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**THESIS TITLE.**

# Analyzing catchment behavior through rainfall-run-off modeling: A case study of Mara Basin in Kenya.

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*Master in **Water Engineering track.***

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**DECLARATION:**

I **Birundu A. Mogoi**, do declare that this report is my original work and to the best of my knowledge, it has not been submitted for any post graduate degree award in any University or Institution.

Sign..... Date_____

**CERTIFICATION:**

This is to certify that the above named student carried out the project work detailed in this report under my supervision.

Sign..... Date_____

**DEDICATION:**

To the hearts of those who stood by me in prayers, knowledge, encouragement and motivation.

**ACKNOWLEDGEMENT:**

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**ABSTRACT.**

Hydrological models nowadays are considered as an important and necessary tool for water and environment resource management. However, the challenge facing modelling is in poorly gauged watersheds. Research done recently has shown potential to overcome this challenge through incorporating satellite based hydrological and meteorological data in the measured data.

This research has used the semi-distributed conceptual HBV Light Model to model the rainfall-run-off in the Mara River Basin. The model simulates run-off as a function of rainfall. It is built on the basis established between satellite observed and in-situ rainfall, evaporation, temperature and the measured run-off.

The model's reliability was evaluated over two sub-catchments namely; Nyangores and Amala in the Mara River Basin using Nash - Sutcliffe Efficiency which the model referred to as $R_{eff}$ and the coefficient of determination ($R^2$). The $R_{eff}$ for Nyangores and Amala during the calibration and (validation) period were 0.65(0.68) and 0.59(0.62) respectively.

The model showed good flow simulations in particular during the recession flows, in the Nyangores sub-catchment whereas it simulated poorly the short term fluctuations of the high-flow for Amala sub-catchment.

Key words: hydrological models, satellite data.

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**List of abbreviations.**

| | |
|---|---|
| ASCII | American Standard Code for Information Interchange. |
| DEM | Digital Elevation Model. |
| EGM96 | Earth Gravitational Model 96. |
| EUMETSAT | European Organisation for the Exploitation of Meteorological Satellites. |
| FAO | Food and Agriculture Organization. |
| FEWS | Famine Early Warning System. |
| GCMs | Global Circulation Models |
| GeoSFM | Geospatial Stream Flow Model. |
| GeoTIFF | Geo-referenced Tagged Image File Format. |
| GIS | Geographic Information System. |
| GTS | Global Telecommunication System. |
| HBV | Hydrologiska Byrans Vattenavdelning model. |
| IPCC | Intergovernmental Panel on Climate Change. |
| IR | Infrared. |
| KMD | Kenya Meteorological Department. |
| MCS | Monte Carlo simulations. |
| MIKE-SHE | MIKE System Hydrologic European. |
| MRB | Mara River Basin. |

| | |
|---|---|
| MSE | Mean Square Error. |
| NSE | Nash - Sutcliffe Efficiency. |
| RFE | Rainfall Estimate Product. |
| SMHI | Swedish Meteorological and Hydrological Institute. |
| SRTM | Shuttle Radar Topography Mission. |
| STREAM | Spatial Tools for River Basins and Environment and Analysis of Management Options. |
| SWAT | Soil and Water Assessment Tool. |
| UNEP | United Nations Environmental Program. |
| USGS | United States Geological Survey. |
| WRMA | Water Resources Management Authority. |

**CHAPTER ONE:**

# 1 INTRODUCTION.

In Kenya, water is a vital resource since it is key not only in the conservation of ecosystems but also in the development of economic activities such as: agriculture, industry, power generation, livestock production. The country is characterized as water stressed since the per capita water availability is at 792m$^3$ with a population of approximately 40 million people (UNEP, 2010). With the increasing population, expanding urbanization, modernised lifestyles, climate changes and other global changes, the pressure for sustainable planning and management of our finite water resources is more evident than ever.

There are fundamental components of the water balance that need to be quantified which include; precipitated water, consumed water, water withdrawals, and non-consumed water. Relating precipitation and/or withdrawals to consumptive use through evapotranspiration provides a basis for an assessment of weekly or monthly surplus (that is, groundwater recharge, drainage, and surface runoff dynamics) or deficit (Molden, 2014) .

This research focuses on the Mara River Basin that cuts across Kenya and Tanzania. The Mara River, faces numerous interaction that require effective management to ensure sustainability of its water resources since many livelihoods depend on it. The basin has undergone several changes over the last 50 years as a result of increased human population. This increase appears in the form of land use change, which resulted into changes in the river hydrology, threatening the very existence of the river. (Abwoga, 2012)

In order to effectively plan the water resource use, and to protect it under the changing conditions requires the use of basin runoff models that can simulate flow regimes under different scenarios of change. Accurately modelling future runoff regimes is challenging in African catchments with limited current and historical runoff data, but an increasing number of model applications suggest that useful simulations are possible (Mango et al, July 2011).

The satellite observed rainfall products and the 30m resolution Shuttle Radar Topography Mission (SRTM) DEM used in this research are derived from open sources. Also, the Hydrologiska Byrans Vattenavdelning model (HBV Light Model) for run-off simulation of

the measured rainfall, was downloaded from Swedish Meteorological and Hydrological Institute (SMHI).

Caution must be applied when interpreting and communicating the results of these modelling efforts, and value must be measured in both heuristic and algorithmic terms, even though, their development positively contributes to water resource planning efforts.

This research seeks to build upon past experiences in run-off modelling in the East African basins such as: river Nzoia and Sagana catchment and, thereafter, well inform water resource planning in, the Mara Basin. This will be essential for coping with tensions between water availability and water demand. (UNESCO-IHE, March 2011).

## 1.1 Problem statement.

The Mara River Basin is a sub-catchment of the Lake Victoria Basin and the larger Nile River Basin. The Mau Forest Complex is found in the upper part of the basin and this is also where the Mara River originates. The forest complex is a major water tower since it is the source for rivers such as: Sondu, Njoro and Ewaso Ng'iro's river (Mwania, 2014). The unique Mara-Serengeti ecosystem, which is famous for the scenic large-scale seasonal migration of the Wilde beast, is in the middle part of the catchment. Also, the tropical savannah vegetation is found here. The Mara Wetlands ecosystem is in the south western parts of the basin. According to Mwania (Mwania, 2014), the only perennial rivers in the basin are, Mara River and its two tributaries, the Amala and Nyangores. The ecosystems, thriving tourism industry, agriculture and pastoral farming depend on these rivers especially during the dry seasons (Melesse, 2012). According to Mellese (2012), a third of the available arable land in the basin is under small scale farming.

Studies done previously show that there have been changes in the Mara river flow regime. Mati et al. (2005), studied the impacts of land use or cover on the hydrology of the Mara River using Geo Spatial Stream Flow Model (GeoSFM) and found out that the peak flows had increased by 7% and occurred 4 days earlier during the period between 1973 and 2000. They also, found out the changes in the land cover or use in the same period using Landsat images. It was worth noting that, agricultural and wetland areas had increased by 203% and 387% whereas the savannah vegetation and forest areas were found to have reduced by 79% and 32% respectively. A study done to investigate the impacts of land use and climate on

the hydrology of the upper Mara River Basin by Mango et al (July 2011), using Soil Water assessment Tool (SWAT) showed that, conversion of forest areas into agriculture and grassland areas was most likely reducing the dry season flows while increasing quick peak flows. Human activities in the basin was also affecting both the flow regime and the water quality of the Mara River. Study on the Nyangores River were done using a 44 year old historical data to study its rating curve uncertainty and change in the discharge time series. Notably, a reduction in the lowest base flow was detected from four Flow Duration Curves of 8 year data intervals (Juston, 2013).

In order to sustain the Mara ecosystem and the economic activities that take place in the basin, in the wake of the rapid increase in the land degradation, there is need to effectively manage the Mara River's resources. The best way to predict hydrological response to changing landscape is to use hydrological models. However, hydrological modelling faces challenges in the case of lack of proper understanding of the hydrological processes in data scarce environments as is the case of the Mara basin. This creates a challenge for basin managers to make informed decisions and take appropriate actions with respect to anthropological activities, in management of the basin to ensure sustainability of this resource. Modelling the hydrology of the basin can partly address this challenge. The developed rainfall-run-off model can then be used to simulate hydrological extreme (exceptionally dry and wet years) conditions to generate scientific data. This could be used to inform policy and management decision as well as improve understanding of the underlying hydrological processes.

## 1.2 Rationale.

An estimated population of 573,883 people are supported by the Kenyan side of the Mara Basin (Barno, 2011). Approximately, 75% of the Mara flows are contributed by the Upper Mara and it is therefore, critical for the preservation and also ensuring sustainability of the Mara ecosystem (LVBC & WWF-ESARPO, 2010a) .

Over the past 50 years in conjunction with significant population growth, the area under agriculture has tripled and now covers approximately 3,000 $km^2$ (Mati et al., 2008). The highest concentration of agriculture is distributed among small scale farmers on the slopes of the Mau escarpment and upper middle reaches of the basin. Increase in agricultural lands has occurred in tandem with a 34% decrease in rangelands and a 32% decrease in forested

areas (Mati et al., 2008). This land use change is believed to have impacted on the hydrological processes and the water availability in the downstream part of the basin- increased frequency of flooding problems on the lower parts of the basins. The problem is being exacerbated by the increasing rainfall variability in the basin (Abwoga, 2012). Therefore, it is important to understand how the rivers flow in this basin in order to understand how to mitigate the adverse impacts of extreme flows.

## 1.3 Objective.

The overall objective of the study is to use both satellite based and in-situ rainfall products for quantifying the run-off of the Mara River Basin.

Specific objectives are:

1. To develop a conceptual model simulating Mara river run-off as a function of the satellite observed and in-situ rainfall data.
2. To account for the water balance in the basin.

For this purpose, possible hydrographs will be developed based on trends and information from the area.

## 1.4 Research questions.

The objectives defined above led to the following questions which the research sought to answer:

1. Is there a relationship between satellite observed rainfall and measured run-off of the Mara River?
2. How does the performance of the developed model, in terms of simulating the Mara hydrograph compare to those of previous modelling efforts in the Mara basin?
3. How do the model parameters behave for the different sub-catchments?

## 1.5 Study area.

### 1.5.1 Geographical Location.

The 395 km long Mara river, is found in the Mara basin which is a trans-boundary basin of approximately 13,750 $Km^2$, lying between South Western Kenya and North Western Tanzania. It lies between longitudes 33° 47' E and 35° 47' E and Latitudes 0° 28' S and 1° 52' S. The Napuiyapui swamp in the Mau Forest Complex, is the source for the Mara River where it flows at an altitude of approximately 3000 metres above sea level (m.a.s.l) South West before draining into Lake Victoria in Musoma Tanzania at an altitude of 1134 metres above sea level (Mwania, 2014). The Nyangores and Amala Rivers are the two main perennial tributaries of the Mara River and their respective sub-basins form part of the Upper catchment. The other tributaries are: Talek, Sand and Engare Ngobit rivers on the Kenyan side and the Bologonja River on the Tanzania side as shown in figure 1.1 below. Analysis from historical discharge data from 1970 to 1996 from the Mara mines, Nyangores at Bomet and Amala at Mulot showed a mean of 33.9$m^3$/s, 8.4 $m^3$/s and 9.9 $m^3$/s with a standard deviation of of 60 $m^3$/s, 7.1 $m^3$/s and 19.9 $m^3$/s respectively (Melesse, 2012).

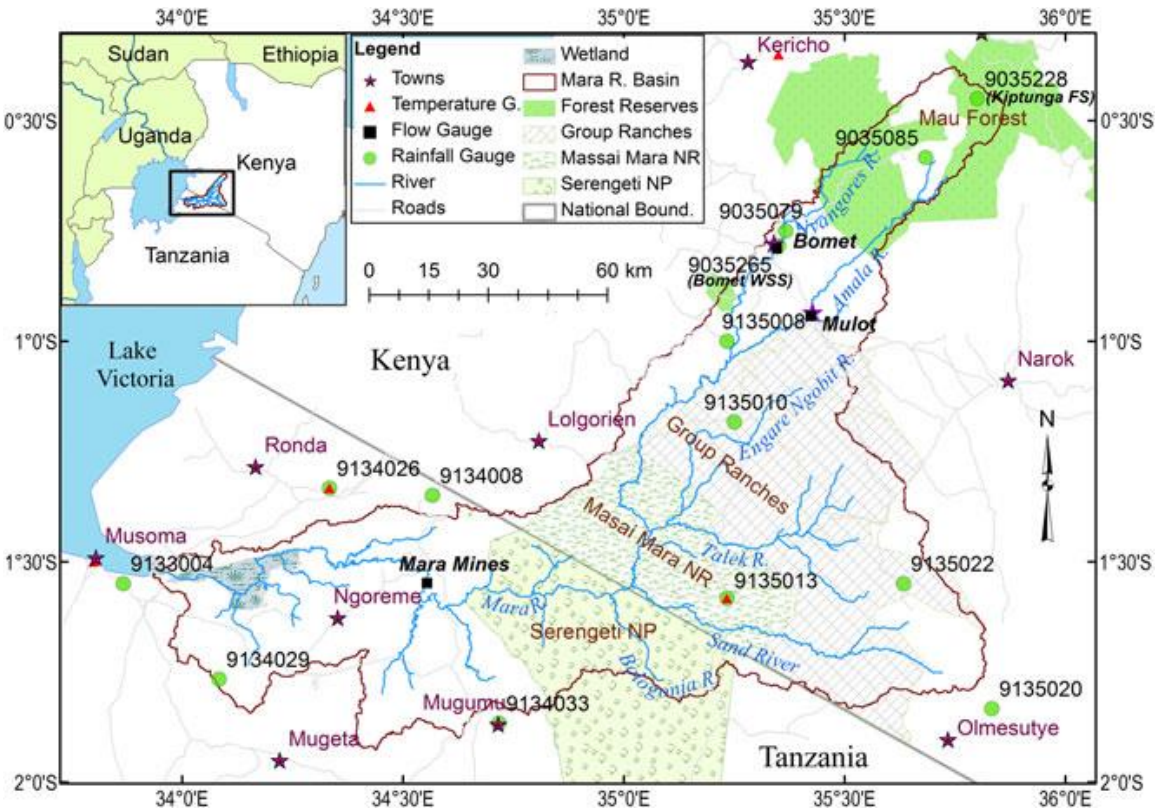



Figure 1.1: Site map of the trans-boundary Mara River Basin, showing the Mara River with its tributaries. Source: (Melesse, 2012)

### 1.5.2 Climate.

There are two rainy seasons in the basin. The long rains are experienced between March and June whereas, the short rains are in November and December. The mean rainfall varies from 1000 mm/year to 1750 mm/year in the upper catchment, 900 mm/year to 1000 mm/year and 300 mm/year to 800 mm/year in the middle and lower parts of the catchments respectively (Mwania, 2014).

The average mean temperature range in the highlands and midlands is 18°C and 25°C respectively. The highland plateau in the lowlands modifies the temperature making it range between 20°C to 27°C with a mean average of 25°C depending on the month of the year (Mutie et al, 2006).

According to Brown et al (1981) the potential evaporation is about 1820 mm/year. The maximum evaporation rate during the dry season is 165mm which occurs in October. He also, estimated that the potential annual evapotranspiration was equal to approximately 71% of free water evaporation in the middle and lower parts of the watershed .The high, reliable, and well-distributed rainfall in the highlands and the fertile soils are favourable for agriculture, livestock, and wildlife activities. These favourable conditions have attracted heavy migration into the basin exerting high pressure on the limited land and water resources (Brown et al, 1981).

### 1.5.3 Soils.

The type and distribution of soils in the basin are determined by geology, topography and rainfall. Soil data was extracted from the Harmonized World Soil Database (HWSD) and then it was identified into soil types according to FAO et al, (2012) with respect to the classifications. Figure 1.2 below shows the soil map of the Mara River Basin extracted from the 1:5 million HWSD raster map.

Andosols are found in the forested highlands of the basin. These soils are originally volcanic and form good water aquifers. Nitosols are dominant in the midlands and lowlands. These soils have a high and uniform clay content throughout the horizon. Alisols, Fluvisols, Gleysols, Greyzems, Leptosols, Pheozems, Planosols, and Vertisols are other soils which occur in association to Nitosols as shown below.

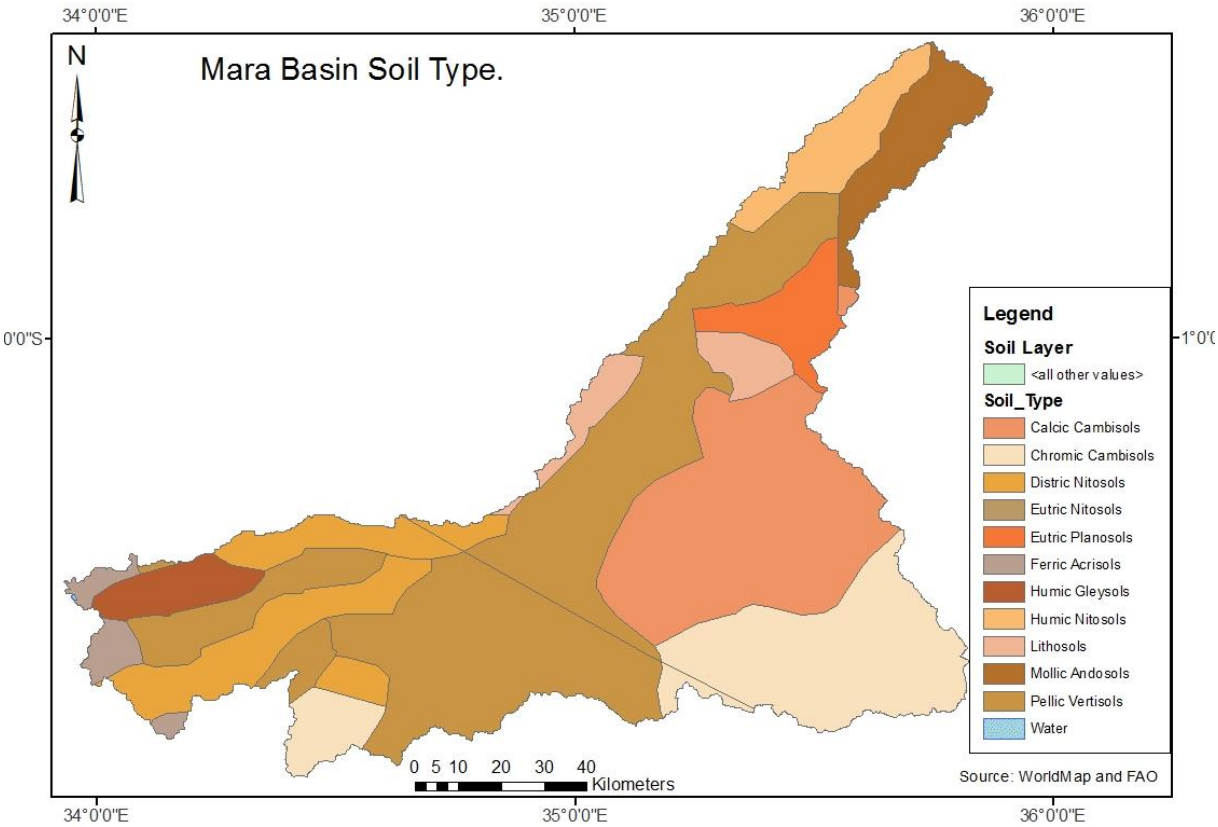



Figure 1.2: A Map showing the Soil Types in Mara Basin.

### 1.5.4 Wetlands.

The Mara River basin has two wetlands, the 23 hectares Napuiyapui swamp at the source of the Amala tributary in the Kaptunga forests. Which is surrounded by undisturbed natural forest. The second wetland is the Mosirori wetlands which is at the mouth of the River Mara near Lake Victoria. The two wetlands are served by Mara River before it discharges into Lake Victoria and are at their maximum spatial extent during April to May (long rains) when they extend about 45 km from the shores of the Lake. There have been seasonal variations in the volumetric flows as a result of the seasonal fluctuation in the size of the wetlands. During the dry season, not only does the Mara River affect the extent of the wetland, but also the backflow from Lake Victoria when the surface elevation of the Lake water is higher than that of the wetlands.

### 1.5.5 Socio Economic characteristics.

The basin is characterised by a diversity of land use patterns ranging from natural forests which have decreased to about 23% over the last 50 years in the upper reaches to large-scale mechanized farms, smallholder subsistence farms, communal pastoral grazing lands, open savannah in the animal parks, and wetlands and marsh vegetation just before the river discharges into Lake Victoria (Mango et al, July 2011).

It is interesting to note that, despite the diversity in spatial extent and land use, the dominant social-economic activity to the majority of the population remains crop farming as shown in figure 1.3 below. About 62% of the households are smallholder farmers, with livestock rearing being a second dominant activity, yet agriculture occupies about 28% of the available arable land (Mati et al, 2005).

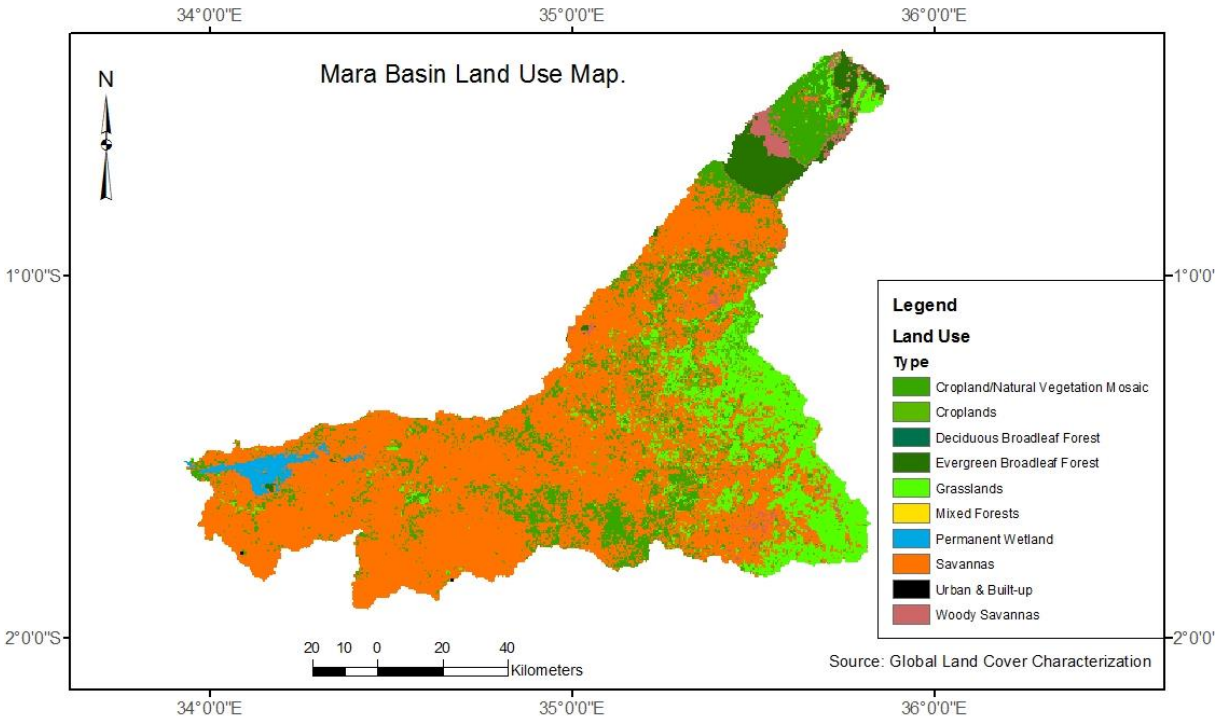



Figure 1.3: Land use Map of the Mara Basin.

# CHAPTER TWO:
# 2 LITERATURE REVIEW.

Rainfall run-off models have been used very successfully to estimate runoff at small and large catchments under different climate regimes (McMillan, Krueger, & Freer, 2012). Generally, rainfall-run-off models use rainfall and other climate data like: temperature and or potential evaporation to estimate runoff. Even though the main emphasis of rainfall-run-off models is to estimate runoff, they are normally designed to simulate actual evapotranspiration to account for soil water balance. However, they have no direct interest in quantifying surface energy fluxes (McMillan, Krueger, & Freer, 2012). The parameters in the rainfall-run-off models are usually optimized such that the runoff simulated matches as closely as possible to the recorded runoff. A variety of model calibration techniques (including manual calibration and automatic calibration techniques) have been developed and implemented to ensure conformity between the model simulations of system behaviour and observations (Hongxia, Pongqiang, & Xinyao, 2015).

## 2.1 Water Availability.

The average annual flow rate of the Mara River is 30 $m^3$/sec and it is characterized by a seasonal flow regime (LVBC & WWF-ESARPO, 2010a).It has two periods of high flow from March to May and October to December separated by periods of marked low flows. During the 60 years that discharge has been monitored, there have been no reports on either the river failing to flow or dried up. Even so, with increasing anthropological activities in the basin characterised by increased abstractions and land use change pose a serious threat to the continual flow of the river (Abwoga, 2012).

## 2.2 Hydrological modelling.

According to Sorooshian et al. (2008), a model is a simplified representation of real world system. The best model is the one which give results close to reality with the use of least parameters and model complexity. Models are mainly used for predicting system behaviour and understanding various hydrological processes. A model consists of various parameters that define the characteristics of the model. A runoff model can be defined as a set of equations that helps in the estimation of runoff as a function of various parameters used for

describing watershed characteristics. The two important inputs required for all models are rainfall data and drainage area. Along with these, watershed characteristics like: soil properties, vegetation cover, watershed topography, soil moisture content, characteristics of ground water aquifer are also considered. Hydrological models nowadays are considered as an important and necessary tool for water and environment resource management (Sorooshian et al, 2008).

## 2.3 Hydrological Modelling Overview.

Models are being routinely used for prediction of responses of a catchment or river basin to a rainfall event. They help in providing decision makers with information to make decisions and inform policy for basin management as well as facilitating scientists to understand the underpinning hydrological processes. The main reason for rainfall run-off modelling is the limitation in the measurement of hydrological processes and the challenge being that most of the runoff generation processes take place below the ground surface presenting difficulties in measurement. Therefore, modelling offers a practical way of trying to understand these processes (Abwoga, 2012).

According to Beven (1996), "Every hydrological model requires two essential components, one to determine how much of rainfall becomes part of the storm hydrograph and the other takes account of the distribution of the runoff in time, to form the shape of the hydrograph otherwise referred to as routing" (Beven K. , 1996).

### 2.3.1 Types of models.

Hydrological models provide a framework to conceptualise and investigate the relationships between climate, land use changes and water resources. They are classified into three categories, empirical or black box, conceptual or grey box and physically based distributed or white -box models.

Black box models do not explicitly consider governing physical laws of the process involved but only relate input to output series. Physically based models are normally more feasible as research tools for process studies in the small scale where physical parameters are well under control and their variability small. Conceptual models are more basin oriented than physically based models. The parameters of a conceptual model thus represent an average

over a large area and often integrate several processes and their variability. Conceptual models show their strength in limited data demand and thus great applicability in operational hydrology. Physically based models are often said to be superior to conceptual models as they demand less calibration or tuning of the parameters (Bergstrom, 1991).

Legesse et al. (2003) further argues that "because white box models relate model parameters directly to physically observable land surface characteristics, spatially distributed hydrological models have important applications to the interpretation and prediction of the effects of land use change and climate variability."

## 2.4 Evaluation of Hydrological Models.

Advancements in the science of hydrology and hydrological modelling have resulted in the development of hundreds of hydrological models. It is inevitable today that current modelling efforts involve numerous comparisons, resulting in an obvious need for platforms to base such comparisons or evaluations. The process of evaluating the performance of models is important not only at the stages of model development and calibration but also during the communication of results to other researchers and stakeholders (Schaefli & Gupta, 2007).

According to Sivakumar (2008b) "Model comparisons are good provided the purpose is not simply to compare different models but to identify the specific advantages and limitations of each of the models. This would provide important clues towards possible integrations of the two or more models/concepts, making the most of their advantages and minimizing their limitations for better representation of hydrologic systems and processes" (Sivakumar, 2008b).

Hydrographs are time series of hydrological variables. They are key in evaluation and comparison of hydrological modelling efforts. This is often done by comparison of simulated values against observed. According to Ewen (2011), "The gold standard in hydrograph comparison is manual inspection by hydrologists, because even the best available automatic methods are poor substitutes for the hydrologist's eye and brain, especially at spotting and interpreting patterns" (Ewen, 2011).

The Mean Square Error (MSE) and the related normalisation, the Nash - Sutcliffe Efficiency (NSE) are the two criteria most widely used for calibration and evaluation of hydrological models with observed data (Gupta et al, 2009). According to Schaefli and Gupta (2007), "the

NSE is a normalized measure (infinity to 1.0) that compares the mean square error generated by a particular model simulation to the variance of the target output sequence. In doing so it represents a form of noise to signal ratio comparing the average "size" (variability) of model residuals to the "size" (variability) of the target output. It is implicitly comparing the performance of the particular model to that perhaps the simplest imaginable model, one that uses as its prediction the (constant) mean value of the observed target.

$$NSE = 1 - \frac{\sum_{t=1}^{N}(Q_{obs}\,(t) - Q_{sim}\,(t))^2}{\sum_{t=1}^{N}(Q_{obs}\,(t) - \overline{Q_{obs}})^2}$$

Where;

$Q_{obs}(t)$ = discharge at time step t.

$Q_{sim}(t)$ = simulated discharge.

$\overline{Q_{obs}}$= Mean observed discharge over simulation period N.

This means that an;

a) NSE value = 1.0 indicates perfect model performance (the model perfectly simulates the target output).
b) NSE value = 0 indicates the model is on average performing only as good as the use mean target value as prediction.
c) NSE value of < 0. indicates an altogether questionable choice of model.

It is therefore preferred to have NSE values larger than Zero (0) and approaching 1.0.This corresponds to an apparent normalisation because the implicit reference model has different implications for different case studies." It therefore follows that the NSE does not measure how good a model is in absolute terms (Nash & Sutcliffe, 1970).

However, according to Ewen (2011), one of the strengths of the NSE, as a result of being based on the square, is that it is sensitive to differences for peaks. One of its weaknesses is that it is also quite sensitive to differences in timing. Handling and interpreting differences in timing is one of the most difficult problems faced when computing hydrographs. The sensitivity of NSE to timing arises because even quite small misalignments in the timings of peaks can give rise to large differences in amplitude between the hydrographs. This sensitivity can result in poor value for NSE even when the size and shapes of the peaks in the two hydrographs are very similar. However, it is common practice for modellers to show hydrograph time series plots in which model simulation" goes up and down" in a similar

fashion as that which is measured as an indication of modelling success (Schaefli & Gupta, 2007).

## 2.5 Modelling efforts in the Mara Basin.

According to Mati et al (2005), currently limited historical hydrological and hydro chemical data exists for the Mara river basin. Consequently, there is limited understanding of the hydrology of the Mara Basin, which was once fairly well gauged but most of the stations are no longer working with either staff gauges washed away or no data recording taking place now (Mati et al, 2005).

### 2.5.1 Approaches.

Hydrological studies in the Mara have mainly focussed on modelling the impacts of land use changes such as those by Mati et al. (2008) and Mango et al, (2011). These studies have mainly focussed on the upper Mara consisting of either the Nyangores, Amala or both major tributaries of the Mara. Mati et al. (2008) studied the impacts of land use/cover changes on the hydrology of the trans boundary Mara River, in Kenya and Tanzania. On the other hand Mango et al. (2011) investigated the land use and climate impacts on the hydrology of the upper Mara river basin. Mango used the SWAT (Soil and Water Assessment Tool) model, which is a semi distributed model. The SWAT model requires the use of spatially explicit datasets for land topography, land use or land cover, soil parameters for hydrological characteristics and climate and hydrological characteristics, and climate and hydrological data on daily time steps (Mango et al., 2011).

Modelling changes in the flow regimes between 1973 and 2000 was established with the geospatial stream flow Model, GeoSFM, a physically based semi distributed geospatial hydrological model by Mutie et al. (2006). The model used remotely-sensed data, numerical weather forecast data, ground observation and geographical datasets that describe the soils and land surface to calculate different parameters of basin hydrology (Mutie et al, 2006).

In 2012, Abwoga modelled the Mara hydrograph using a simple rainfall-runoff model using a PC raster and later on used this to simulate impacts of three land use change under various scenarios of partial deforestation, conversion of forests to agriculture and reforestation. (Abwoga, 2012). He found greater success in modelling Nyangores River than Amala River.

This was attributed to the fact that the precipitation data used in modelling was collected within the Nyangores catchment with an additional station at Narok. This incidentally worked against the efficiency of modelling Amala as the same data was regionalised over the Amala catchment, whereas Amala was observed to be a much drier catchment than Nyangores. This showed that with better rainfall data the probability of successfully modelling Amala would be greatly increased. In the land use scenarios developed, he found that deforestation resulted in an increase in peak flows of 2% for Nyangores and 1% for Amala. The 7 day minimum flows reduced by 9% for Nyangores and 3% for Amala. The afforestation scenario resulted in reduction of flows both peaks and 7 day minimum flows. 7 day minimum flows reduced by 17% for Nyangores and 11% for Amala. Peak flows reduced by 2% for both Nyangores and Amala. The reduction in peak flows was as a result of increased interception and evapotranspiration, indicating that with the current model parametisation most of the water was lost through interception and evapo-transpiration and little recharge of the aquifer took place (Abwoga, 2012).

Finally, in 2014 Mwania developed a STREAM model to simulate the Mara hydrograph and subsequently used it to simulate the impacts of land use change. He used satellite observed rainfall products and soil moisture data as inputs in the model. He found that the Nyangores sub-catchment had higher recordings of Evapotranspiration as compared to the Amala and Mara Mines sub-catchments. This he attributed to the forest cover in Nyangores which promoted infiltration and therefore more water for evapotranspiration. The analysis of the simulated run-off components showed that Nyangores, Amala and Mara Mines contributed approximately 12%, 54% and 32% of the total simulated run-off in the sub catchments respectively. He further concluded that the dry season of the Mara River is largely sustained by ground water storage of the two upstream sub-catchments (Mwania, 2014).

### 2.5.2 Outcomes.

Mati et al. (2008) concluded from the simulation studies that significant changes have occurred in the flow regime of the Mara between the periods 1973 and 2000 resulting in increasing and earlier occurrences of high flows. This was corroborated with observed changes in the basin, such as reducing vegetation land cover and the expanding wetland at the mouth of the river resulting from increased erosion. Mango et al. (2011) on the other hand modelled the Nyangores tributary hydrograph using the SWAT model and developed

land use and climate change scenarios. The climate change scenarios were developed from projected climate change as indicated in the IPCC fourth assessment report (IPCC, 2007), the variables usually considered from these GCMs are precipitation and temperature.

### 2.5.3 Research Gaps.

The use of the SWAT in modelling the Mara hydrograph resulted in modest results and the model did not satisfactory simulate the hydrograph. Mango et al. (2011), found that for Nyangores simulations using rain gauge data the model had an NSE of - 0.53 and $R^2$ of 0.09 for the calibration period and NSE values of -0.06 and $R^2$ of 0.32 for the validation period. It was later concluded that there was consistent overestimation of the discharge when visually comparing the observed against the simulated for Amala and underestimations for Nyangores sub-catchments. It was later concluded that the model performed poorly because of the scarce data from the rain gauges used despite using additional remotely sensed data from the FEWS network (Mango et al, July 2011) .

In using the USGS Geo stream flow model, Mutie et al, (2006) found that the model performed better for bigger catchments from the calibration and validation data. The $R^2$ values for the six years calibration period were 0.76, 0.74 and 0.83 for Amala, Nyangores and Mara mines gauging stations respectively. The three year validation resulted in $R^2$ values of 0.72, 0.69, and 0.87 for Amala, Nyangores and Mara mines respectively. The model also accurately simulated the hydrograph rising limbs and peaks, but was unable to accurately simulate the recession limbs and low flows (Mutie et al, 2006).

From the above three models, it is clear that, modelling the Mara basin has had different successes with SWAT model performing poorly. The GeoSFM model was better suited in understanding the trends since its temporal scale does not promote understanding of the underpinning hydrological processes. The STREAM model posted the best results as compared to the above two mentioned models. This is because it used satellite observed soil moisture and rainfall products and in situ measured rainfall as forcing data.

There is need for a model that simulates the Mara hydrograph at acceptable performance levels, and promotes understanding of the hydrological processes. This would in turn generate information needed for basin management. Relevant, accurate and timely management information would serve as an impetus to basin managers to take appropriate measures in management of the resources of the Mara basin.

## 2.6 Review of hydrological model structures.

There are numerous model structures that have been developed over time. This research has adopted from existing conceptual model structures.

From literature three (3) potential model structures were identified and considered these were:

1. HBV Light model (Hydrologiska Byrans Vattenavdelning model) (Seibert, 2002).
2. TOPMODEL (Beven & Kirkby, 1979).
3. MIKE SHE model (*Système Hydrologique Europeén*) (DHI, 1976).

The three model structures were evaluated based on the following considerations, the complexity of the model structure, data requirements, flexibility for adaptation, and suitability for modelling rainfall-run-off and previous modelling success in hydro climatic environments.

MIKE SHE model requires extensive model data and physical parameter which may not be available all the time and make it difficult to set up the model. Also users are unable to modify the code but it has high processing ability compared to other models. It has extensive graphical capabilities for pre and post processing and thus makes the modelling easier (Gayathri, Ganasri, & Dwarakish, 2015). Yang et al. (2000), found that it will produce models of equal or superior ability compared to other codes.

TOPMODEL is a semi distributed conceptual rainfall runoff model that takes the advantage of topographic information related to runoff generation. But according to Beven and Kirby (1979), the TOPMODEL is considered as a physically based model as its parameters can be theoretically measured. The major factors considered in this are the catchment topography and soil transmissivity. The main aim is to compute storage deficit or water table depth at any location. The storage deficit value is a function of topographic index ($a/\tan\beta$) (Beven 1986), where; a is drained area per unit contour length and $\tan\beta$ is the slope of the ground surface at the location. Since the index is based on basin topography, the model give calculations only for representative values of indices. It is obtained by manual analysis of contour maps. The model uses exponential Green-Ampt method of Beven (1984) for calculating runoff and it is advised to reduce the number of parameters. The output is in the form of area maps or simulated hydrographs (Beven & Kirkby, 1979). Ahmed (2011) used this model to study the runoff response of Ammammeh watershed in Iran and results shows

the ability of the model in both event based and daily simulations. More accurate results was obtained in daily modelling as it uses soil moisture conditions.

The HBV model was found to be simple in using and required minimal model data. It was found to be used mostly in the Nordic countries and later on it has been applied in African catchments. The model boosts of generating hydrographs that clearly describe the underpinning hydrological processes in the catchment. Uhlenbrook et al. (2010) used this model to successfully model the Gilgel Abay in Ethiopia and found it produced representative hydrographs of the area despite the limited input data (Uhlenbrook et al, 2010).

All the three structures are distributed model structures and are thus suited to modelling rainfall - run-off.

# CHAPTER THREE:

# 3 LONG-TERM SERIES DATA COLLECTION AND PROCESSING.

## 3.1 Data collection.

Field work was undertaken between June 8th to July 15th, 2016 and the main objectives were;

a) To collect rainfall data.
b) To obtain run-off data.

### 3.1.1 Rainfall data.

The measured rainfall data was used to investigate the reliability of the satellite rainfall product. The Mara Basin has forty four rainfall gauging stations within and around the basin. The data for the stations on the Kenyan side of the basin was obtained from Kenya Meteorological Department (KMD) and the Head Quarters office of the Water Resources Management Authority (WRMA). For the stations in the Tanzanian side, eight in total (8 No.), it was a challenge to obtain the data. Out of the thirty six (36No.) stations, on the Kenyan side, only three (3No.) stations were meteorological and had sufficient daily data falling within the span of the satellite rainfall data used also in this research as shown in figure 1.1 above. The others were 'Volunteer stations' which are privately owned and the data is not up to date. The data is recorded daily at 0900hours and is expressed in millimetres per day (mm/day).

Table 3.1: Location of Metrological stations used in the HBV Light Model.

| Station Name. | Latitude (°S) | Longitude (°E) | Start Year |
|---|---|---|---|
| Narok | 35.833 | -1.330 | 1937 |
| Kisii | 34.783 | -0.667 | 1911 |
| Kericho | 35.267 | -0.367 | 1939 |

### 3.1.2 Run-off data.

The run-off data was needed for the calibration and validation of the rainfall-runoff model. The Mara River and its tributaries have seven river gauging stations as shown in table 3.2 below. Out of the seven, only three have a longer time series with minimal gaps. They are, the Nyangores, Amala and Mara Rivers. The data for all the seven gauging stations were

collected from WRMA Head Quarters and Regional Office in Nairobi and Kisumu, in Kenya respectively. The data was daily averages expressed in cubic meters per second ($m^3/s$). Rehabilitation and installation of automatic gauges for the Nyangores, Mara at Emarti and Amala rivers were done in 2012. Subsequently, in 2013 and 2014, manual gauges were fitted for Sand and Talek rivers respectively. The data used for this research is up to November 2013. Two readings of the water level are taken daily, in the morning at 0600hrs and in the evening at 1800hrs. Rating curves were then used to estimate daily average discharges.

Table 3.2: River Gauging Stations along the Mara River. Only Nyangores, Mara and Amala gauging stations have relatively long historical data.

| River Name | Station Code | Latitude (°S) | Longitude (°E) | Start Year | Type of Station |
|---|---|---|---|---|---|
| Amala | 1LB02 | 35.4375 | -0.8972 | 1955 | Automated |
| Nyangores | 1LA03 | 35.3472 | -0.7861 | 1963 | Automated |
| Mara | 1LA04 | 35.0361 | -1.2333 | 1990 | Automated |
| Mara at Emarti | 1LA06 | 35.2312 | -1.0566 | 2012 | Automated |
| Sand River | 1LA07 | 35.2154 | -1.6533 | 2013 | Manual |
| Talek | 1LA08 | 35.2083 | -1.4433 | 2014 | Manual |

## 3.2 Satellite data sets.

The satellite data sets used in this research were:

a) African Rainfall Climatology, version 2 (ARC2.0).
b) Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM).

All these data sets were downloaded from open source internet data bases as shown in table 3.3 below.

Table 3.3: Satellite data sets and their open sources.

| Data | Web Source |
|---|---|
| ARC2.0 | http://www.cpc.ncep.noaa.gov/products/international/africa/africa.shtml |
| SRTM DEM | http://opentopo.sdsc.edu/raster?opentopoID=OTSRTM.082015.4326.1 |

### 3.2.1 African Rainfall Climatology, version 2 (ARC2.0).

ARC 2.0 rainfall data was used as a forcing data to the rainfall-run-off model in the research.ARC 2.0 data is a result of a project to create a satellite-estimated precipitation climatology over the Africa domain. This climatology has been created to compliment the daily operational rainfall estimate product (RFE) in order to generate anomaly fields over Africa over various timescales. ARC 2.0 uses inputs from two sources: a) 3-hourly geostationary infrared (IR) data centred over Africa from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) and b) quality controlled Global Telecommunication System (GTS) gauge observations reporting 24-hour rainfall accumulations over Africa. This is due to the absence of microwave-derived estimates over a long-term historical record, and the large amount of data which makes up the operational half-hourly GPI input. The data range of the ARC 2.0 product is from 1st January, 1983 up to date.

In this research we used a dataset consisting of daily, gridded 0.1°x0.1° resolution rainfall estimates and longitudes and latitudes of 40°S and 55°E respectively. The data was downloaded in Tagged Image File Format (TIFF) which was then converted into American Standard Code for Information Interchange (ASCII) file which was then opened in an Excel spread sheet for further processing.

### 3.2.2 Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM).

This research used the NASA SRTM DEM with a 30m spatial resolution (1arc second). The DEM has been resampled using cubic convolution and voids filled using interpolation algorithms and other sources of elevation data. The DEM product specifications are listed in table 3.4 shown below. The DEM was downloaded through the Open Topography as Geo-referenced TIFF (GeoTIFF). It was then processed using Arc-hydro toolbox in Arc Map. The delineation was done for Nyangores, Amala, Talek and Sand sub-catchments with respect to their corresponding river gauging stations. The area of Nyangores and Amala sub-catchments was found to be approximately 2150km$^2$ and 1312 km$^2$, respectively. Figure 3.1 shows the delineated catchments and the drainage network. The sub-catchment shape files were used in masking the satellite observed evapotranspiration and rainfall products for data extraction. The DEM indicates the highest and lowest points in the basin to be 3094 m.a.s.l. and 1134m.a.s.l. respectively.

Table 3.4: SRTM DEM Specifications. Source: (USGS, 2012).

| **Product Specifications.** | |
|---|---|
| Projection. | Geographic |
| Horizontal Datum. | WGS84 |
| Vertical Datum. | EMGM96 (Earth Gravitational Model 1996) |
| Vertical Units. | Meters. |
| Spatial Resolution. | 1 arc-second for the United States (~30meters). |
| Raster Size. | 1 degree tiles |
| C-band Wavelength. | 5.6cm |

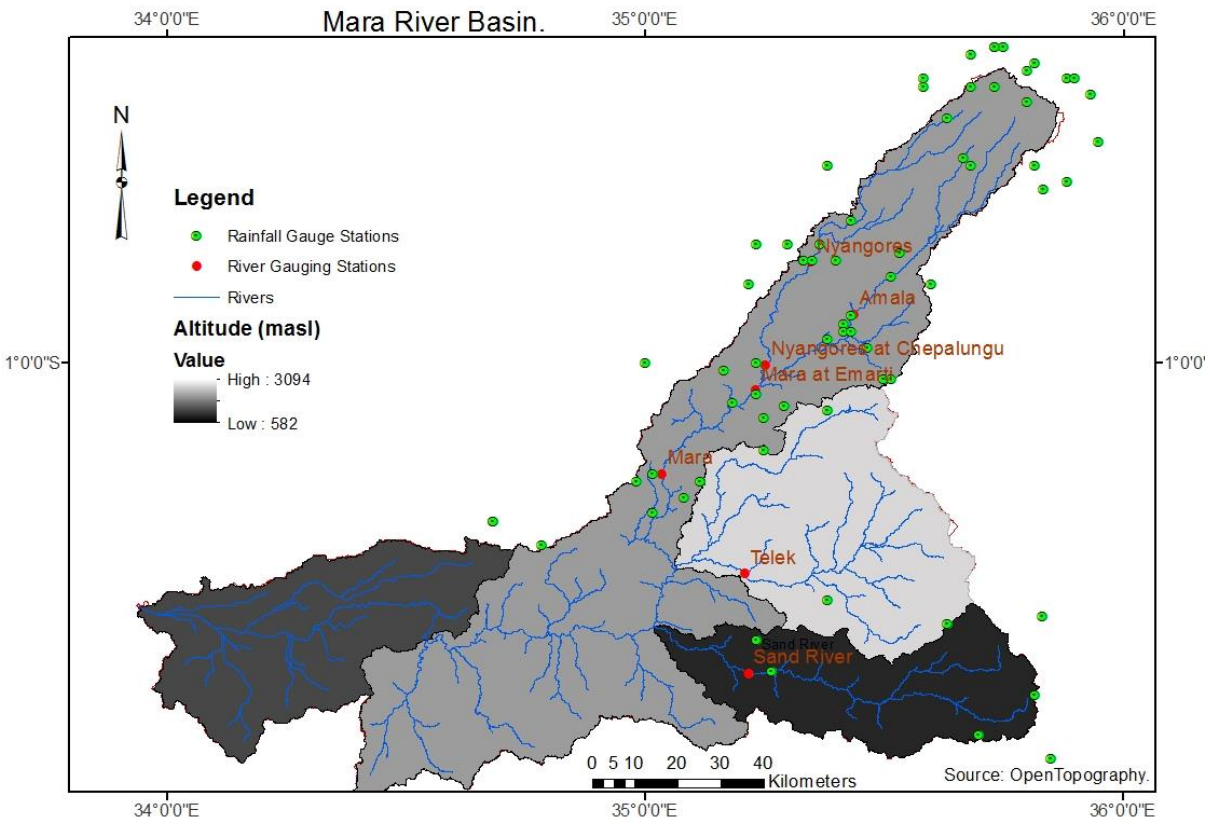



Figure 3.1: Processed SRTM DEM showing the Elevation, Rainfall gauging stations and the River gauging stations of the Mara River Basin.

## 3.3 In-put data Processing.

The input data collected were checked for consistency as well as filling in the missing data gaps for precipitation, discharge and temperature datasets. The main approached used was of correlations between the three meteorological station data. Thereafter, multiple linear regressions were used to develop relationship equations which were then used to fill the missing data gaps.

### 3.3.1 Rainfall data.

The rainfall data used was for the selected period of 1990 to 2013, for the stations described above. For use in the model, areal average precipitation $P_{area}$ was calculated as weighted mean of precipitation stations in and around the catchment. This was achieved through using thiessen polygons which is a function in Arc Tool box in Arc GIS. This is shown in the Appendix A attached.

### 3.3.2 Temperature data.

The data used was from the three hydro-meteorological stations namely Narok, Kericho and Kisii. The data from the stations had several gaps. The monthly maximum and minimum temperature data from were first checked for any abnormal readings (outliers), and thereafter, the missing data was filled using multiple linear regressions as shown in figure 3.2 and 3.3 below. It is interesting to note that the minimum temperature of the Kisii station is higher than the other two stations. This is because it has more cloud cover than the other two stations. Then, the temperature was calculated as weighted mean of the stations in and around the catchment.

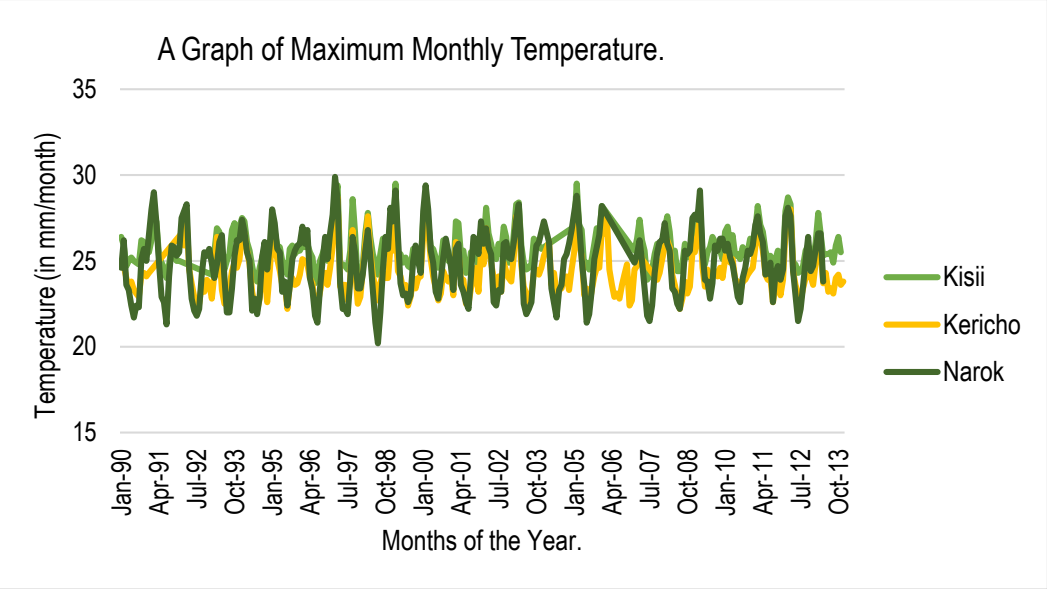



Figure 3.2: Monthly Maximum Temperature for Narok, Kisii and Kericho stations.

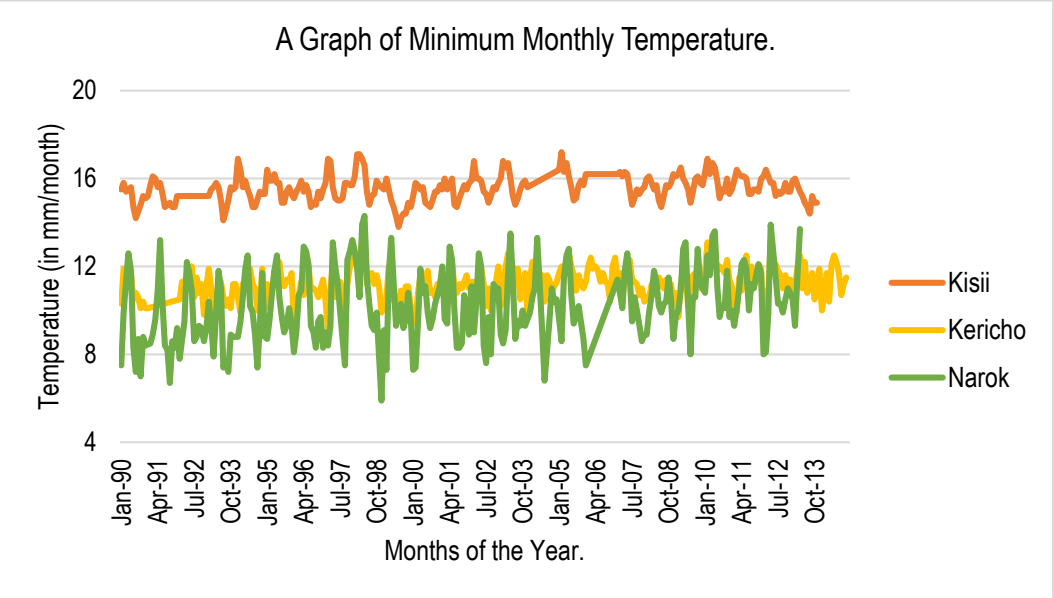



Figure 3.3: Monthly Minimum Temperature for Narok, Kisii and Kericho stations.

### 3.3.3 Discharge data.

Nyangores and Amala Rivers daily discharge data were used in this research. This is due to the fact that they have long term data series as compared to the other rivers (Mara, Talek and Sand). The period of data used was from 1990 to 2013. From the figure 3.4 below, it is evident that Nyangores has been experiencing really high peaks over the years as compared to Amala River. There was a five year period where no recordings (gaps) of discharge was

done. This was because of destruction of the river gauging station equipment by floods, vandalism and negligence.

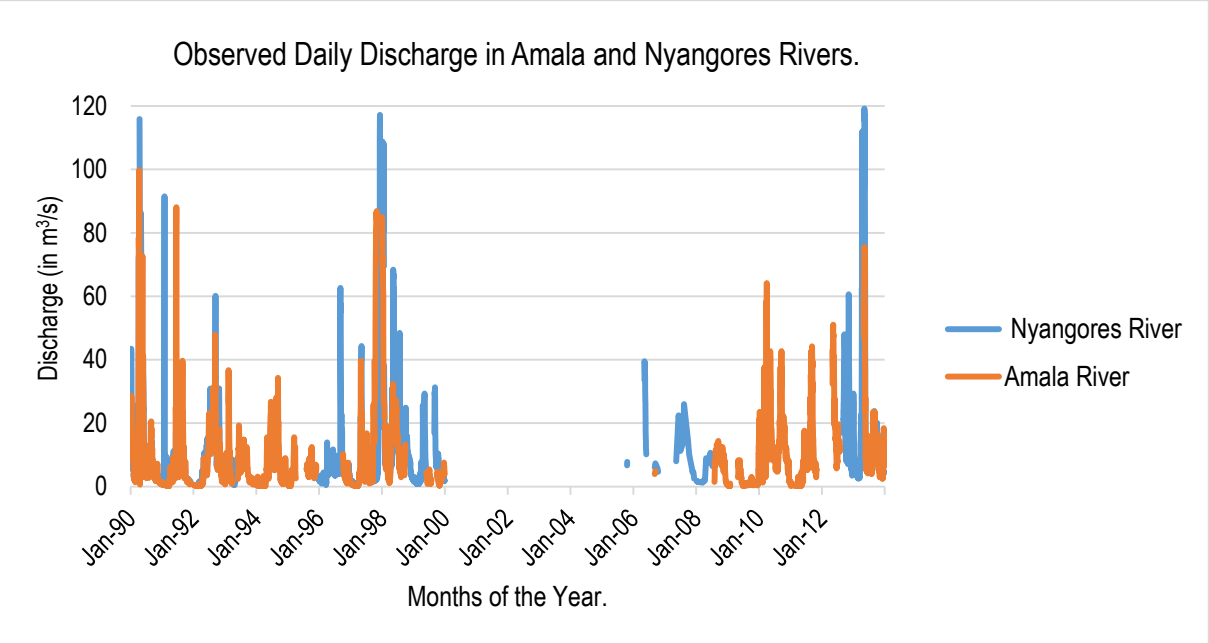



Figure 3.4: A Graph showing the Measured Daily Discharge data for Amala and Nyangores Rivers.

### 3.3.4 Evaporation data.

The data used was mean monthly data from the meteorological stations in Narok, Kericho and Kisii. This was the only input parameter with some level of consistency in terms of availability of data. The gaps in the data were filled in by interpolation and a graph was plotted as shown in figure 3.5 below.

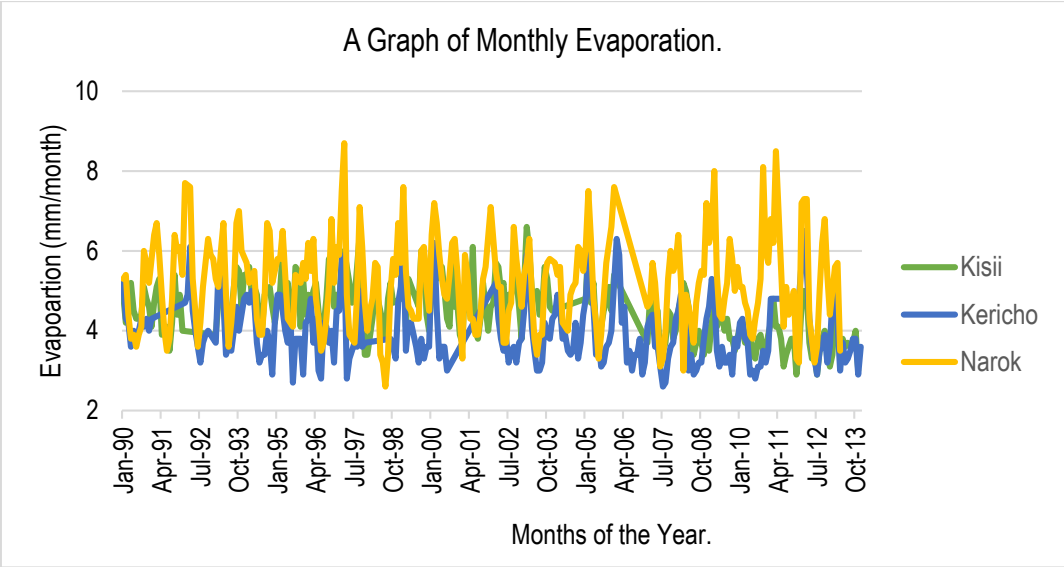



Figure 3.5: A graph showing the Mean monthly Evaporation data for Kericho, Kisii and Narok stations.

### 3.3.5 Discharge and Rainfall data.

A plot of discharge measured and rainfall received in Mara Basin shows a few instances where there seems to be inconsistency (outliers) between the observed discharges at the catchment outlet compared to the received rainfall in the catchment. These dates have been highlighted in the Figure 3.10 below. The study period of 1st January, 1997 to 31st December, 2008 was chosen as the calibration input since there was a sufficient amount of data.

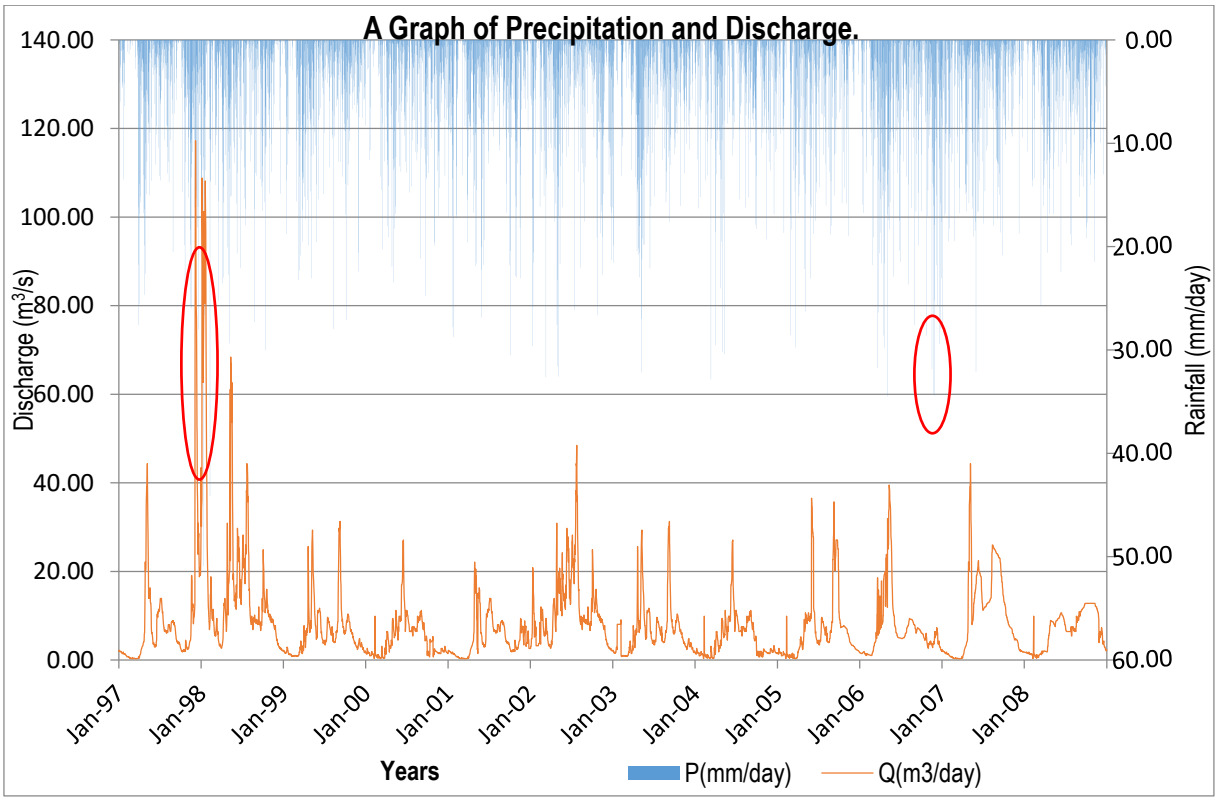



Figure 3.6: A Graph of Precipitation and Discharge Analysis.

The year 1998 was marked not because of inconsistency of the data but because this was the year that Kenya experienced El Nino. From the graph, a good relationship is depicted between the amount of rainfall received and discharge observed over time since the rising and falling of the limbs are well related.

**CHAPTER FOUR:**

# 4 METHODOLOGY.

It is increasingly becoming challenging to predict the future state of the water resources in view of the impacts from climate and anthropogenic changes to hydrological system dynamics. The primary focus of the research was to model a rainfall-run-off hydrograph using HBV Light Model which has been used in some of the African Basins including the Nile (Bergström, 2014).

## 4.1 Hydrological Model Description.

The model structure chosen for modelling the Mara hydrograph is a semi-distributed conceptual model, which reduces the challenges associated with model complexity such as: equifinality, parameter identification and calibration amongst others. To prevent uncertainty the numbers of calibration parameters are kept to a minimum. The model structure adopted is the HBV Light Model. The idea behind this model, is to model the hydrology of the basins in a simplified way but which at the same time allows sufficient insight into the major hydrological processes which take place in the basin (Seibert, 2002).

### 4.1.1 HBV Model (Hydrologiska Byrans Vattenavdelning model).

This model is an example of semi distributed conceptual model, which simulates the discharge using input variables of rainfall, temperature and potential evapotranspiration (Bergström,1976). The HBV model was selected to simulate the rainfall runoff processes in the studied catchments as its suitability has been demonstrated under different hydro climatic conditions world-wide (Bergstr¨om, 1995; Lindstrom et al., 1996).

The general structure and equations of HBV can be summarized in Figure 4.1. The reservoirs are connected to each other by means of exchange fluxes which define the amount of water between the different zones. The general water balance equation is shown in equation *[1]* and *[2]*. HBV has four routines which include the snow, soil moisture, response function and routing routines. HBV-light uses the Microsoft windows platform and was re-written by Marc Vis at the University of Zurich using Visual basic (Seibert & Vis, 2012)

$$\frac{\Delta S}{\Delta t} = Input - Output \quad Where: \Delta S = Change\ in\ storage. \qquad [1]$$

$$\Delta t = Change\ over\ time.$$

$$P - E - Q = \frac{d}{dt}(SP + SM + UZ + LZ + lakes) \qquad [2]$$

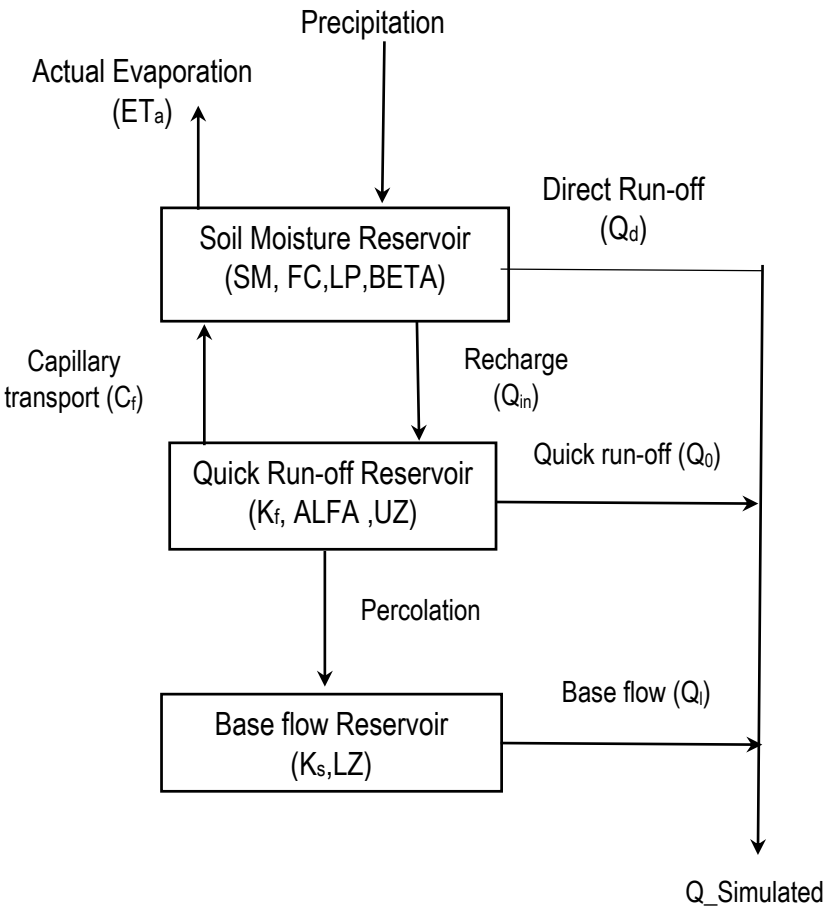



Figure 4.1: The General Structure and Equations of the HBV Model.

Where;

P is precipitation.

E is evaporation.

Q is runoff.

SP is the snow pack.

SM is the soil moisture.

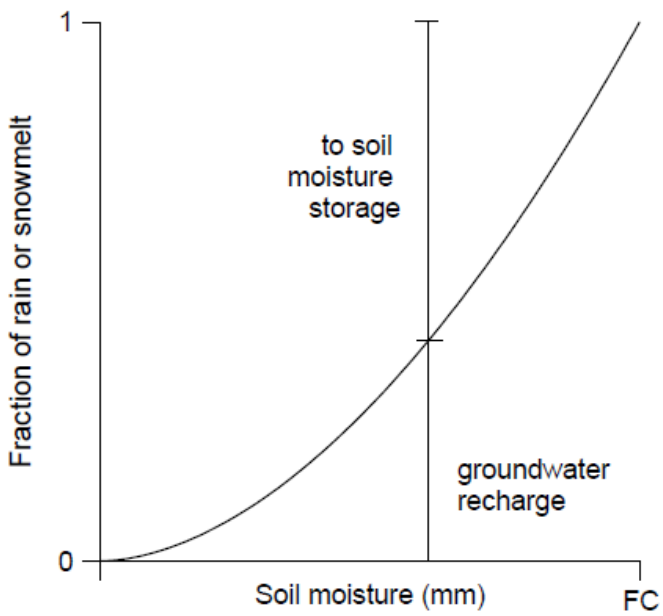
UZ and LZ are the upper and lower ground water zone.

Lakes represent the volume of lake.

HBV uses sub-catchments as the primary hydrological units. The catchments classifications of land use, and area-elevations are used clearly defined for input into the model. The model can be run with daily precipitation time series data but higher resolution can also be used in the model. The use of the snow routine of HBV requires data for simulation and is only applicable to areas that experience snow. This routine controls snow accumulation and function depending on the elevation and vegetation zones.

#### 4.1.1.1 Soil Moisture Accounting Routine.

The soil moisture routine utilizes the potential evapotranspiration data and in this case the mean standard values are good enough. This routine uses interception and soil moisture storage which determines the wetness index of the basin. These datasets can be retrieved using the Penman formula. However systematic errors need to corrected when evaporimeters are used to collect potential evapotranspiration datasets.




$$\frac{\text{recharge}}{\text{P}} = \left(\frac{S_{sm}}{FC}\right)^{BETA}$$

Figure 4.2: Contributions from rainfall or snowmelt to the soil moisture storage and to the upper groundwater zone.

Where;

FC = maximum soil moisture storage (mm).

LP = soil moisture value above which $ET_{act}$ reaches $ET_{pot}$ (mm).

BETA= parameter that determines the relative contribution to runoff from rain or snowmelt (-).

The rate of contribution of rainfall or snow to the soil moisture zone is at a maximum when the soil is dry and is at a minimum when the soil is saturated i.e when the soil moisture reaches its maximum value, FC, the field capacity. Conversely, the rate of contribution to the upper zone is maximum when the soil moisture is at the maximum value, FC, and is minimum when the soil is dry.

Climatological data from precipitation stations is computed for the sub-catchments by weighting procedures where station weights are given values by climatological and topographical numerations or by using interpolation methods such as thiessens polygons. Correction of inputs such as temperature is done using elevations above the sea level using the lapse rate of -0.6ºC for every 100 meter vertical deviation from the height of the station.

#### 4.1.1.2 Response Routine.

The response function transforms excess water in the soil moisture zone into run-off. It includes the effect of direct precipitation and evaporation on the part representing lakes, rivers and other wet areas. It consists of an upper zone and a lower linear reservoir as shown in figure 4.3 below. The two, form the origin of the quick and slow run-off components of the hydrograph, respectively.

Three runoff components are computed by three linear reservoir equations$Q_0$, $Q_1$, and $Q_2$ using the three recession coefficients$K_0$, $K_1$, and$K_2$, respectively. These runoff components typically represent direct runoff $Q_0$ (quickly generated, fast runoff component), interflow $Q_1$ (intermediate runoff component) and base flow $Q_2$ (slow runoff component, normally originating from groundwater).

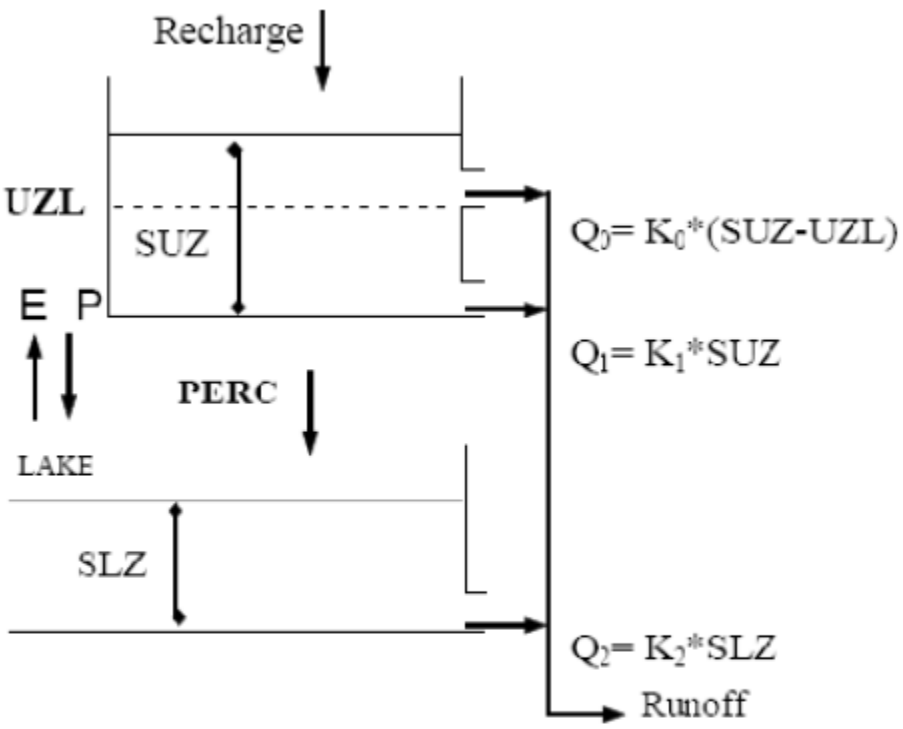



Figure 4.3: Schematization of the response routine of the used HBV Model; note that the lake part was not applied. (Seibert,2002)

Where:

recharge = input from soil routine (mm day$^{-1}$).

$S_{UZ}$ = storage in upper zone (mm).

$S_{LZ}$ = storage in lower zone (mm).

$U_{ZL}$ = threshold parameter (mm).

$P_{ERC}$ = maximum percolation to lower zone (mm day$^{-1}$).

$K_i$ = Recession coefficient (day$^{-1}$).

$Q_i$ = runoff component (mm day$^{-1}$).

**NOTE:**

a) $S_{UZ}$ has no upper limit.
b) $Q_2$ can never exceed $P_{ERC}$ $S_{LZ}$ can never exceed $P_{ERC}/K_2$.

When the yield from the soil (*recharge)* into the upper zone exceeds a certain percolation capacity ($P_{ERC}$), the water in the upper zone will start to drain through more superficial channels into the rivers and streams at a higher drainage coefficient, $K_1$. When the superficial channels are full to capacity, and the storage, $S_{UZ}$, of the upper zone exceeds $U_{ZL}$ , the limit of high recession, more rapid drainage will start with the high drainage coefficient, $K_0$. The lower zone reservoir, represents the total ground water storage of the catchment contributing to the base flow. $P_{ERC}$, is the parameter governing the recharge of this zone. As long as there is water in the upper zone, the storage of the lower zone, $S_{LZ}$, is increasing asymptomatically approaching the value of $P_{ERC}/K_2$. When the upper zone dries up, the ground water storage, $S_{LZ}$, starts declining to zero exponentially.

#### 4.1.1.3 Channel Routing.

The channel routing is by a triangular weighing function through MAXBAS (length of weighing function). The soil moisture threshold for reduction of evapotranspiration defines LP. The maximal flow from upper to lower groundwater box is defined by $P_{ERC}$; β is shape coefficient for the non-linear storage behaviour of the soil zone.

HBV-Light, uses a warming up period of one year (Vis et al, 2015). The warm-up period refers to the time that the simulation will run before the final results are collected and it allows the acclimatization of input data-set to the running conditions normal to the system being simulated.

A simplified flowchart of the major input datasets and processes for HBV-Light is as shown in Figure 4.4.

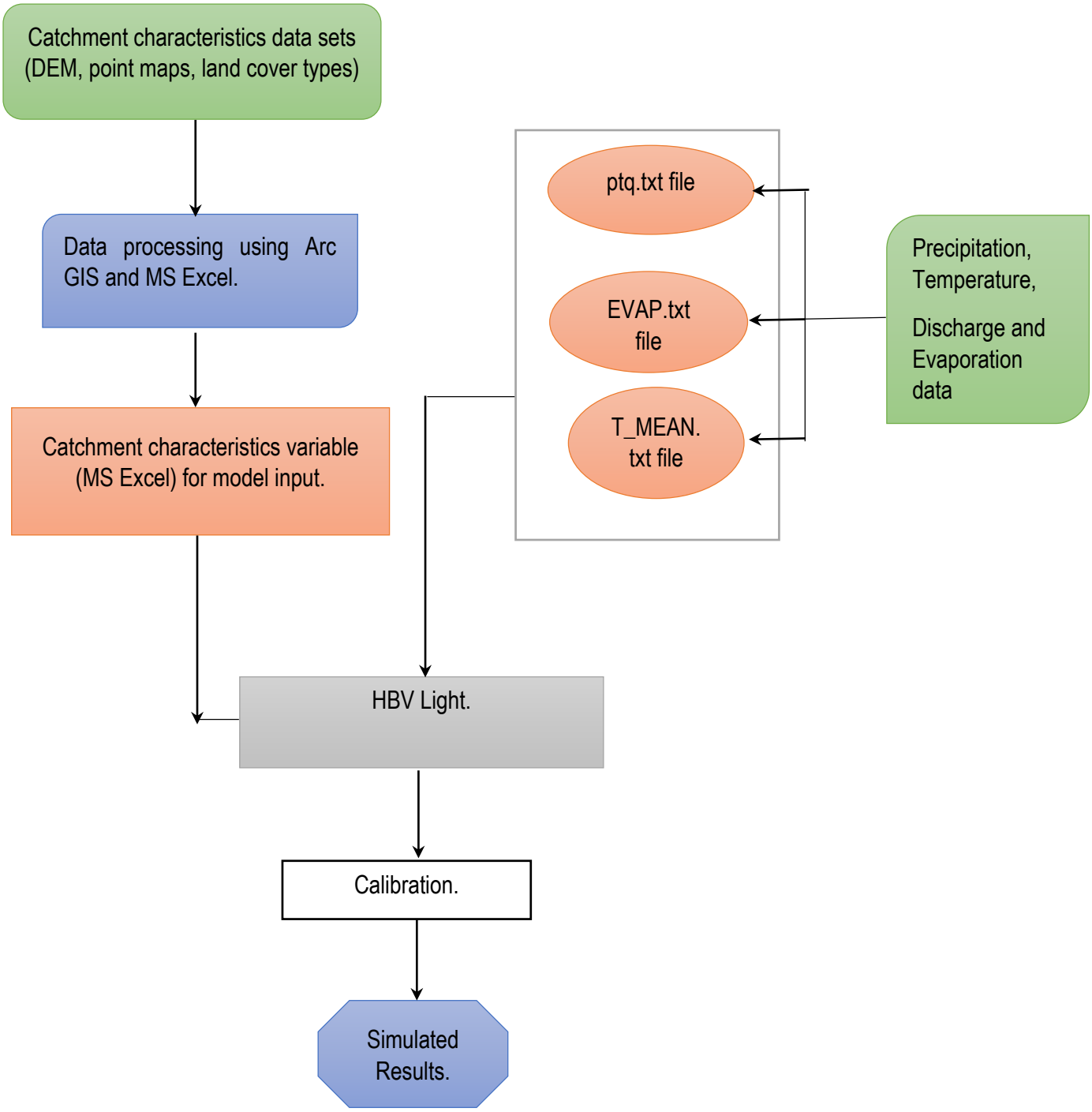



Figure 4.4: Flowchart showing the Input and Output Process of the HBV Light Model.

**CHAPTER FIVE:**

# 5 RESULTS AND DISCUSSIONS.

In this chapter, the results of successfully running the rainfall –run-off model are presented and discussed.

## 5.1 Model Run.

The model was run in dynamic mode in order to simulate a combined period of eleven (11) years translating to a total of 4,017 time steps. The time steps were on a daily basis.

## 5.2 Model Calibration.

A models reliability, predictiveness and accuracy has to be proved before application (Rientijes, 2015). The model calibration function involved optimization of input parameters to output a simulation that had an acceptable efficiency value.

Calibration was done by using the trial and error method. A schematic representation of the calibration process is summarized in Figure 5.1.

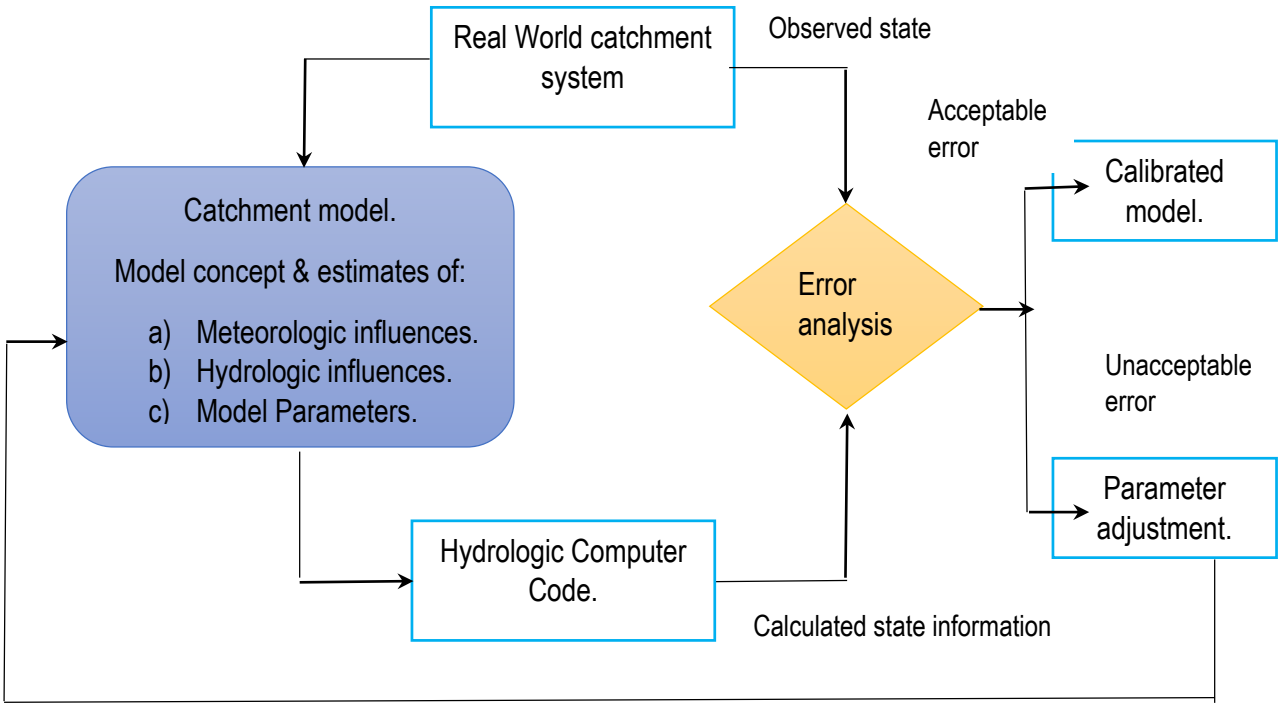



Figure 5.1: Model calibration process (Adapted from Rientijes, 2015).

The Monte Caro runs were generated to investigate the catchment response characteristics, and to explore physically realistic model's parameters ranges. Initial Monte Carlo simulations were generated using parameter values from the literature (tuned with preliminary model runs) to define possible parameter ranges as shown in Table 5.1 below.

Table 5.1: Parameters and their ranges applied during the Monte Carlo Simulations. However, the time dependent units change for simulations with more aggregated time steps (15 and 30days).

| **Parameter** | **Explanation** | **Unit** | **Minimum** | **Maximum** |
|---|---|---|---|---|
| Soil and evaporation routine: | | | | |
| FC | Maximum soil moisture storage | mm | 100 | 550 |
| LP | Soil moisture threshold for reduction of evaporation | — | 0.3 | 1 |
| β | Shape coefficient | — | 1 | 5 |
| Groundwater and response routine: | | | | |
| $K_0$ | Recession coefficient | $d^{-1}$ | 0.1 | 0.5 |
| $K_1$ | Recession coefficient | $d^{-1}$ | 0.01 | 0.2 |
| $K_2$ | Recession coefficient | $d^{-1}$ | 5E-05 | 0.1 |
| UZL | Threshold for $K_0$-outflow | mm | 0 | 70 |
| PERC | Maximal flow from upper to lower GW-box | mm/d | 0 | 4 |
| Routing routine: | | | | |
| MAXBAS | Routing,length of weighting function | d | 1 | 2.5 |

Different parameter sets were produced by running more than 300, 000 MCS for each catchment representation of the Nyangores and Amala sub-catchments on daily time steps. The coefficient of efficiency, $R_{eff}$, was used for assessment of simulations by the HBV model and the results obtained give highest model efficiency.

$$R_{eff} = 1 - \frac{\sum(Q_{sim}(t) - Q_{obs}(t))^2}{\sum(Q_{obs}(t) - \overline{Q_{obs}})^2}$$

$R_{eff}$ compares the prediction by the model with the simplest possible prediction, a constant value of the observed mean value over the entire period.

Several model parameter sets with $R_{eff}$ comparable to the highest values were obtained. In the Nyangores sub-catchment, a $R_{eff}$ >0.65 was obtained after running, 250,000 MSC. The

performance of the model were termed satisfactory. In the case of Amala sub-catchment, a $R_{eff}$ >0.59 was obtained from running 100,000 simulations of the Monte carlos. The performance of the model was acceptable.

In the above sub-catchments, the highest $R_{eff}$ values resulted in a volume error of 0%, in Nyangores and Amala respectively during the calibration process. Volume error is the mean annual difference between observed and simulated runoff volumes.

In addition, to visual inspection of the hydrographs and evaluation of low flows ($\log R_{eff}$), we consider $R_{eff} > 0.65$ and $R_{eff} > 0.59$ as satisfactory the model. The calibration results are shown in Figure 5.2 below and Table 5.2 together with their corresponding statistical measures for model performance assessment.

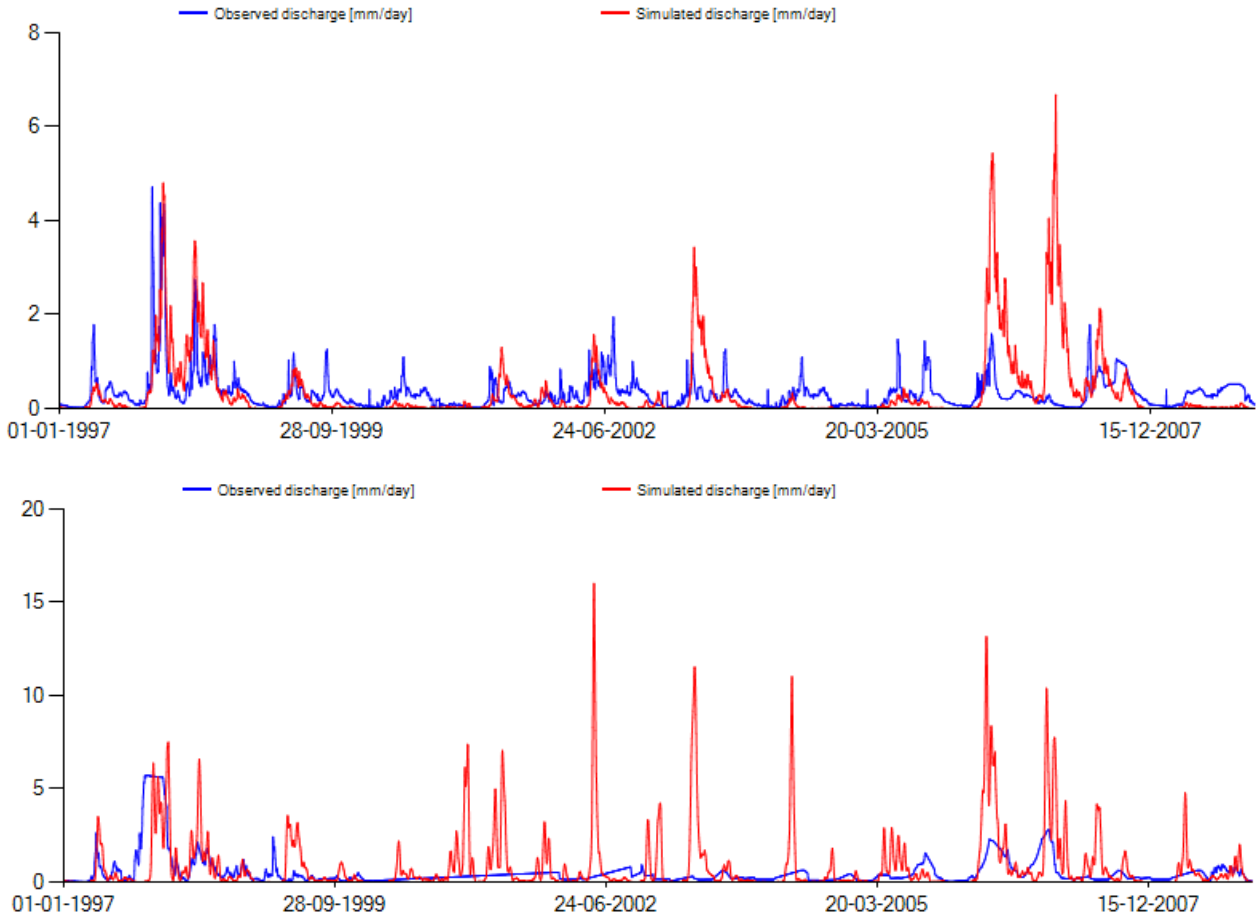



Figure 5.2: Simulated and Observed discharge in mm/day for Nyangores and Amala Sub-catchments above and below respectively for the calibration using daily time steps between January 1996 to December 2008.

From the visual inspection of the hydrographs as shown in figure 5.2 above, it indicates generally good flow simulations in particular during the recession flows, in the Nyangores sub-catchment with a bit of high peaks towards the end of the simulation period. In comparison to the Amala sub-catchment, the short-term fluctuations during the high-flow season were not modelled well. In fact, the model overestimated the discharge as clearly shown in the hydrograph.

The mean annual, ($\Delta Q$) differences between observed and simulated runoff was negligible. There is a good relationship between the simulated and observed low flows in the Nyangores catchment with a $\log R_{eff}$ >0.63 whereas the $\log R_{eff}$ >0.57 for the Amala sub-cathcment. The coefficient of determination, $R^2$ was >0.73 and >0.65 for the Nyangores and Amala respectively. The parameter values for which the model was highly sensitive (yielding good simulations) only for comparable small intervals, were relate to the soil moisture storage and run-off generation routine as shown in the standardized parameter values given in table 5.2 above. The table shows the smallest and largest parameter values that produced $R_{eff}$ > 0.65 for the Nyangores and >0.59 for Amala respectively.

A satisfactory model performance ($R_{eff}$ > 0.65) was attained in Nyangores with a soil moisture storage,FC, in the range of 408mm<FC< 514mm near the maximum parameter range whereas in Amala, the FC was lower ranging between 265mm <FC< 350mm. This shows that the soils in the Amala sub-catchment retain more water than the ones in Nyangores.

The run-off routine parameters $P_{ERC}$ (maximum flow from upper to lower reservoirs) and UZL (threshold for $K_0$ flow) and the soil routine parameter, $\beta$ (shape coefficient) were found to be the most sensitive parameters in that order in Nyangores sub-catchment. In Amala, the only sensitive parameters were $K_2$, $P_{ERC}$ and $K_1$ respectively in that order. The $K_0$ value for Nyangores was found to be 0.11 while for Amala was 0.05.

This means a major portion of the rainfall received in Amala leaves the catchment quickly as direct run-off, while the rainfall falling in Nyangores is stored and later on released as base flow. This is supported by literature, which says that Nyangores has more forest cover resulting to higher evapotranspiration losses as compared to Amala. The argument is that the forest cover promotes infiltration hence more water is available for evapotranspiration.

Similarly, Amala with less forest cover and steep slopes quickly drains most of the rainfall as quick run-off with little left for evapotranspiration.

The difference in sensitivity of the parameters reflects on the different hydrological processes between the two sub-catchments suggesting different dominant run-off generation processes.

## 5.3 Validation.

The validation period for the two sub-catchments was done for the period between 1st January, 2009 to 30th November, 2013 and the results indicated better efficiencies as compared to the calibration as shown by the hydrographs (figure 5.3) and table 5.2 below.

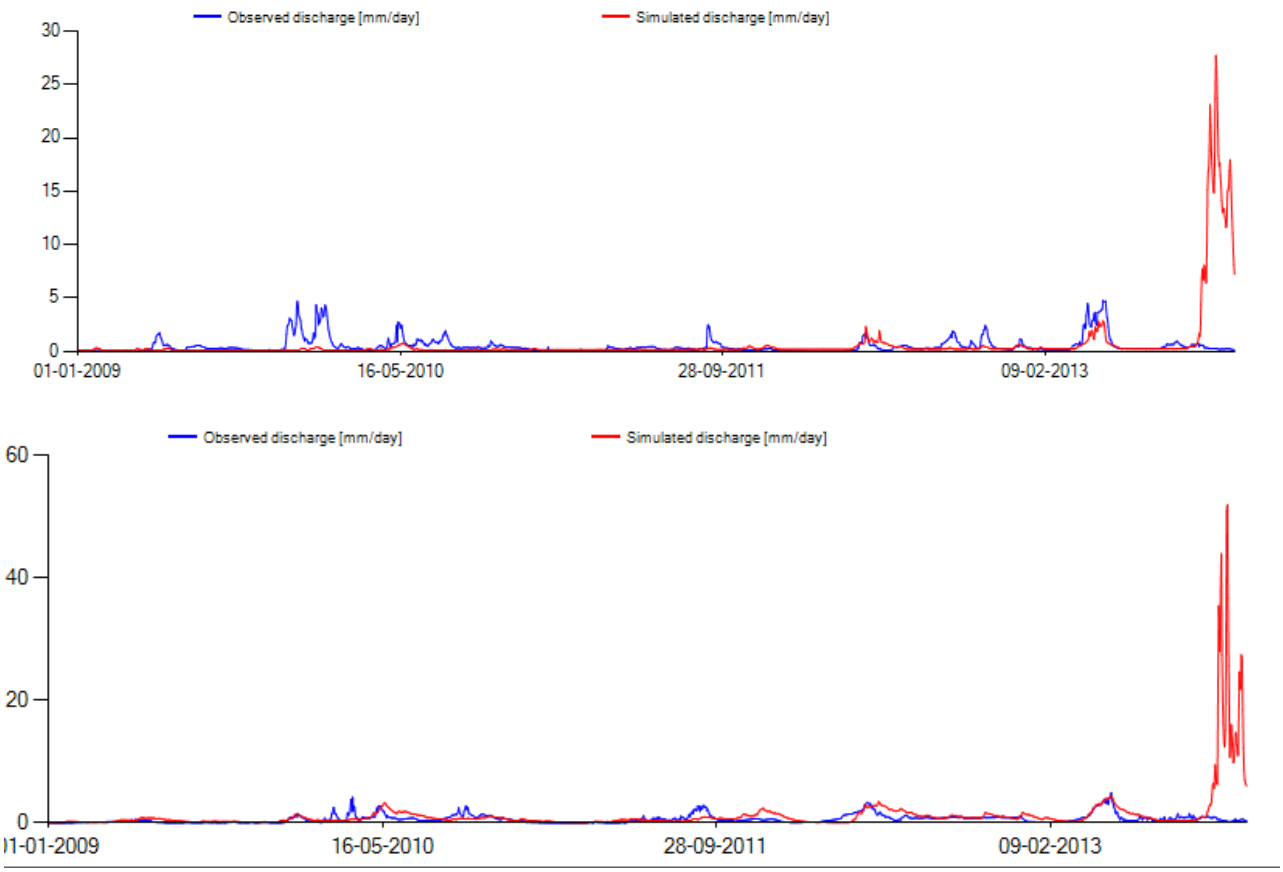



Figure 5.3: Simulated and Observed discharge in mm/day for Nyangores and Amala Sub-catchments above and below respectively for the validation using daily time steps between January 2009 to November 2013.

The $R_{eff}$ values for Nyangores and Amala sub-catchments were $R_{eff}$ >0.68 and $R_{eff}$ >0.62 respectively. These efficiencies were generally good, even though the model overestimated

the observed discharge by about 131 mm/a (70%) in the Amala sub-catchment. Low flow simulations were acceptable with Nyangores and Amala having $\log R_{eff} > 0.64$ and $\log R_{eff} > 0.59$ respectively.

The model showed better performance during the validation period as compared to the calibration period posting higher coefficient of determination $R^2 > 0.75$ and $R^2 > 0.69$ for Nyangores and Amala respectively. The reason as to why the model simulations during this period were better than the calibration period could be attributed to better data quality-fewer gaps for the later years.

The model tried to simulate the base flow hydrographs as shown in figure 5.3 above in order to have a good representation of the catchment characteristics that govern the water storage and delayed flow components generation. This showed the strength of the HBV Light model's soil routine and run-off generation routine. Also, the ability to reproduce good rainfall-run-off relation during mean and low flow periods.

Table 5.2: Calibration and validation parameters and model efficiency results for the daily models for Nyangores and Amala Sub-catchments for the period of 1996-2008 and 2009-2013 respectively.

| **Calibration/Validation Parameters** | **Parameters** | **Units** | **Nyangores Catchment** | **Amala Catchment** |
|---|---|---|---|---|
| | FC | (mm) | 408.61 | 350.00 |
| | LP | (—) | 0.32 | 0.90 |
| | β | (—) | 5.20 | 12.00 |
| | $K_0$ | ($d^{-1}$) | 0.11 | 0.05 |
| | $K_1$ | ($d^{-1}$) | 0.11 | 0.99 |
| | $K_2$ | ($d^{-1}$) | 0.92 | 0.99 |
| | UZL | (mm) | 46.75 | 56.36 |
| | PERC | (mm/d) | 0.10 | 0.45 |
| | MAXBAS | (d) | 1.50 | 15.00 |
| | $R_{eff}$ | (—) | 0.62 | 0.48 |
| | $\log R_{eff}$ | (—) | 0.60 | 0.46 |
| **Calibration** | $R^2$ | (—) | 0.73 | 0.65 |
| | ΔQ | (mm/a) | 0.00 | 0.00 |
| | $R_{eff}$ | (—) | 0.65 | 0.59 |
| | $\log R_{eff}$ | (—) | 0.63 | 0.57 |
| **Validation** | $R^2$ | (—) | 0.75 | 0.69 |
| | ΔQ | (mm/a) | -8.00 | -131.00 |

## 5.4 Assessment of model performance.

In order to obtain a process-based representation of the hydrological characteristics in the two sub-catchments, manual adjustments of the model parameters were done following Monte Carlo simulations (MCS).An automatic calibration of the model was avoided because of limitations of data quality and quantity. This hindered any sensible efforts for automatic calibration or sophisticated uncertainty analysis. Obtaining acceptable parameter sets for further analysis was considered more important than a slightly higher model efficiency for a calibration data set of limited quality. The MCS was carried out to identify the sensitivity of the catchments' runoff generation characteristics, and to explore ranges of model parameters. This was done by generating more than 300, 000 MCS, according to the approach introduced by Beven and Binley (1992) for each of the catchment representation in both the Nyangores and Amala sub-catchments.

Sensitivity analyses of model parameters have been done through:

(i) Assessing model results for different model structures (two catchment representations), and;
(ii) Analysing the results of the MC runs (over a 100,000 model runs for each catchment representations).

The ranges for model parameters for the MC analysis were kept wide as shown in Table 5.2 above, however, a search for suitable parameter sets with not plausible parameter values was avoided. In this regard, the experiences of related studies with the same model were used to define the ranges for each parameter (e.g. Seibert, 1997; Uhlenbrook et al., 1999). Daily models were used for all the sensitivity analyses.

Assessment of the model performance was done both visually and statistically using the objective functions by:

(i) Maximizing the model efficiency according to Nash and Sutcliffe (1970), for both normal and logarithmic values $R_{eff}$, and $\log R_{eff}$, and; (Nash & Sutcliffe, River flow forecasting through conceptual models, Part 1 – A discussion of principles, 1970)
(ii) Minimizing the volume error which is given as mm/a. According to Schaefli (2007), $R_{eff}$ has its own limitations, but it was still considered as a suitable measure to assess

the simulation results in combination with other objective function and visual inspections (Schaefli B. a., 2007).

An automatic calibration procedure was not used since the aim of the calibration was to optimize the above mentioned objective functions and it was also important to obtain a meaningful parameterization from a process point.

## 5.5 Water Balance Analysis.

A summary of the simulated and observed discharges at the outlet of the sub-catchment shows that the water balance closure was achieved at 127 mm per year and 119 mm per year for the $Q_{simulated}$ and $Q_{observed}$ for the Nyangores Sub-catchment respectively as shown in table 5.3 below. A simple water balance closure using the water balance equation shows 457mm of precipitation cannot be accounted for. The $Q_{simulated}$ and $Q_{observed}$ for the Amala Sub-catchment was found to be 318mm per year and 188mm per year respectively. 279 mm of precipitation cannot be accounted for. This is shown in from the simulation results. The results can be attributed to the interpolation method used either for the rainfall quantification or abstraction of the water rivers.

Table 5.3: Summary of the Water balance closure and model run.

| | **Mara_Land** | |
|---|---|---|
| **Water Balance (mm/year)** | **Nyangores subcatchment** | **Amala Subcatchment.** |
| Sum Qsim | 127 | 318 |
| Sum Qobs | 119 | 188 |
| Sum Precipitation | 1574 | 1663 |
| Sum AET | 1455 | 1348 |
| Sum PET | 1624 | 1624 |
| Contribution of QSUZ | 0.85 | 0.803 |
| Contribution of QSLZ | 0.149 | 0.196 |
| **Goodness of fit.** | | |
| Coefficient of determination | 0.734956873 | 0.619856317 |
| Model efficiency | 0.752345971 | 0.651058947 |
| Efficiency for log(Q) | 0.631254575 | 0.639856231 |
| Flow weighted efficiency | 0.619856324 | 0.581458923 |
| Mean difference | -8 | -131 |
| Efficiency based on intervals of 15 timesteps | 0.791211451 | 0.681987562 |
| Efficiency based on intervals of 30 timesteps | 0.830123172 | 0.739856723 |
| Volume Error | 0.834985124 | 0.658723952 |
| MARE Measure. | -0.428579321 | -0.663847861 |
| Lindstrom Measure | 0.751245819 | 0.641238965 |
| Spearman Rank | 0.901458954 | 0.681243689 |
| QobsSample | -999 | -999 |

## 5.6 Sensitivity Analysis.

The sensitivity analysis was done to calibration parameters of HBV to determine which ones influence the model performance more than the other. These were sensitivity analysis for calibration parameters for soil moisture routine and for the response and routing routines. The results are shown in Figure 5.4. The analysis was done by reducing and increasing the final calibration values by 10% and the results plotted in a graph.

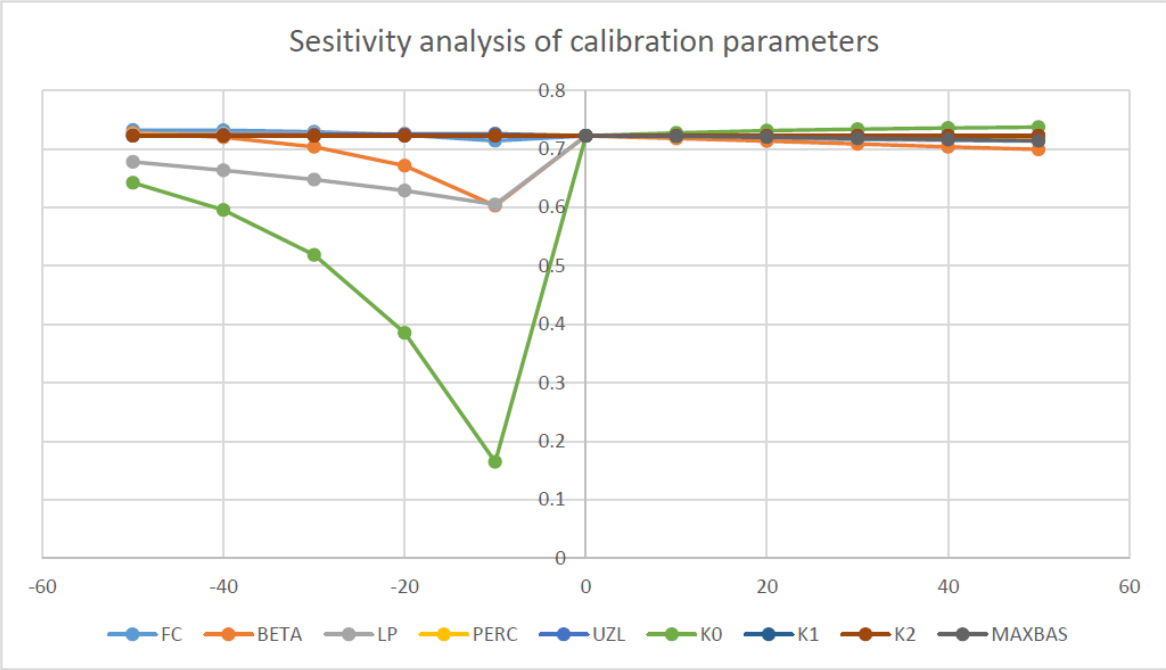



Figure 5.4: HBV Model Sensitive Parameters Analysis.

From the sensitivity analysis, it was clear that some calibration parameters were more sensitive to the model performance as compared to others.$K_0$ was the most sensitive of all the calibration parameters. It is a coefficient of storage and a slight change of this value shows a great variation in the model performance. LP and BETA are also sensitive in that order. FC is the fourth in sensitivity. Other parameters such as UZL, $K_1$ and $K_2$ show very low sensitivity to the model performance.

## 5.7 Discussion of Modelling Results.

Here we discuss results of varying modelling time steps and assess implications on the simulated runoff. Also, the separation of runoff hydrograph was tested as an additional output of the modelling process

### 5.7.1 Effect of varying time steps.

When the computational time step was increased from daily to 15 days and 30 days' time step by using aggregated 15 and 30 days data sets respectively, the new calibration results gave better model performance for the two sub-catchments as compared to daily simulations.

This was expected as large daily fluctuations during the wet season were smoothened out. The simulated average peak discharge was higher than the observed, except in the years 1999/2001and 2004/2005 for Nyangores and 2003/2004 and 2006/2007 for Amala.

The model efficiencies for the 15 days were, $R_{eff} > 0.79$ and $R_{eff} > 0.68$ for Nyangores and Amala respectively. Also the mean annual ($\Delta Q$) differences were negligible in both sub-catchment. Interestingly, low flows were better simulated by the model in the Amala sub-catchment as compared to Nyangores. The log $R_{eff}$ was > 0.71 and >0.62 during the calibration and validation period respectively.

### 5.7.2 Partitioning of the flow hydrograph.

The model was able to partition the total hydrograph into three components-the mean annual direct run-off, $Q_{DR}$, the interflow, $Q_{IF}$ and the base flow, $Q_{BF}$. This is shown in table 5.4 below.

Table 5.4: Statistics of direct runoff $Q_{DR}$, and base flow $Q_{BF}$ components (computed from $Q_0$, $Q_1$ and $Q_2$ in Figure 4.3) of the models for the period1997 to 2008.

| | | Run-off Component | |
|---|---|---|---|
| **Catchment representation** | | $Q_{DR}$ | $Q_{BF}$ |
| Nyangores (mm/a) | Mean Q | 18 | 101 |
| | % to total | 15% | 85% |
| Amala | Mean Q(mm/a) | 151 | 37 |
| | % to total | 80% | 20% |

Generally, the base flow is noticeably dominant in the Nyangores sub-catchment at 85% as compared to Amala's 20%. The direct run-off is however dominant in Amala at 80% as compared to Nyangores at 15%. The large difference in the run-off components between the two sub-catchments, demonstrates a distinct difference in the fast response characteristics between the two. This findings are supported by previous studies done by Dessu and Mango who found that Nyangores had higher infiltration than Amala (Melesse, 2012). In this research, we assumed the ground water run-off to be the base flow. The above results clearly

demonstrate that the dry season run-off of the Mara River is largely sustained by ground water storage of the two sub-catchments.

## 5.8 Model performance efficiency.

Model performance efficiency is often carried out using the established methods of NSE and $R^2$ (Abwoga, 2012).In addition to these indices, visual evaluation of the hydrographs is carried out evaluating the simulation of peaks, low flows, recessions and timings. However for model comparison of these efficiencies it is challenging to do so if the modelling time periods are different. However, for purposes of how efficient the model was in simulating the observed flow, the indices are suffice. This is tabulated in Table 5.5 below.

Table 5.5: Comparison of Model Efficiencies.

| **Statistics.** | **Model Type.** | | | | | |
|---|---|---|---|---|---|---|
| | **SWAT** | | **STREAM** | | **HBV Light.** | |
| | **Amala** | **Nyangores** | **Amala** | **Nyangores** | **Amala** | **Nyangores** |
| NSE (Calibration) | 0.076 | -0.533 | 0.56 | 0.59 | 0.59 | 0.65 |
| NSE (Validation) | 0.407 | -0.057 | 0.35 | 0.52 | 0.62 | 0.69 |
| $R^2$ (Calibration) | 0.303 | 0.085 | 0.81 | 0.8 | 0.65 | 0.73 |
| $R^2$ (Validation) | 0.413 | 0.321 | 0.66 | 0.79 | 0.69 | 0.75 |
| Modelling Period | 2002-2006 | 2002-2008 | 1999-2007 | 1999-2007 | 1996-2013 | 1996-2013 |

The above table shows that the HBV Light model performed better in comparison to either SWAT or STREAM Model in simulating the hydrograph of the Nyangores and Amala Rivers. However, the STREAM model had a higher $R^2$ efficiency both at the calibration and validation as compared to HBV.

**CHAPTER SIX:**

# 6 FINAL REMARKS.

## 6.1 Conclusion.

The Mara River Basin is facing unprecedented threat as a result of deforestation, expansion of agriculture, human settlement, sedimentation and erosion, flooding and low flows. Therefore, understanding the relation between the natural processes and anthropogenic activities that occur in the basin requires a reliable representation of the relevant hydrologic activities. The research assessed the ability of the HBV Light Model in simulating the long-term rainfall-run-off of the basin.

The overall objective of the research study was to develop a run-off simulation model based on both satellite based and in-situ rainfall products for the Mara River Basin. Based on the research questions the study was answering in its bid to achieve this objective, the following conclusions can be made:

a) There is a linear relationship between the in-situ rainfall and measured run-off, and the run-off simulation model was developed on the basis of this relationship.
b) The model was found to be sensitive mostly on the response rountine paremeter, $K_0$ which was responsible to the direct run-off (coefficient of storage in the upper zone), followed by soil moisture routine parameter BETA (β) and LP. The research found that the $K_0$ parameter is affected by catchment parameters like land cover (forests), infiltration or ground water storage capacity which in turn affects the evapotranspiration. Nyangores has the highest evapotranspiration and has the lowest $K_0$ while Amala is assumed to have the least evapotranspiration has the highest $K_0$.
c) The model's performance in terms of NSE and $R^2$ were better as compared to previous rainfall- run-off modelling by SWAT and STREAM model. The values for NSE were 0.65and 0.59 for the calibration period and 0.69 and 0.62 for the validation of Nyangores and Amala respectively.
d) The model tried to simulate the recession flow hydrographs in order to give good representation of the catchment characteristics. However, it was not able to simulate well the peak flows in the catchment. It had a tendency of over estimating the peaks. This could be because of the interpolation of the rainfall and discharge data to fill the gaps.

## 6.2 Recommendations.

The following recommendations can be made from the findings and lessons learnt from this research.

a) In order to improve on the peak simulations, there is need to do more investigation on improving the routing process of the model.
b) Investigation should be done on the validation of the simulated groundwater storage components with in-situ borehole piezometric measurements and terrestrial water storage data from Global Land Data Assimilation System (GLDAS) model and Gravity Recovery and Climate Experiment (GRACE) for example.

**CHAPTER SEVEN :**

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**CHAPTER EIGHT:**

# 8 APPENDICES.

## 8.1 ptq.txt files for Nyangores and Amala sub-catchments.

### 8.1.1 Nyangores sub-catchment.

```
Maraland

date  Prec. Temp  Q_Nyangores(mm/day)

19960101    0.00  0.60  0.083020193

19960102    0.00  0.60  0.083020193

19960103    0.00  0.60  0.077641572

19960104    5.67  0.60  0.072404727

19960105    1.83  0.60  0.067311789

19960106    12.77 0.60  0.072404727

19960107    8.43  0.60  0.077641572

19960108    2.07  0.60  0.083020193

19960109    1.30  0.60  0.072404727

19960110    1.40  0.60  0.062365047

19960111    4.80  0.60  0.062365047

19960112    15.57 0.60  0.083020193

19960113    0.43  0.60  0.137497201

19960114    0.00  0.60  0.137497201

19960115    2.37  0.60  0.0999863

19960116    0.37  0.60  0.08853846

19960117    1.97  0.60  0.072404727

19960118    0.73  0.60  0.062365047

19960119    0.30  0.60  0.067311789

19960120    0.00  0.60  0.072404727

19960121    1.50  0.60  0.062365047

19960122    1.40  0.60  0.052920402

19960123    0.77  0.60  0.062365047

19960124    2.53  0.60  0.052920402

19960125    5.03  0.60  0.057567074
```

| | | | |
|---|---|---|---|
| 19960126 | 0.20 | 0.60 | 0.052920402 |

### 8.1.2 Amala sub-catchment.

Maraland

| date | Prec. | Temp | Q_Nyangores(mm/day) |
|---|---|---|---|
| 19960101 | 0.00 | 0.60 | 0.083020193 |
| 19960102 | 0.00 | 0.60 | 0.083020193 |
| 19960103 | 0.00 | 0.60 | 0.077641572 |
| 19960104 | 5.67 | 0.60 | 0.072404727 |
| 19960105 | 1.83 | 0.60 | 0.067311789 |
| 19960106 | 12.77 | 0.60 | 0.072404727 |
| 19960107 | 8.43 | 0.60 | 0.077641572 |
| 19960108 | 2.07 | 0.60 | 0.083020193 |
| 19960109 | 1.30 | 0.60 | 0.072404727 |
| 19960110 | 1.40 | 0.60 | 0.062365047 |
| 19960111 | 4.80 | 0.60 | 0.062365047 |
| 19960112 | 15.57 | 0.60 | 0.083020193 |
| 19960113 | 0.43 | 0.60 | 0.137497201 |
| 19960114 | 0.00 | 0.60 | 0.137497201 |
| 19960115 | 2.37 | 0.60 | 0.0999863 |
| 19960116 | 0.37 | 0.60 | 0.08853846 |
| 19960117 | 1.97 | 0.60 | 0.072404727 |
| 19960118 | 0.73 | 0.60 | 0.062365047 |
| 19960119 | 0.30 | 0.60 | 0.067311789 |
| 19960120 | 0.00 | 0.60 | 0.072404727 |
| 19960121 | 1.50 | 0.60 | 0.062365047 |
| 19960122 | 1.40 | 0.60 | 0.052920402 |
| 19960123 | 0.77 | 0.60 | 0.062365047 |
| 19960124 | 2.53 | 0.60 | 0.052920402 |
| 19960125 | 5.03 | 0.60 | 0.057567074 |
| 19960126 | 0.20 | 0.60 | 0.052920402 |
| 19960127 | 6.23 | 0.60 | 0.048427843 |
| 19960128 | 1.97 | 0.60 | 0.044092492 |

## 8.2 T_mean.txt files.

```
Mara temp (Kisii, Narok, Kericho)

18.2

19.1

18.5

18.7

18.4

17.3

17.1

17.3

17.9

18.4

18.0

15.8
```

## 8.3 EVAP.txt file.

```
Mara_evap

5.1

4.6

4.3

4.2

4.1

3.9

4.1

4.3

5.1

4.9

4.6

4.2
```

## 8.4 Results Summary.

### 8.4.1 Nyangores sub-catchment.

Mara_Land_Nyangores.

| Water Balance (mm/year) | Subcatchment 1 | |
|---|---|---|
| Sum Qsim | = | 127 |
| Sum Qobs | = | 119 |
| Sum Precipitation | = | 1574 |
| Sum AET | = | 1455 |
| Sum PET | = | 1624 |
| Contribution of QSUZ | = | 0.85 |
| Contribution of QSLZ | = | 0.149 |

Goodness of fit.

| | | |
|---|---|---|
| Coefficient of determination | : | 0.734956873 |
| Model efficiency | : | 0.752345971 |
| Efficiency for log(Q) | : | 0.631254575 |
| Flow weighted efficiency | : | 0.619856324 |
| Mean difference | : | -8 |
| Efficiency based on intervals of 15 timesteps | : | 0.791211451 |
| Efficiency based on intervals of 30 timesteps | : | 0.830123172 |
| Volume Error | : | 0.834985124 |
| MARE Measure. | : | -0.428579321 |
| Lindstrom Measure | : | 0.751245819 |
| Spearman Rank | : | 0.901458954 |
| QobsSample | : | -999 |

### 8.4.2 Amala sub-catchment.

Mara_Land_Amala.

| Water Balance (mm/year) | Subcatchment 1 | |
|---|---|---|
| Sum Qsim | = | 318 |
| Sum Qobs | = | 188 |
| Sum Precipitation | = | 1663 |
| Sum AET | = | 1348 |
| Sum PET | = | 1624 |
| Contribution of QSUZ | = | 0.803 |
| Contribution of QSLZ | = | 0.196 |

Goodness of fit.

| | | |
|---|---|---|
| Coefficient of determination | : | 0.619856317 |
| Model efficiency | : | 0.651058947 |
| Efficiency for log(Q) | : | 0.639856231 |
| Flow weighted efficiency | : | 0.581458923 |
| Mean difference | : | -131 |
| Efficiency based on intervals of 15 timesteps | : | 0.681987562 |
| Efficiency based on intervals of 30 timesteps | : | 0.739856723 |
| Volume Error | : | 0.658723952 |
| MARE Measure. | : | -0.663847861 |
| Lindstrom Measure | : | 0.641238965 |
| Spearman Rank | : | 0.681243689 |
| QobsSample | : | -999 |