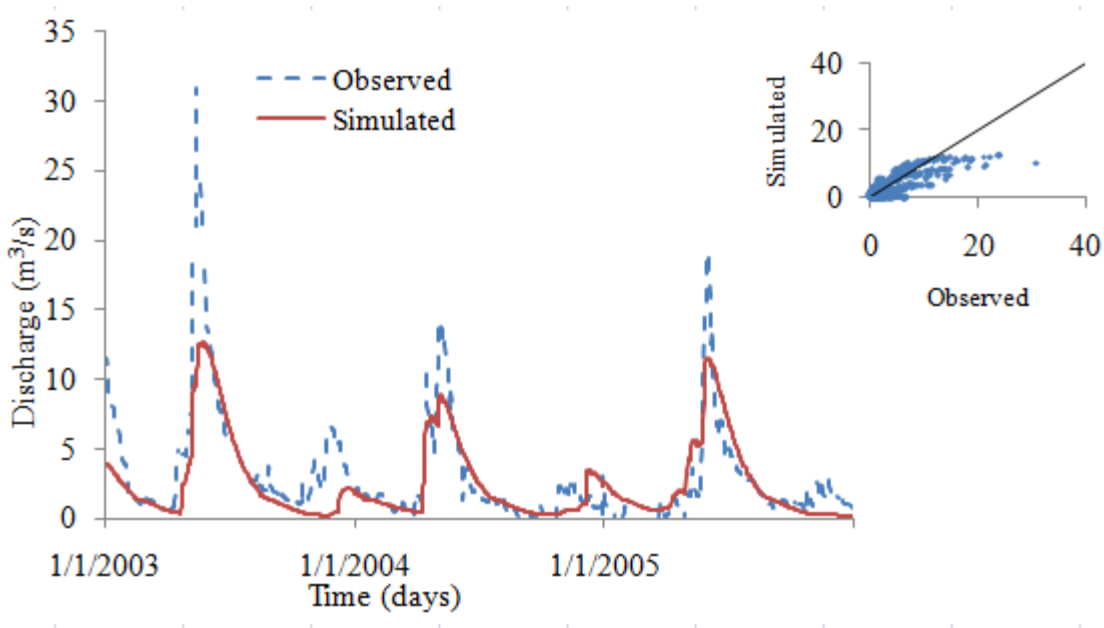


Figure 0.25: Regression-based hydrograph and scatter plot for daily streamflow simulation at sub-watershed 4CB04

Table 0.16: Performance statistics of regression

Sub-watershed	R^2	NSE
4AD01	0.50	0.49
4BC02	0.73	0.45
4BE01	0.63	0.48
4CB04	0.66	0.64

Based on the results in Table 0.17, the transfer methods performed differently in the various sub-watersheds. At sub-watershed 4AD01, the global averages method performed the best with a NSE of 0.53 which is higher than the calibrated value of 0.52. The spatial proximity method performed best at sub-watershed 4BC02 and 4BE01. At sub-watershed 4CB02, the regression method of parameter transfer performed better than the other methods.

Table 0.17: Model performance statistics obtained using the parameter transfer in comparison to the calibrated model

Sub-watershed	Calibration		Spatial proximity		Global Averages		Regression	
	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
4AD01	0.57	0.52	0.50	0.48	0.54	0.53	0.50	0.49
4BC02	0.60	0.58	0.69	0.50	0.65	0.33	0.73	0.45
4BE01	0.68	0.54	0.66	0.46	0.65	0.46	0.63	0.48
4CB02	0.69	0.68	0.68	0.51	0.66	0.54	0.66	0.64

Flow duration curves were developed at each river gauging station to show how the different parameter transfer method affected the low flow simulation. Figure 0.26 to Figure 0.29 shows the different flow duration curves obtained. Q_{90} is one of the commonly studied low flow indices. It is used to estimate the mean baseflow, warn water resources managers of critical streamflow levels and used to describe flow conditions that are limiting (Pyrce, 2004)

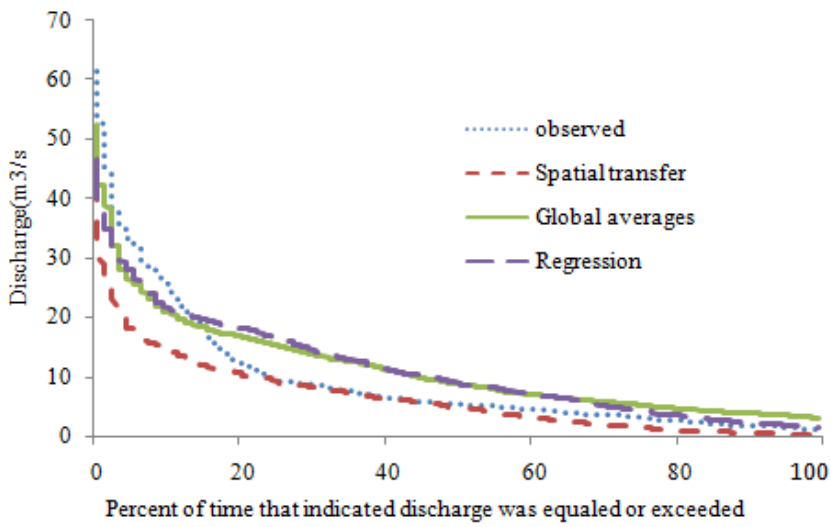


Figure 0.26: Comparison of flow duration curve at sub-watershed 4AD01

From Figure 0.26 it can be deduced that the discharge equaled or exceeded 90% of the time for the period 2003 to 2005 at the 4AD01 station is $2m^3/s$. When using spatial proximity to transfer SWAT parameters, the resulting discharge equaled or exceeded

90% of the time is close to 0m^3/s. The discharge equaled or exceeded 90% of the time is 2m^3/s and 1 m^3/s, respectively for the global average and regression method of transfer. The results show that spatial proximity and global averages method would not give very accurate results when dealing with any water resources projects that require the use of the low flows.

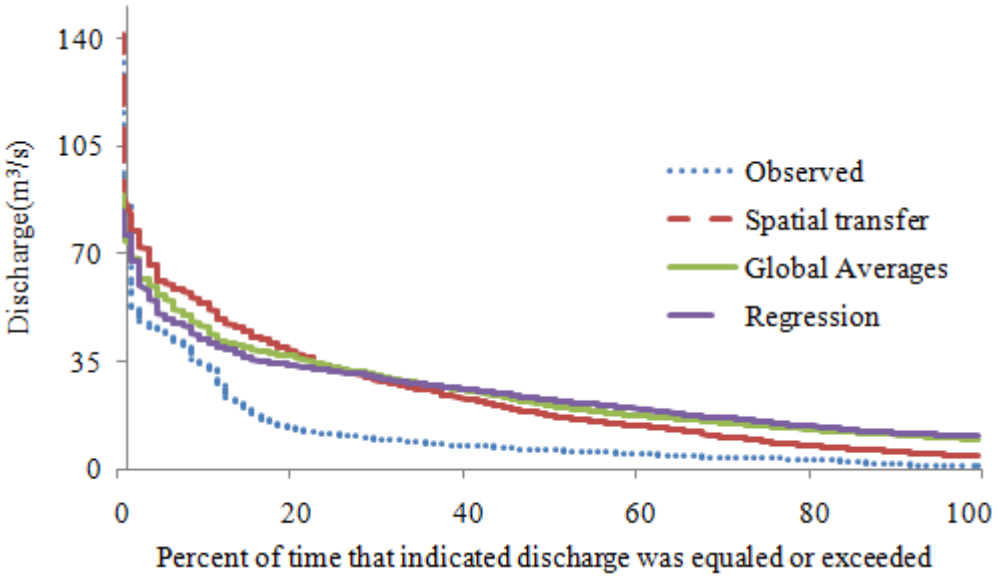


Figure 0.27: Comparison of flow duration curve at sub-watershed 4BC02

Figure 0.27 shows that the discharge equaled or exceeded 90% of the time for the period 2001 to 2005 at the 4BC02 station is about 1.5m^3/s. When using spatial proximity to transfer SWAT parameters, the resulting discharge equaled or exceeded 90% of the time is about 1m^3/s. From the figure, it can be deduced that the discharge equaled or exceeded 90% of the time is 3m^3/s for the global averages method and 4m3/s from the regression method. The results indicate that spatial proximity method yielded the best results regarding low flow simulation at the 4BC02 sub-watershed.

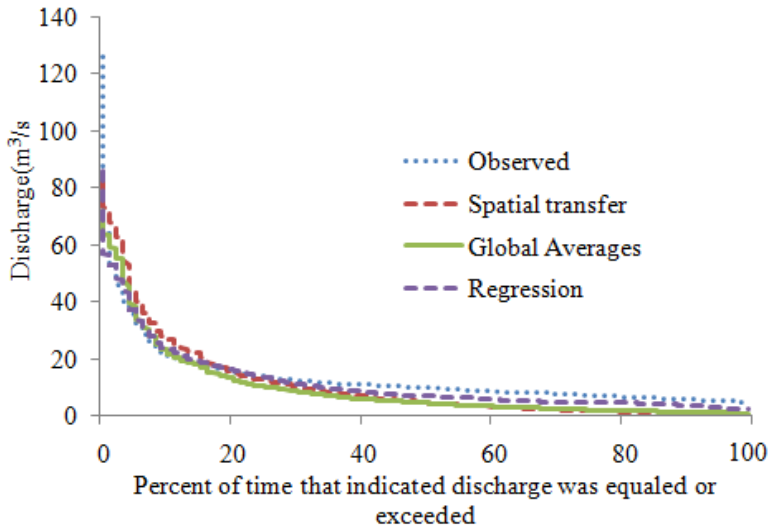


Figure 0.28: Comparison of flow duration curve at sub-watershed 4BE01

The discharge equaled or exceeded 90% of the time at 4BE01 is 5m^3/s as shown in Figure 0.28. 1m^3/s is the discharge equaled or exceeded 90% of the time at 4BE01 when using the spatial proximity method of parameter transfer. The discharge equaled or exceeded 90% of the time is 1m^3/s and 3m^3/s, respectively for the global averages and regression transfer methods. The results indicate that regression method yielded the best results regarding low flow simulation at the 4BE01 station.

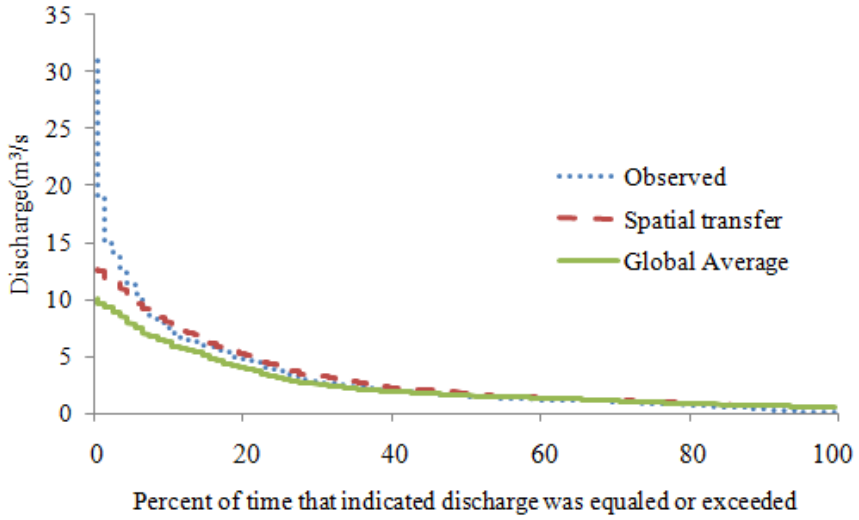


Figure 0.29: Comparison of flow duration curve at sub-watershed 4CB04

Figure 0.29 shows that 0.5m^3/s is the discharge equaled or exceeded 90% of the time at 4CB04. With the spatial transfer method, the discharge equaled or exceeded 90% of the time is 0.3m^3/s. 0.4m3/s is the discharge equaled or exceeded 90% of the time using the global average method. These results show that both spatial proximity and global average methods of parameter transfer have closely simulated the low flows of the 4CB04 sub-watershed.

From the results in Table 0.17, it can be seen that spatial proximity has performed the best. This is because its performance statistics were closer to the calibration performance statistics at sub-watersheds 4BC02 and 4BE01. The flow duration curves also showed that spatial proximity performed better than the global averages and regression. This has also been observed in other studies (Oudin *et al*., 2008; Zhang & Chiew, 2009). It is not clear why any one method performed better at a sub-watershed and not the others. The spatial proximity method has an advantage because it easier to use and involves the transfer of parameters from one sub-watershed to another. The regression method performed well at sub-watershed 4CB02 only. The regression method has various limitations which might be the cause of it not giving better results. It requires more data and time because it involves watershed characteristics (Merz & Bloschl, 2004), actual non-linear relationships between model parameters and watershed characteristics are difficult to investigate with simple multiple regression equations (Wagener, 2007), it is also requires suitable statistical software and been found to work well for lumped models (Gitau & Chaubey, 2010).These factors may be contributing to it not performing well.

The research was faced with data limitations. There were very few rainfall and streamflow gauging stations to work with in the area of study. Satellite rainfall estimates were used in the study to deal with the rainfall gauging station deficiencies. The study was carried out using only four streamflow gauging stations which affected the model performance while transferring parameters. This is because transfer of parameters should be done between sub-watersheds that have similar climatic and physical characteristics.

The Upper Tana watershed was not able to be divided to near perfectly similar sub watersheds because of few streamflow data.

In general, the model performed best with spatial proximity method as compared to global averages and regression. The parameters obtained would give satisfactory performance in the Upper Tana watershed. The results suggest that it is possible to transfer SWAT model parameter values for use in sub-watersheds with minimal or no data for streamflow simulation.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

1.21 Conclusions

Based on the study carried out, the various conclusions were drawn. The SWAT model can effectively simulate streamflow at the Upper Tana watershed. The model performance attained was satisfactory. The coefficient of determination (R^2) between the observed and simulated streamflow the gauging stations in the watershed were between 0.57 and 0.69. The Nash-Sutcliffe efficiency (NSE) values achieved varied between 0.52 and 0.68.

FEWS dataset precipitation estimates can be used in areas where there isn't enough precipitation data. There was a good correlation between the FEWS dataset and observed precipitation which shows that the FEWS dataset can be corrected by a factor in order for it to have a better correlation with the observed precipitation. The FEWS dataset precipitation estimates have two main advantages. First, they give a continuous coverage in time because they are available on a daily time basis. Secondly, the dataset gives with a fairly good resolution, information on the spatial patterns within the watershed.

This study evaluated 3 methods of parameter transfer i.e. spatial proximity, global averages and regression. The R^2 values obtained were between 0.5 and 0.68 for the spatial proximity method, 0.54 and 0.66 for the global averages and 0.5 to 0.73 for the regression method. It is not clear why any one method performed better at a sub-watershed and not the others. From the results, spatial proximity performed better than global averages and regression. This could be due to the fact that neighboring watersheds have relatively homologous climatic and physical characteristics. However, the transfer methods yielded acceptable model performance thus would give satisfactory

results if used in estimation of streamflow at ungaguged watersheds of the Upper Tana watershed.

1.22 Recommendations

Transferability of the SWAT model parameter should be used in estimation of streamflow in ungauged sub-watersheds for the purpose of water resources management.

In this study, only spatial proximity, global averages and regression methods of parameter transfer were analyzed. Other methods of parameter transfer such as kriging can be analyzed.

Parameter transfer can be used in the study of various hydrological processes in the watershed apart from streamflow such as sediments and chemical yields.

The parameter transfer methods should be applied in other climatic regions in order to evaluate how they perform in different hydro-climatic conditions.

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APPENDICES

Appendix 1: Soil names in the Upper Tana

SWAT Soil class	Name
Ach	Haplic Acrisols
Vre	Eutric Vertisols
Acp	Plinthic Acrisols
LVh	Haplic Luvisols
NTr	Rhodic Nitisols
CMx	Chromic Cambisols
SNj	Stagnic Solonetz
NTh	Haplic Nitisols
Ntu	Humic Nitisols
Ple	Eutric Planosols
PHl	Luvic Phaeozema
Cmu	HumicCambisols
GRh	Haplic Greyzems
Glu	Umbric Gleysols
Acu	Humic Acrisols
Fru	Humic Ferrasols
FRh	Haplic Ferrasols