MODELLING IN UNGAUGED CATCHMENTS USING PyTOPKAPI: A CASE STUDY OF MHLANGA CATCHMENT

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Submitted in fulfilment of the requirements for the degree of Master of Science in Engineering, in the Civil Engineering Programme, University of KwaZulu-Natal, Durban, South Africa

February 27, 2018

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DECLARATION I – PLAGIARISM

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As the candidate's supervisor, I have approved this dissertation for submission

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DECLARATION II – PUBLICATION

Publication presented in this work was completed and compiled by the authors: Zeinu Rabba and Bukunmi Seun Fatoyinbo together with Prof Derek Stretch who provided technical suggestions and amendments.

Journal article

Rabba, Z., **Fatoyinbo, B**, Stretch, D. (2017). Implementation of PyTOPKAPI Model in Ungauged Catchments. *Water SA Journal*. Accepted for publication.

ACKNOWLEDGEMENTS

ABSTRACT

Hydrological modeling of rainfall-runoff processes is a powerful tool used in various water resources applications, including the simulation of water yield from ungauged catchments. Many rivers in developing countries are poorly gauged or fully ungauged. This gives rise to a challenge in the calibration and validation of hydrological models. This study investigated the applicability of PyTOPKAPI, a physically based distributed hydrological model, in simulating runoff in ungauged catchments, using the Mhlanga River as a case study. This study is the first application of the PyTOPKAPI model to simulate daily runoff on an ungauged catchment in South Africa.

The PyTOPKAPI model was parameterised using globally available digital elevation data (DEM), satellite-derived land cover, soil type data and processed hydro-meteorological data collected from various sources. Historical 30-year (1980-2009) quaternary monthly streamflow (from a well-tested and calibrated model) and daily meteorological variables (rainfall, temperature, humidity and so on) were obtained. The rainfall data were subjected to double mass curve test to check for consistency. The monthly streamflow was transposed to the catchment and disaggregated to daily streamflow time step.

The PyTOPKAPI model was calibrated using an average runoff ratio as an alternative to matching streamflow data that is usually used for model calibrations. The simulated results were thereafter compared with the disaggregated monthly quaternary data. The model results show good overall performance when compared with the average runoff ratio, monthly disaggregated streamflow and the expected mean annual runoff in the catchment. In general, PyTOPKAPI can be used to predict runoff response in ungauged catchments, and thus may be adopted for water resources management applications.

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LIST OF ABBREVIATIONS

CPI   Current Precipitation Index

DAR   Drainage Area Ratio

DEM   Digital Elevation Mode

DN   Digital Number

DWS   Department of Water and Sanitation

FDC   Flow Duration Curve

GIS   Geographic information system

HWSD   Harmonized World Soil Database

NRM   Normal ratio method

PyTOPKAPI Python based Topographic Kinematic Approach & Integration

QC   Quaternary Catchment ROIs Region of interests

RS   Remote Sensing

SASRI   South African Sugarcane Research Institute

SAWS   South African Weather Service

SCP   Semi-Automatic Classification Plugin

SRTM   Shuttle Radar Topography Mission

TOA   Top-of-atmosphere reflectance

USGS   United States Geological Survey

CHAPTER 1

INTRODUCTION

This chapter provides background information regarding the study. It also present general study objective, specific objectives as well the research questions to be answered. Finally, it gives a brief outline of this thesis.

1.1   Background

Sustainable water resources planning and management (WRPM) policies are being adopted in most regions of the world (Nandagiri, 2007). However, scarcity of hydro-meteorological data; often due to poor or no ground-based streamflow monitoring networks, introduces uncertainty in the hydrological predictions used for design and management of water resources, especially in developing regions (Blöschl, 2013). Previous researches have also shown that efforts towards achieving sustainable WRPM in these regions have suffered setbacks because of constraints in technical resources such as financial and human resources (Ghoraba, 2015, Pedro-Monzonís et al., 2015, Nandagiri, 2007). Despite the increasing demand for hydrological data in these regions, in the last 30 years, the quantity and quality of hydro-meteorological data obtained from stations in these regions has decreased due to constraints in technical resources (Mazvimavi et al., 2007). More so, to set up a perfect network is not feasible as some sites are difficult to reach (Nandagiri, 2007).

Over the years, rainfall-runoff modelling have been introduced to solve these challenges. The rainfall-runoff process is governed by many physical and climatological factors which include drainage pathways, catchment shapes, catchment slopes, elevations, topography, land cover and use, soil types, humidity, temperature, wind speed, sunshine hours and solar radiation. Modeling of these physical processes requires identification and estimation of relevant model parameters. Most of these model parameters are either not readily available at sufficient resolution or may be subject to uncertainties due to technical difficulties in field measurements. This is predominantly the case in developing countries that lack the resources and infrastructure to develop and maintain such complex data resources. Thus, sound methods are required for predicting runoff with limited input data or to source for alternate sources of data, such as remotely sensed (RS) data, where streamflow records are limited or non-existent.

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Previous studies regarding streamflow modelling in ungauged sites have relied on using a regionalization concept (Lebecherel et al., 2016, Westerberg et al., 2016, Song et al., 2015, Wallner et al., 2013). This concept entails transferring hydrological data such as model parameters, hydrological indices, catchment characteristics and runoff values from nearby gauged basins to an ungauged basin which is based on hydrological homogeneity (Blöschl, 2013). Geographical proximity method are mostly used to satisfy hydrological homogeneity(Lachance-Cloutier et al., 2017, Arsenault and Brissette, 2016). However it has been argued that geographical proximity is not a sufficient condition for hydrological homogeneity (Agarwal et al., 2016, Boscarello et al., 2015, Latt et al., 2015, Blöschl, 2013). Therefore, the major disadvantage of this approach is that it relies on a specific reference site(s).

Over the last two decades, physically-based hydrological models are being coupled with geographic information system (GIS) and remotely sensed (RS) data where the model parameters can be linked to the physical processes being modeled within the catchment (Suliman et al., 2015, Blöschl, 2013, Nandagiri, 2007, Stretch and Zietsman, 2004, Bouvier and Delclaux, 1996, Flügel, 1995). These models reproduce river information based on physical assessment of basin characteristics and hydrological processes at the catchment scale (Chen et al., 2017, Khatami and Khazaei, 2014). The models use mathematical expressions to convert meteorological variables and topographic conditions to streamflow information that gives a better knowledge of the complex hydrological process happening in a catchment. However, the reliability and accuracy of the application of the models still need to be calibrated or fine-tuned. For applications of such models in ungauged basins, the calibration procedure is based on the proximity of two or several sites that shared similar physical or climatic hydrological characteristics (Gianfagna et al., 2015).

This study investigates the appropriateness of the application of a physically-based fully distributed PyTOPKAPI (Python based Topographic Kinematic Approximation and Integration) hydrological model, for simulating runoff in an ungauged catchments. The study entails the calibration of the hydrological model for its application in an ungauged site, where there is no relevant data in the neighboring sites. It involves the use of an integral approach based on an average runoff coefficient rather than direct comparisons with streamflow records.

1.2   Problem Statement

Parameterisation of conceptual and process-based models has been a dynamic area of research in water resources management. However, modellers are faced with problems of inadequate and/or lack of stream gauges. Hydrological models usually require a huge amount of data for parsimonious parameterization since the reliability and accuracy of hydrological models depend on data availability. However, these datasets are limited in most regions, mostly in developing countries (Oyebode, 2014). Data limitation has been attributed to high cost of installing and maintaining reliable ground-based hydrological monitoring networks; resulting in difficulty to accurately obtain historical streamflow data (Le and Pricope, 2017). This has been identified as a major obstacle for the implementation of hydrological modeling in ungauged catchments in developing countries.

Moreover, the regionalisation approach has been used to generate synthetic data in ungauged sites (Westerberg et al., 2016, Song et al., 2015, Razavi and Coulibaly, 2012). The limitations of the regionalisation method are that it is based on the reliability of data from neighboring basins for generating the synthetic data (Ergen and Kentel, 2016). Thus, there is a need to consider the case in which an ungauged catchment has no neighboring gauged catchment with similar catchment or hydrological characteristics. The focus of this study is to consider how well a model represents reality in the ungauged catchment where there are no neighbouring gauged catchments.

1.3   Research Questions

1.   PyTOPKAPI model be applicable in ungauged catchments for simulating stream flows?

2.   How can the PyTOPKAPI be calibrated in ungauged catchments where there are no observed stream flow data?

1.4   Aim

The general objective of the study is to investigate the applicability of the PyTOPKAPI model for simulating runoff from ungauged catchments, using the Mhlanga River catchment in South Africa as a case study.

1.5   Objectives

a. To identify and generate the relevant model parameters using a geographic information system (GIS) and remotely sensed (RS) data.

b. To generate daily streamflow data from available monthly time series in the Mhlanga River Catchment.

c. To investigate the calibration and validation of the PyTOPKAPI model for ungauged catchments using the Mhlanga River as case study.

1.6   Dissertation Outline

This dissertation is outlined as follows:

Chapter 1   Introduction

This chapter presents the background to the study. It introduces the challenges of water resources management in many developing countries. It identifies the research problems as well as a brief review of methods that have been used to solve these problems. The chapter introduces the model adopted for this study and finally presents the research questions, objectives, problem statement of the study, as well as an outline of this thesis.

Chapter 2   Literature review

This chapter gives general background of hydrological modelling processes with respect to rainfall-runoff generation. It provides a comprehensive review on some models used for capturing hydrological processes in ungauged catchments.

Chapter 3   Study area and model description

This chapter describes the study area and gives the rationale for choosing the study area. The rationale of selecting the hydrological model for this study is also explained. In addition, the selected model is then briefly described.

Chapter 4   Research methodology

This chapter gives the methodological approach for this study. It describes the type, collection and preparation of data for PyTOPKAPI model application. It also describes the PyTOPKAPI model setup, calibration and validation for simulating stream flows from ungauged catchments.

Chapter 5   Result and discussion

This chapter presents the key findings of the study and their interpretations by means of evidence from the study.

Chapter 6   Conclusion and recommendation

This chapter presents the overall summary of the study. It also provides suggestions and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

In this chapter, relevant literature review to the general study objective is presented. It gives insight into the complexity involved in modeling processes associated with rainfall-runoff generation. The hydrological classification and rationale in selecting a modeling approach are discussed. It also discusses the challenges and approaches in runoff generation from ungauged catchments.

2.1   Hydrological modelling

Hydrological modeling has been a vital tool for runoff prediction in watersheds. It gives information about hydrological processes such as infiltration, baseflow, groundwater as well as predicting the approximation of runoff amount from a given rainfall event in a catchment. Hydrological modeling, pertaining to runoff estimation, is often time referred to as rainfall-runoff modeling (Kherde, 2016, Panhalkar, 2014, Tessema, 2011). Rainfall–runoff models are frequently utilized when there is limited or inconsistent streamflow information to make a true representative of natural flow conditions. They are likewise helpful in evaluating the spatial-temporal impact of land use/cover changes on runoff. Ampadu et al. (2013) stated the purposes of performing hydrological modelling which include:

1. To augment limited streamflow records in ranges where long precipitation records are accessible,

2. To integrate historical hydrological records so as to catch the long-haul variety in the records,

3. To forecast riverflow for flood alert as a result of changes in riverflow abstraction, dam construction, and land-use within the hydrological system,

4. To give a better insight into the modelling techniques as a tool.

The application of hydrological models for catchment assessment is often considered an art as well as a science due to lack of rigor and oversimplification of the physics that indicates essential modeling uncertainties (Kherde, 2016, Ampadu et al., 2013). Thus, there is dire need for the modeler to be cognizant of such uncertainties in the choice and calibration of

hydrological models for specific applications. Generally, hydrological models should be sufficiently comprehensive to portray the key physics of the problem under investigation.

Hydrological models by their nature provides a simplification of the reality that is amenable to testing and used to simulate, rather than mimic natural systems (Devia et al., 2015, Blöschl, 2013, Beven, 1993). In hydrology, a natural system consists of components and processes of the hydrological cycles such as runoff, precipitation, infiltration and evaporation. The knowledge of these processes is important in the light of the fact that they give sustenance to humankind and nature as a whole. Critical examination of these model techniques, their strenghts and weaknesses are important because of their role in water resource planning, development and management. These are discussed in the next section.

2.2   Hydrological model classifications

In the literature, modeling approaches have been classified in numerous ways (Ampadu et al., 2013, Refsgaard and Knudsen, 1996, Singh, 1977). These classifications have common characteristics which can be grouped by techniques that include their modeling scales (both time and space) and process (Ampadu et al., 2013). A better understanding of these characteristics will enhance the choice of suitable hydrological models for specific requirements.

2.2.1 Model Scale

Model scale can be classified as temporal and spatial scale. Temporal scale defines the time interval/scale used in model parameterization, internal computation as well as interval used for model output and calibration (Deckers, 2006). Hydrological model time interval can be categorized into event-driven models, continuous-process models, or models suitable for recreating both short-term and continuous events (Devia et al., 2015). Spatial scale describes the spatial distribution of the real word characteristic within the hydrological model. Classification of hydrological model based on the spatial scale has been widely used by subdividing the system by means of the modern techniques like geographical information system (GIS) or remote sensing (RS) (Fuka et al., 2016, De Freitas and Tagliani, 2009, Store

and Kangas, 2001, Flügel, 1995). The spatial scale can be categorised into three, namely, fully distributed, semi-distributed, and lumped.

Fully distributed models are grid-cell based which capture information regarding the spatial distribution of input variables including meteorological conditions (rainfall, temperature and others.) and physical parameters (land use, soil, and elevation to assess the impact of this distribution in simulating rainfall-runoff pattern. This model, mostly require a lot of information for parameterization in each grid cell, as opposed to scarce data availability in a watershed area. Nevertheless, if properly applied, they can provide the highest degree of accuracy. Typical examples of these models include MIKE SHE (Refsgaard and Storm, 1995), CASC2D (Ogden, 1998)and CEQUEAU (Couillard et al., 1988).

Lumped models treat the catchment as a single unit. This unit is then used in the model input which is believed to be representative at the catchment scale and produce output at a single point. Lumped models were considered inappropriate due to their spatial discretization and averaging of data such as meteorological and geographical, distributed in all grid cells for its parameterisation. Conventional lumped hydrological models are IHACRES (Jakeman et al., 1990), WATBAL (Yates, 1996) and TOPLATS (Famiglietti and Wood, 1994).

Semi-distributed models somewhat permit parameters to fluctuate in space by isolating the basin into smaller sub-basins. The system under study is divided into relatively large units that are often selected and bounded by watershed within the catchment. The importance of these models is that their structure is more physically-based than that of the structure of lumped models, and they require fewer input data than completely fully distributed models. However, the model have some of the disadvantages of lumped models such as simulating the average behaviour through small homogeneous units for the entire catchment. SWAT(Arnold et al., 1998), HEC-HMS (Anderson et al., 2000), HSPF (Johnson et al., 2003), PRMS (Leavesley et al., 1983), DWSM (Borah et al., 2001), TOPMODEL (Beven, 1993), HBV (Bergström and Singh, 1995), are regarded as semi-distributed models.

2.2.2 Process Description

Hydrological models can be classified based on their processes as Empirical (black-box), Conceptual (grey-box) and physically based (white box).

Empirical

Empirical models are developed using the observed time series to describe the physical procedures in the catchment as opposed to using a scientific expression which describes the physical processes that is instrumental in the hydrological behavior of the system. In such models, rainfall which is used for model input is related to the streamflow as output by means of statistical techniques (Ampadu et al., 2013). The essential characteristic of empirical models is that they are primarily based on observations and seek to characterise the system response from the available data. They are further grouped on: (1) statistical techniques, for example, ARIMA (Autoregressive Integrated Moving Average); (2) unit hydrograph and (3) Data-driven models for example, artificial neural networks and model trees (Ampadu et al., 2013). However, such models give insufficient insight into their internal working principles; with no description of the physical process of the hydrologic system.

Conceptual

Conceptual models use empirical formulations to represent complex processes such as overland flow, runoff and soil storage in a simplified form in the catchment. They have enjoyed wide application in ungauged basins due to their simplicity of applications, less time consuming and easy to parameterize (Nayak et al., 2013, Perrin et al., 2003). Nevertheless, the major challenges associated with them include (a) errors in model structure due to approximation of the model equations that describe the hydrological processes, (b) errors associated with input data and runoff output which result in errors in model parameters calibrated, (c) lack of explicit description of heterogeneities to properly describe processes, (d) uncertainty in parameter estimation when subjected to mimic all essential hydrological processes inside a catchment, and requires modeller priori knowledge of both model operation and hydrological processes within catchment. Thus, its use in ungauged catchments is quite challenging due to these setbacks.

Physically based

In physically based model, catchment processes are represented by one or more fractional differential mathematical expression that give more physical representations of the catchment. Such mathematical expressions include the equation of conservation of mass, momentum and energy. These models are very helpful in evaluating impact of changes in land use, climate variability, prediction of runoff, catchment spatial variability and pollutant and sediment transportation. Though the model is data intensive, once data can be sourced, it can then be applied to solve most hydrological problems (Devia et al., 2015). The model parameters have physical meaning which can be directly related to ground measured values. With the recent integration of GIS and RS data into physically based models, the model parameters are easily obtained. This has solved the issue of data intensiveness. Thus, applications of such models are valuable in catchments where there are no data. Table 2.1 presents the comparison of the three classes of models.

Table 2- 1: Characteristics of the three model class

Empirical model	Conceptual model	Physically-based model
Data based or black box model	Parametric or grey box model	Mechanistic or white box model
Involve mathematical equations, derive value from available time series	Based on modeling of reservoirs and include semi empirical equations with a physical basis.	Based on spatial distribution, evaluation of parameters describing physical characteristics
Little consideration of features and processes of system	Parameters are derived from field data	Required data about initial state of model morphology of catchment
High predictive power, low explanatory depth	Simple and can be easily implemented in computer code.	Complex model. Require human expertise and computation capability
Cannot be generated to other catchments	Require large hydro-meteorological data	Suffer from scale related problems
ANN, unit hydrograph	HBV model, TOPMODEL	SHE or MIKESHE model, SWAT
valid within the boundary of given domain	calibration involves curve fitting make difficult physical interpretation	valid for wide range situations

Source: Devia et al. (2015)

2.3   Criteria in selecting hydrological modeling approach

The choice of any hydrological model for solving specific hydrological problem(s) has been a challenge to the practicing hydrological community. Currently, variety of hydrological models are available at different spatial and temporal scales, there are no perfects norms for settling on a choice between models (Blöschl, 2013). Modelers are faced with problems in choosing a suitable model for a particular exercise.

However, in considering appropriate modelling approach to be used, it is key to consider four principal issues highlighted by Lewarne (2009) which are: what is the motivation behind the use of the model? (Model appropriateness for the study area and problem being investigated); what sorts of information are accessible to create and determine the model? computer requirements, ease of use, model clients and; what prerequisites are there on the scales and configurations of model output. In addition, the prospect model should be well understood, be freely accessible, and have accurate input data for the area and the problem being studied.

2.3.1 Choice of physically-based model for ungauged catchments

Following the classification scheme presented in section 2.2 and the criteria for the choice of hydrological model as summarized in section 2.3, a physically based model approach is selected for the study. This approach is descriptive in nature, that is, it represents the behaviour of a physical process with the aim of giving a better understanding. Its choice over the other approach is the incorporation of readily available data directly into the model. For example, catchment topography, land use, and soil parameters which are important characteristics that govern hydrologic response are spatially available (L. Ciarapica and E. Todini, 2002).

The physical significance of the parameter values for this type of model also allows applications in ungauged basins which is the principal motivation for this study. Field measurements or remotely sensed (RS) spatial data can be used to establish realistic parameter values, these values can be used to generate at least approximate hydrological forecasts without the use of observed streamflow data for calibration (Domeneghetti et al., 2014, Artan et al., 2007). Some catchment characteristics and hydrological information can also be inferred from other regional gauged catchments and incorporated directly into the modeling process for the ungauged system (Kherde, 2016, Beven et al., 1980).

Other approaches were not selected because of their inability to use spatial data such as topography, soil types and didtribution of vegetation types (L Ciarapica and E Todini, 2002). Moreover, they need sufficiently long hydro-meteorological records for their calibration which are limited in most catchments. Often time, the calibration involves curve fitting, which makes physical interpretation of the fitted parameter values very difficult.

2.3.2 Physically-based approach to runoff modelling in ungauged catchments

A number of physically based hydrological models have been utilized for different applications such as flood forecasting and water resource management in both gauged and ungauged catchments. Rapid advances in remote sensing technology and GIS have led to increase interest in developing improved model representations. However, each model exhibits its own distinctive applications and characteristics. Each model should give a clear statement of its benefits and limitations and description of dominant physical processes must be communicated to modellers for proper guidance in the choice of a model for desired task. This section reviews some of physically-based runoff models that has been utilized in ungauged catchments.

i.)   Mike-SHE has gained popularity due to its wide application in water quantity and quality assessments in most parts of the world (Tetsoane et al., 2013). Several researches have shown that Mike-SHE can be used in a wide range of spatial scales (Zhang et al., 2008, Singh and Frevert, 2003). Zhang et al. (2008) applied the model in Loess Plateau to simulate basin runoff. The results showed that the model can be successfully used to quantify hydrologic response to land use change and climate variability. Thompson et al. (2004) applied MIKE-SHE to a lowland wet grassland in England and found consistent results when compared with observed data. Jayatilaka et al. (1998) utilized the model for irrigation purposes in Australia and concluded that it can be efficiently used for the management of water for agricultural purposes. Recent development of the model includes pre-and post-processing tool and for graphical presentation, and GIS for data preparation which makes it user friendly (Golmohammadi et al., 2014). Going by application of MIKE-SHE in modelling hydrological systems, some areas of concern have been identified. Jayatilaka et al. (1998) reported inadequacies in its channel flow component. Thompson et al. (2004) also noted that the model fails to represent rapid flow through its

soil macropores formation. Devia et al. (2015) noted that the model is data intensive; making it tedious to set up especially in regions where there are limited or no data. Although, Mike-SHE has been successfully employed in water resource applications as highlighted above, limitations in terms of huge data requirements makes it inapplicable in ungauged or poorly gauged catchments.

ii.) Agricultural Catchments Research Unit (ACRU) is a multi-purpose agro hydrological model developed in Southern Africa and have enjoyed wide application in other countries such as United States, Germany, and Canada for more than two decades. Area of application of the model include irrigation water demand/supply (Kienzle and Schmidt, 2008), nutrient loading (Mtetwa et al., 2003), climate change impacts and land use impacts (Warburton et al., 2010, Lecler, 2003) and ecological requirements (Pike and Schulze, 2000). Studies have demonstrated the use of ACRU in ungauged catchment (Smithers et al., 2013, Hamer et al., 2007, Tewolde and Smithers, 2006). It incorporates water balance and runoff production components of any hydrological system (Warburton, 2010). The model requires daily data such as rainfall and temperature and spatial data prepared with GIS as input (Tetsoane et al., 2013, Schulze and Pike, 2004). Despite its successful application, Warburton (2010) highlights that most of the model default parameters are based on South African data sets. Thus, making it most suitable for South Africa catchments only. Schulze and Pike (2004) highlighted that the model has a small spatial range (1km to 50km). Chetty and Smithers (2011) and Smithers et al. (2013) highlight that the soil conservation service (SCS) techniques used for hydrograph generation in the model fails to account for infiltration and surface storage during rainfall events of varying intensity resulting in inadequate representation of unit hydrograph shapes on catchments. Thus, its use in an ungauged catchment may not give an accurate prediction due to the uncertainty in the model structure.

iii.) SWAT (Soil Water Assessment Tool) is a well-known distributed physically based model developed by the Agricultural Research Service of the United State Department of Agriculture (ARSUSDA). SWAT model simulates eight components of environmental systems. These include (1) weather data generation, (2) sedimentation process, (3) soil energy balance, (4) crop growth, (5) nutrient and pesticide leaching and (6) agricultural management (Tetsoane, 2013). The SWAT model has been applied to solving water

related issues worldwide for both gauged and ungauged catchments. Ficklin et al. (2009) applied the model to study the impact of climate change to hydrologic response in an agricultural area. The results showed that SWAT can be used to illustrate water resources changes due to climate change in an agricultural areas. Oeurng et al. (2011) applied SWAT to simulate discharge and sediment transport at daily time steps in south-western France. The results showed that SWAT performed well in assessing hydrology and sediment yield of the area over long periods. Gassman et al. (2007) categorized SWAT applications into hydrologic studies, pollution studies, comparison with other models, climate change studies, GIS interface descriptor, calibration and sensitivity analysis, land use changes effect, hydrologic response unit, and other input effects and adaptation studies.

Despite the widely use of SWAT model, some areas of concern have been highlighted. The riparian buffer zones, wetlands and other BMP (Best management practice) cannot be spatially represented due to the non-spatial aspect of its Hydrological response unit (HRU) (Daniel et al., 2011). Flow and Pollutant routing are ignored and targeted grassland placement or other related land use are not well represented (Daniel et al., 2011). It requires huge amount of data and this complicates model parameterization and calibration. Recent developments have been made which provides a decision support framework that incorporates semi-automated calibration (Kang et al., 2016, Rusli et al., 2016, Arnold et al., 2012, Kumar and Merwade, 2009, Rouhani et al., 2009, Veith and Ghebremichael, 2009). Although SWAT has been used in various ungauged catchments, its performance in ungauged cases is assessed through available regional streamflow data (Arnold et al., 2012, Gitau and Chaubey, 2010, Srinivasan et al., 2010, Ndomba et al., 2008). Thus, its use in site where there is no nearby streamflow information may be difficult.

iv.) Storm Water Management Model (SWMM) is used globally to solve urban hydrology and water quality related issues. It has become a robust model used in water conveyance systems for storm water runoff and waste water management (Niazi et al., 2017). The model comprises of 6 major components which include, external forcing data, land-surface components (such as infiltration and surface runoff), a surface component, a conveyance component, build up, fate and transportation of contaminants, and low impact

development (LID) controls. Detailed applications and area of concerns of SWMM have been reported in Niazi et al. (2017). Among its limitations include lack of user guidance for parameter estimation, sensitivity analyses, automated calibration, and uncertainty assessments. There is a lack of adequate information for specifying the surface spatial heterogeneity in the overland flow simulation, and a lack of mechanistic reactive fate and transport processes for contaminants in either the conveyance system, inside LIDs, or storage structures. There are limited options for direct simulation of urban land management operations, and a need for more explicit handling of interflow and groundwater flow pathways for water quality loading. Moreover, the model is data intensive and its assessment is based on comparing the predicted runoffs with measured data. Thus, its application in an ungauged catchment is extremely difficult.

v.) Hydrological simulation program (HSPF) is a comprehensive model which has been extensively used for continuous, dynamic event, or steady-state behaviour modelling of hydrology and water quality processes over pervious or impervious surfaces in a catchment (Pike, 1998). The implementation of the model to a catchment requires physical data, land use, Soil and climatic data which can be prepared with the use of GIS techniques. The model comprises of three applications and six utility modules. The application module is used on pervious land surfaces to simulate water quality and runoff processes while utility module is used in data analysis and estimation (Yan et al., 2014, Pike, 1998). The model has been successfully applied in various climate regions around the world. Ribarova et al. (2008) applied the model to describe nutrient pollution during a flood event in a semi-arid region. Results suggest that HSPF model can provide a better understanding in forecasting nutrient concentrations during first flood events. Yang et al. (2015) also applied it to simulate the spatial-temporal variation of hydrological processes in ungauged polluted area in China. The results showed that HSPF could simulate the hydrological process excellently. (Tong and Chen, 2002) examined the hydrologic effects of land use in Miami River.

Despite the widely use of the model, some areas of concern have been reported. Li et al. (2012) highlighted the major limitation of the model to include: limited spatial definition, extensive data requirement, lack of information on parameter estimation, limited usage to a well-mixed, reservoirs and 1D water bodies only, extensive user training is required

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to operate the model, and intensive skill required to run the simulation and calibration (Li et al., 2012, Bicknell et al., 1996). Thus, its use in ungauged catchment is extremely tedious.

vi.) HEC-HMS (hydrologic engineering system-hydrologic modelling system) was developed by the United States Army Corps of Engineer to simulate rainfall-runoff processes of dendritic watershed systems (Bhuiyan et al., 2017, Gebre, 2015, Freitas and Billib, 1997). The model has been applied in a wide range of climatic areas for solving large area water supply, flood hydrology, urban and natural catchment runoff problems, and other water related issues (Dhami and Pandey, 2013). The model can be used for both continuous and event-based modelling (Bhuiyan et al., 2017). The model is classified into four components which include the watershed physical component such as DEMs, Soil and land use, the meteorological model, the input data manager and the control manager. This is one of the hydrologic models that is compatible with various graphics and visual packages, for example, Surfer and GIS etc. It has been used in both gauged and data scarce regions for various studies such as Urban flooding studies (Suriya and Mudgal, 2012, Ali et al., 2011), Flood frequency studies (Halwatura and Najim, 2013, Dawdy et al., 2012), flood-loss reduction studies(Müller and Reinstorf, 2011, Bakir and Zhang, 2008), flood warning system planning studies (Montesarchio et al., 2009), reservoir spillway capacity studies (Halwatura and Najim, 2013, Bakir and Zhang, 2008, Goodell, 2005) and stream restoration studies (Rakovan and Renwick, 2011, Copeland et al., 2001). Though it has wide applications, among its reported challenges by Scharffenberg and Fleming (2006) includes: (1) the mathematical expressions in the model formulation are deterministic, which implies that, the boundary conditions, models conditions and model parameters use a constant parameter values. This assumption made it to be time stationary. Thus, it fails to account for possible changes in the catchment conditions due to human or other processes for long period of time. (2) HEC-HMS was solely developed with data from small agricultural watersheds in Midwestern US, so applicability elsewhere is uncertain. (3) The design of the model only allows for a dendritic stream network. (4) Infiltration rate usually approaches zero during a storm of long duration. Thus, its application in an ungauged catchment will be difficult due to lack of direct physical relationship of parameters and watershed properties. It also requires expertise.

vii.) The Topographic Kinematic Approximation and Integration (TOPKAPI) Model is a comprehensive distributed-physically based approach. This model comprises five modules such as evapotranspiration, snowmelt, soil water, surface water and channel water components which represent hydrological processes (Liu and Todini, 2002). The model has been used in various climatic regions of the world where there are either available or limited data. Studies shows that TOPKAPI can give high resolution information on the hydrological state of a catchment through its field of applications. These include: catchment hydrology (Théo Vischel et al., 2008, L Ciarapica and E Todini, 2002), flood forecasting (Bartholmes and Todini, 2005, Liu et al., 2005), reservoir management (Anghileri et al., 2016), land use and climate change (Mcintyre et al., 2014, Liu and Todini, 2002), irrigation and drought (Vicente-Serrano et al., 2011, Sinclair and Pegram, 2010), and landslides (Carpentier et al., 2012, Martina et al., 2009). Despite its wide applications, some areas of concern have been highlighted. Théo Vischel et al. (2008) reported an assumption made in its infiltration module formulation. The assumption was that, as precipitation falls directly into the soil, it results into saturation excess thereby generating overland runoff. The disadvantage of this is that overland volume cannot be produced when subjected to short time high-intensity rainfall on the moist soil (Sinclair and Pegram, 2013). Liu et al. (2005) reported that the model does not accurately depict its physically meaning. Another limitation to this model is the seemingly high cost of purchase and huge amount of data for efficient application. It needs observed streamflow for its calibration, thus, its use in an ungauged catchment is challenging.

viii.) PyTOPKAPI model was developed as a modification to TOPKAPI model which simulate hydrological processes (Sinclair and Pegram, 2013b). T Vischel et al. (2008) applied the model to estimate soil moisture at regional scale on South Africa catchment. The model result showed a good correspondence when compared with remotely sensed soil moisture. Sinclair and Pegram (2013) investigated the sensitivity of the model to systematic bias in the rainfall and evapotranspiration variables, as well as the physically based soil properties that describe the model behaviour. The result showed that the best estimates of soil water could be obtained by improving estimate of the forcing parameters. Although PyTOPKAPI has not been used in an ungauged catchment, it has been reported

that the model will be suitable for applications in ungauged basin (Sinclair and Pegram, 2013).

Furthermore, Table 2-2 and Table 2-3 present characteristics of a number of physically based hydrological models reviewed. This will help resolve the challenge of data acquisition and model parametrization. The Table provides water managers, planners, and modellers with a summary of the models capabilities in terms of input, output, application (ungauged), advantages and disadvantages.

Table 2- 2: Characteristics of some physically based hydrological models

Model	Area applied	Inputs	Outputs
MIKE SHE (Refshaard et al., 1995)	Europe, USA (Magombeyi, 2011) Semi-arid regions (e.g. South Africa) (Prucha et al., 2016)	Topography, soils, land use, hydraulic conductivity (aquifer), manning's roughness, coefficient, Evapotranspiration, drainage time and weather data.	- Streamflow - Soil water balance
ACRU (Schulze and Smithers, 2004, Smithers, 1995)	Southern Africa, USA, Germany, New Zealand and Canada(Warburton, 2010)	Rainfall, Temperature (max and min), land cover, soil properties, catchment characteristics and climatic data	- Runoff - Yields (Crop, sediment, and reservoir) - Soil water balance - Irrigation Demand
SWAT (Arnold et al., 1998)	Global (Merwade et al., 2017)	Terrain data, Soils, DEM, land cover/use, weather data, Agricultural practices data, and Reservoir and Aquiver characteristics.	- Streamflow - Soil water balance - Crop yield - Nutrient Balance - Climate data - Loses (percolation &Channel)
Hydrological Simulation Program In FORTRAN (HSPF) (Donigian Jr et al., 1995)	USA, Turkey (Magombeyi, 2010)	DEM, soil properties, land use/cover, meteorological data.	- Runoff - Water quality (sediment load, Nutrient and pesticide concentrations) (Daniel et al., 2011)
TOPKAPI (Topographic Kinematic Approximation and Integration) (Liu and Todini, 2002)	Italy, Spain, China, South Africa, Chile, USA.	DEM, Soil, Land cover, Channel and surface roughness.	- Runoff - Subsurface, Overland, and channel flow - Soil water balance
HEC-HMS (Feldman, 2000)	Humid, Tropical, sub-tropical and Arid (Abushandi and Merkel, 2013)	Soil, Land use, Physical characteristics of Catchment, Channel geometry, Topography, Potential evapotranspiration, Geological data, Meteorological data.	- Runoff - Soil Balance - Ground water flow - Channel flow - Evapotranspiration

PyTOPKAPI (Sinclair and Pegram)	South Africa	DEM, Soil, Land cover, Channel and surface roughness, Meteorological data, Evapotranspiration(Actual and Reference)	- Runoff - Subsurface, Overland, and channel flow - Soil water balance	
SWMM (Storm Water Management Model) (Huber et al., 2005)	World wide	Precipitation, climate data, soil characteristics, landuse characteristics, Depression storage, Water quality characteristics	- Runoff quantity and quality (Rossman, 2015)	

Table 2- 3: Comparison of some hydrological models used for application in the study

Model name	GIS Capability	Application	Advantages	Disadvantages
MIKE SHE	yes	- Water quality - Surface and Groundwater movement - Irrigation Management - Water use management	- Large spatial scale range (Butts et al., 2005)	- Requires huge data - Takes long computational time - Base flow overestimation - Real complexity of hydrological systems. - Cannot be used in an ungauged catchment. - Model use requires technical expertise (Ma et al., 2016)
ACRU	Yes	- Land use - Crop yield - Irrigation - Sediment yield - Water resources assessment - Design hydrology - Climate change - Impact analysis - Environmental flows estimation - Risk analysis	- Confidence in assessing climate and land use change - Good structure for hydrological responses and sediment mechanism	- Model availability and support is difficult. - Limited spatial range (1-50km^2)(Schulze and Pike, 2004) - Requires huge data. - Data pre-processing, and GIS analysis are difficult (Beckers et al., 2009) - Not robust in semi-arid regions (Magombeyi, 2010) - Default values are based on the south African dataset. - limited spatial range
SWAT	Yes	- Agricultural purposes - Subsurface drainage - Irrigation and Reservoir operation - Water quality - Hydrological studies - Land use - Climate change - Sediment yield - Pollution loading	- Automatic calibration - Well adopted using remotely sensed data. - Flexibility and robust	- Does not simulate single-event storms adequately - non-spatial aspects of the Hydrologic response unit (HRUs) (Daniel et al., 2011). - Mainly for agricultural purposes.
HSPF	Yes	- Hydrological studies - Water Quality - Pollutant analyses - Sediment transport - Agricultural practices	- It gives a detailed representation of land a watershed land, stream processes, and watershed pollutant sources.	- Huge data for setup - Not fully physically based - Not User's friendly - Difficult to calibrate - Difficult to setup in ungauged.

			- Flexibility and adaptability most watershed conditions. - Well-designed code modularity and structure.	
TOPKAPI	Yes	- Catchment hydrology - Water resources management - Reservoir management - Flood forecasting - Land use change - Climate change - Irrigation and drought	- Easy to calibrate - Run event and continuous simulation. - Low computational time	- Expensive - The model fails to account for infiltration into the soil layer - Not robust in ungauged catchment
HEC-HMS	Yes	- Water balance - Water resources management - Flood hydrology - Urban drainage - Stream restoration - Urbanization impact - Reservoir Operation	- User's friendly - Auto calibration - Low computational time - Can be applied in a lake - Modelling and forecast impacts of climate changes on runoff (Gebre, 2015)	- Required high number of parameters - Cant simulate in large watershed scale - Cannot be used in the ungauged catchment, the observed discharge must be available. - Suitable for flood studies
SWMM	Yes	- sewer and storm water applications - Pollutant Load Simulation	- Robust hydraulic module - User-friendly interface - Continuous simulation - Meaningful results with very rough to very refined inputs - The ability to route flows and pollutants through a drainage and/or sewer system	- Lack true physical representation - weak groundwater simulation capability (Yang and Wang, 2010) - Hydraulic model takes longer time in simulating - Data intensive - Mainly Urban model. (Yang and Wang, 2010)
PyTOPKAPI	Yes	- Catchment hydrology - Water resources management - Reservoir management - Flood forecasting - Land use change - Climate change - Soil moisture estimate	- Well adopted using remotely sensed data. - Ease of use - Robust to errors (Sinclair and Pegram, 2013) - Simulate at finer resolution (minutes, hourly etc.) - Less computational time - Appropriate to be applied in ungagged basins.	- Much time needed in preparing input data.

2.4 Runoff generation for ungauged catchments

Many hydrological problems require hydro-meteorological data for model input and calibration. This data is usually limited, or unavailable in sufficient and reliable quantity. Though the modern method of data collection has eased this problem, however, they still required qualitative authentication for their usage. The quality of the available database influence estimation accuracy regardless of the method used. Challenges of sparse and missing data pose a great concern to hydrologists. These maybe as a result of either bad weather condition, malfunction equipment, data contamination, processing errors or high cost of ground based maintenance. They raise inconsistent and biased estimations in model performance.

The application of GIS and RS creates a platform for technological advancement in relation to measurement and computation; thereby fostering creative exploitation of process-based gridded models(Bhatt et al., 2014, Vieux, 2001). The speedy advancements in geographical information system (GIS) and remotely sensed technology have assumed a wide usage in catchment hydrology, specifically in rainfall-runoff modeling. They offer spatial information about the land use, soil, and topography as model input for both gauged and ungauged basin. Several studies have utilized RS and GIS in hydrological modeling. Gangodagamage (2001) examined the potential use of remote sensing to estimate spatial variation of hydrological parameters which serves as model input. Fortin et al. (2001) checked the application of RS and GIS of distributed rainfall- runoff model. The result showed that integrate remote sensing together with spatial data handling capabilities of GIS is significant to data processing for distributed hydrologic modelling. Devantier and Feldman (1993) reviewed the trend and approaches in the use of RS and GIS to perform hydrologic. Milzow et al. (2009) utilized remote sensing to obtain spatially distributed data such as topography, aquifer thicknesses, channel positions, evapotranspiration and precipitation. These data were for the model parametrization and calibration. There are several applications of RS in hydrology but it is out of the scope of this thesis to describe them in detail.

Data exploration sources from satellite images have enhanced application of rainfall-runoff model in an ungauged catchment (Quan, 2006).These data sources from satellite images are free and have been in many applications such as Generation of DEM using SRTM,TRMM and METEOSAT for rainfall estimation (Quan, 2006). GIS is a tool used for pre-processing and

post processing of remotely sensed data such as data storing, map analysis and overlay. This tool contributes to generating spatial distributed model parameters. These parameters such as hydrologic or physical characteristics of a catchment can then be used for model simulation.

Most ungauged basin and scarce data regions have employed regionalization method in the past (Athira et al., 2016, Gianfagna et al., 2015, Hellebrand et al., 2015, Blöschl, 2013). Different regionalization approaches exist for predicting runoff in an ungauged basin. These approaches transpose data from gauged to the ungauged catchment. Some of the methods used in regionalization are spatial proximity, similarity, drainage area method, model averaging and regional calibration approach (Parajka et al., 2013). These have been used either to generate synthetic data for the ungauged catchment or to calibrate the model for simulation. These methods are summarized below.

The Proximity method uses geostatistical distances techniques in transposing data through nestedness of the catchments (Alam and Hossain, 2016, Gardner et al., 2003, Phillips et al., 1992). The Similarity approach offers an alternative catchment donor based on a comparison between climate and catchment characteristics similarities for the two basins (Alam and Hossain, 2016, Blöschl, 2013, Samuel et al., 2011). The model averaging method works on a weighted combination of the above two methods, while the parameter regression analysis method offer alternative approach through empirical or measured data correlation between the stations (Parajka et al., 2013). The conventional drainage area ratio (DAR) method is a common and simple method for transposing data (Nruthya and Srinivas, 2015, Fry et al., 2013, Mohamoud, 2008). This method is implemented by multiplying the drainage area of an ungauged area to that of a nearby gauging station.

Regional calibration method relates estimated model parameters at a gauged site(s) and then transposed them to the target catchment in a region. The reason for this is to find more dependable parameters for calibrating the models for use in an ungauged basin. In real sense, the model parameters and the catchment characteristics relationship must be hydrologically justifiable to give certainty for extrapolation to the ungauged catchment. Related studies and application of this various method are available in the literature (Khan et al., 2016, Weng, 2001, Phillips et al., 1992).

More so, continuous generation (hourly or daily) of runoff in most ungauged catchments are required for various water quantity and water quality studies such as irrigation water demand, ecological use, water demand, water allocation, hydropower generation and water quality purposes. Continuous generation of streamflow is very cumbersome; resulting from inadequate and damaged gauges, inability to take readings on hourly basis and complexities and sophistication associated with hydrological models (Ly et al., 2011, Srikanthan and Mcmahon, 2001). Some catchments however have observed discharge available at monthly, daily and hourly time series. The implementation of hydrological modelling studies at a finer time step in areas with limited data tend to be a challenging task. Thus, there is need to disaggregate coarser available streamflow data to finer time steps.

Various methods have been used to disaggregate streamflow. Acharya and Ryu (2013) described simple and adaptive approached used to disaggregate monthly data to daily data. A good correlation between the disaggregated flow and observed streamflow for all cases over the study period is evident in the result. Al-Zakar et al. (2017) utilized a statistical approach to disaggregate annual streamflow to monthly. Result showed that the disaggregation approach has the ability to provide a variety of monthly sequence flows that can then be utilized to analyse the performance of the water resources planning system in the site. Smakhtin (2000) describes the use of flow duration curve to generate continuous time series of daily flow. The major limitation to the above methods is that it depends solely on streamflow as decision variable.

Smakhtin and Masse (2000) overcame the problem by incorporating rainfall as a decision variable in generating continuous daily streamflow time-series from monthly, and yearly observed streamflow. Hughes and Slaughter (2015) presents a disaggregation method by incorporating rainfall as a decision variable to generate daily flow simulations from existing monthly simulations. The technique use current precipitation index generated from daily rainfall data. The major limitation to this approach is that frequently overestimate low flows (Smakhtin and Masse, 2000).

In conclusion, existing methods for predicting runoff in an ungauged catchment depend on the availability of data in neighbouring site(s). These methods have been successful in applications. In the present study the method developed does not require the use of data from neighbouring catchments.

The identification of these knowledge gaps introduces novelty to this study, as an intuitive water balance principle is used in calibrating a physically based model - PyTOPKAPI. This study is therefore aimed at achieving reliable and accurate runoff prediction in ungauged catchments without using information from nearby catchments.

2.5   Conclusion

This chapter gives detailed information about hydrological modelling such as techniques, approach and choice of modelling approach. Tables 2-2 and 2-3 summarizes some hydrological models based on their modelling approach (such as the degree to which they represent the physical processes), model robustness, advantages and disadvantages. It also describes existing models, problems, technological advancement (RS and GIS) and methods in generating runoff in ungauged catchments. Based on these considerations, PyTOPKAPI model was study. More so, though the model selected has not been used in an ungauged catchment, it has been reported to be a promising tool due to its ease of use, physically-based, robustness to error, less computational time, accommodation of high spatial range, finer temporal scale and so on (Sinclair and Pegram, 2013). The rationale for PyTOPKAPI application in this study will be further explained in section 3.3 and section 3.4.

CHAPTER 3

STUDY AREA AND MODEL OVERVIEW

This chapter presents an overview of the study area and the hydrological model used. It additionally described the rationale for choosing the study area, the choice of the hydrological model used, the model structure, operation, and modeling principles.

3.1   Choice of the study area

The Mhlanga estuary is ecologically important and heavily impacted by influent from waste water treatment works (WWTW) located within the catchment. It is characterized by severe eutrophication and changes in flow characteristics due to the WWTW discharges. Runoff strongly influences such eutrophication processes in the system. The runoff is associated with the nutrient discharges from the WWTW.

The study catchment is ungauged because it has rainfall data but does not have runoff data. A reliable quantification of runoff is required for appropriate management of the water resources of the catchment. The catchment is small but it is ecologically important. Past studies carried out on the catchment (Lawrie et al., 2010, Stretch and Zietsman, 2004, Cooper, 1991) noted that lack of flow information hinders an accurate analysis of the water balance for the catchment which is needed to understand its ecological functioning. Therefore, there is a need to implement a robust model that is capable of simulating continuous runoff in order to understand the eco-hydrological responses of the catchment.

3.2   Overview of the study area

The Mhlanga catchment is found in east coast of South Africa in the KwaZulu-Natal Province, North East of Durban which is approximately 19km from Durban. The catchment is geographically located at 29º42'9" S and 31º6'0" E and drains an area of about 80 km². The river mouth is characterized by an estuary with an area of 70 hectares (Stretch and Zietsman, 2004). The river is 25 km long with an average slope of 0.6%. Two waste water treatment works, Phoenix and Mhlanga, are situated along the river which are 12 km and 2.5 km from the estuary as shown in Figure 3-1 (Lawrie., 2007). The natural and present-day mean annual

runoff (MAR) are 0.4m³/s and 0.63m³/s respectively (Lawrie et al., 2010, Stretch and Zietsman, 2004). The higher value of the present day MAR compared to the natural state MAR is due to the discharges from the WWTWs.
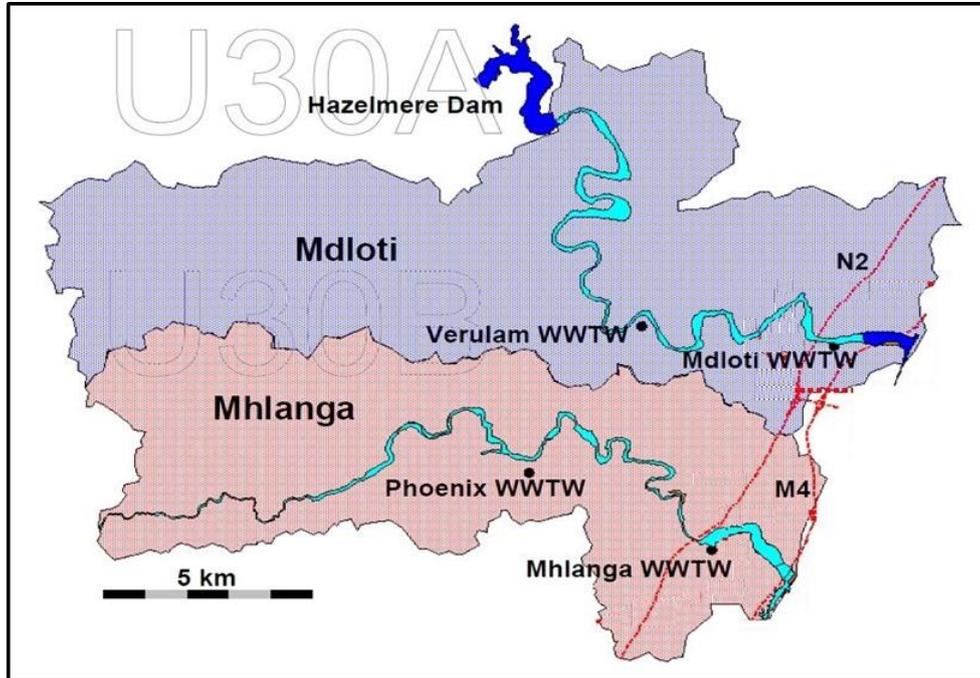
Figure 3-1: The map of Mhlanga and Mdloti catchments (Stretch and Zietsman, 2004)

The study area is found within the Mvoti-Umzimkulu water management area as defined in WR90 (Midgley et al., 1994). As showed in Figure 3-1, the U30A catchment contributes flow to the neighboring Mdloti river upstream of the Hazelmere Dam, while U30B feeds both the Mdloti and Mhlanga rivers having a total area of 221 km² (Stretch and Zietsman, 2004). The area contributing to the Mhlanga river is 80 km².

The warm moist air over the continent from the Indian Ocean is an important influence on the weather patterns over the catchment. The area experiences seasonal rainfall where most rain falls between October and March (see Figure 3-2). Peak rainfall is usually experienced between November to March with mean annual evaporation and rainfall of 1210mm and 1000mm (Lawrie et al., 2010, Stretch and Zietsman, 2004). The mean annual temperature ranges from 16.7°C to 25.5°C. Maximum temperatures are experienced in the summer months from December to February with minimum temperatures in winter (June and July) (South Africa

Department of Water and Forestry 2004). Figure 3-2 summarises 30 years of monthly averaged climatic data (temperature, rainfall, and evaporation) for the catchment.
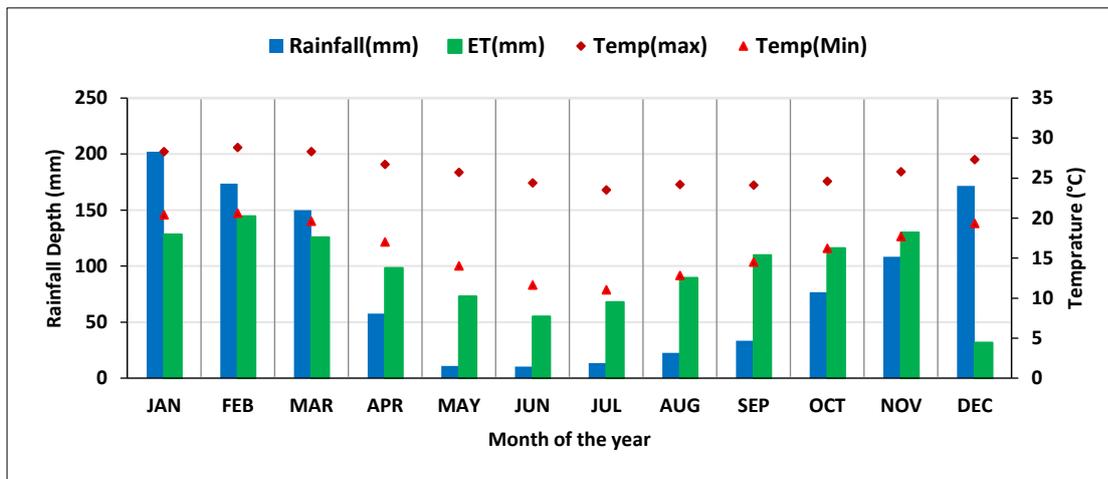
Figure 3-2: Mean monthly climatic data over the Mhlanga Catchment. This includes rainfall (blue color bars), evaporation (green color bars), maximum temperature (triangles) and minimum temperatures (diamond).

The flood plain elevations/ topography of the study area are between 10 m and 40m MSL (above mean sea level) followed by hilly uplands ranging from 140m to 375m MSL which is evident in Figure 3.3.
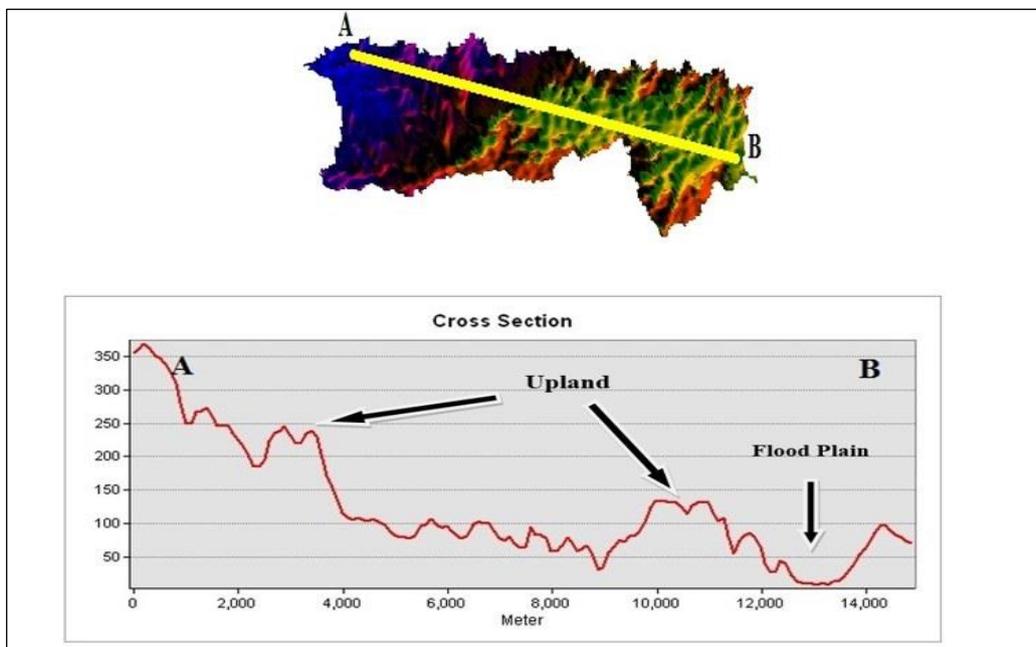
Figure 3- 3: The 3D DEM view of the study area and topography cross section.

The land cover map for the study area was processed from the remotely sensed data. It is evident that the major land cover over the catchment is urbanization and agriculture. According to the coastal management 2007 report (Ferguson, 2007), it was noted that the catchment is highly vegetated with sugar cane cultivation. This is evident from the remotely sensed processed land cover map as shown in Figure 3-4 developed for this study (see section 4.1.8).
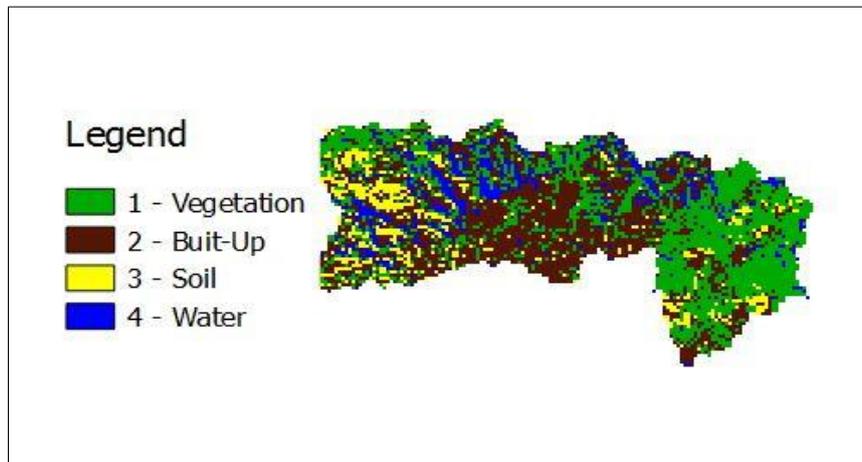
Figure 3- 4: The land cover map of the Mhlanga Catchment.

3.3   Choice of PyTOPKAPI model for this study

Hydrological models that have the potential of addressing the water resources challenges in the study area have been analyzed in the previous section (section 2.9). The PyTOPKAPI model was selected because of its GIS capability, in-situ data provision, and ability to simulate runoff from an ungauged basin, support and visual-spatial analytical tools (Sinclair and Pegram, 2013, Pegram and Sinclair, 2012, Théo Vischel et al., 2008). Although PyTOPKAPI has not been tested for ungauged basins, the modelling approach is expected to be robust for such applications (Théo Vischel et al., 2008). Moreover, the model has advantages over regionalization methods that have been used in generating runoff in ungauged catchments. For example it does not require any information about the other catchments with respect to hydro-meteorological homogeneity. Its strength over other models include: physical realism, spatial representation of the catchment characteristics, parameterization based on observed values, use of remotely sensed data, low cost, high computational speed, accuracy, modularity, and ease

of use. Following these strengths, it will be suitable for application in the study area and to other ungauged sites that are typical of developing countries (Théo Vischel et al., 2008).

3.4   PyTOPKAPI model description

PyTOPKAPI is a physically based distributed hydrological model developed as a modification to TOPKAPI model for simulating rainfall runoff (Sinclair and Pegram, 2013). The TOPKAPI model was developed by Liu and Todini (2002) and has been used in several countries globally. Its application in South Africa is not new - details of other applications of the model in South Africa are given by T Vischel et al. (2008) and Sinclair and Pegram (2013).

TOPKAPI model is based on 5 main modules that represent soil, overland, channel, evapotranspiration and snow processes. The first 4 processes govern the horizontal flow and control the soil moisture balance, especially with regards to saturated areas (Théo Vischel et al., 2008, L Ciarapica and E Todini, 2002).

The drawback of the TOPKAPI model was that it failed to account for infiltration of water into the soil layers and its influence on discharge. In TOPKAPI model, the assumption made was that passage of water into the overland store can only be achieved through saturation of excess soil stores at any time step. Following Sinclair and Pegram (2013) the disadvantage of this assumption was that the overland flow cannot be produced when subjected to short time high-intensity rainfall on the moist soil. Liu et al. (2005) subsequently made improvements to the model by adding an infiltration module, nevertheless, it did not accurately depict the physical process.

The limitation of TOPKAPI model brought about the development of PyTOPKAPI. In PyTOPKAPI, an infiltration module that modifies the conventional method used in calculating the inflow into the channel in TOPKAPI was formulated. The infiltration module utilized the Green & Ampt. model due to its popularity, simplicity, and parameter estimation from readily available soil information all over the world, hence a better physically representation of infiltration in real sense was realized (Sinclair and Pegram, 2013). Moreover, it provided a mechanism for the model to generate a swift overland runoff when subjected to high rainfall. The Green & Ampt. infiltration method used in PyTOPKAPI is formulated as

$$F_{t+\Delta t} - F_t - \psi\Delta\theta \ln\left(\frac{F_{t+\Delta t}+ \psi\Delta\theta}{\psi\Delta\theta}\right) - k_s\Delta t = 0 \qquad\qquad 3\text{-}1$$

where $F_{t+\Delta t}$ is the cumulative infiltration depth at time $t + \Delta t$, F_t infiltration cumulative depth at time t, ψ is the wetting front soil sunction head, $\Delta\theta$ change in soil moisture content. The original overland store and the modified overland store in PyTOPKAPI model are expressed as

$$Q_0^{in} = Q_s^{in} - \left(\frac{\Delta V_s}{\Delta t} + Q_s^{out}\right) \qquad\qquad 3\text{-}2$$

$$Q_0^{in} = Q_s^{in} - \left(\frac{\Delta V_s}{\Delta t} + Q_s^{out}\right) + P_{excess} \qquad\qquad 3\text{-}3$$

$$P_{excess} = p - F \qquad\qquad 3\text{-}4$$

where Q_0^{in}= overland store inflow, Q_s^{in}= soil store inflow, ΔV_s= coil store change in storage, Q_s^{out}= overland and soil stores discharge to the down-slope cell, Δt= change in time , p = average precipitation input rate during time step and F = infiltration rate. The three-main module of the model (soil, overland, and channel) are represented in a grid cell (See. Figure 3-6).
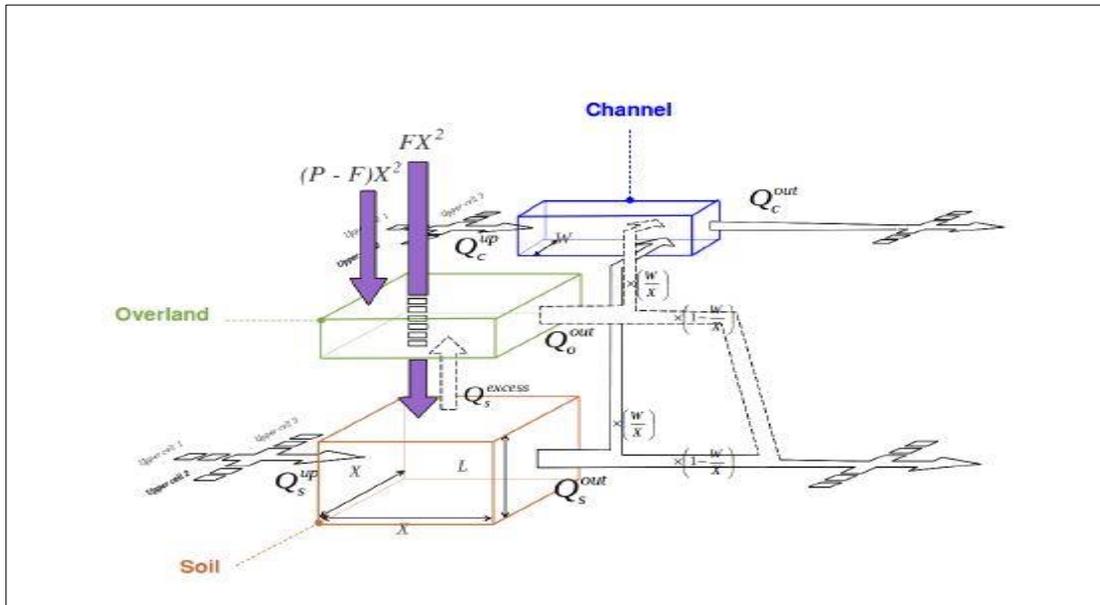
Figure 3- 5: Schematic diagram of water balance in the 3 main PyTOPKAPI module in a cell (Théo Vischel et al., 2008). The evapotranspiration loses are not represented in the figure.

The PyTOPKAPI model uses finer time steps and distributed parameters which account for some spatial differences in channel morphology, soils, land use, climate, and topography. It treats each homogenous area separately, connecting outflows to inflow through unique, discrete areas. It then lumps the results at the outflow of each unique area; ultimately summarizing them for the whole watershed at the final outlet. The model uses a resolved mass continuity equation as an underlying model equation that relates the three main reservoirs (overland, soil, and channel) in a cell (T Vischel et al., 2008),namely

$$\frac{dV_i}{dt} = Q_i^{in} - b_i V_i^{\alpha} \hspace{4cm} 3\text{-}5$$

where Q_i^{in} is the reservoir inflow rate, V_i is the reservoir volume stored, b_i represents the geometric and physical characteristics of the reservoir, and α is an exponent parameter. Table 3-1 summarizes the expressions used for b_i and α in equation 3-5 in relation to their reservoirs within a cell.

Table 3- 1: Mathematical expression of b_i and α for the three reservoirs from Théo Vischel et al. (2008).

Reservoir	b_i	α
Soil	$b_i = \frac{C_{si}X}{X^{2\alpha}}$ with $C_{si} = \frac{L_i K_{si}\tan(\beta_i)}{(\theta_{si}-\theta_{ri})^{\alpha}L_i^{\alpha}}$ where: L_i- soil depth K_{si}- saturated hydraulic conductivity $\tan(\beta_i)$ – ground slope (β_i) tangent θ_{si} –soil moisture content(saturated) θ_{ri} –soil moisture content(residual) X – horizontal DEM dimension	$\alpha = \alpha_s$ with $2 \leq \alpha_s \leq 4$ where: α_s – pore size distribution (Brooks and Corey, 1964)
Overland	$b_i = \frac{C_{oi}X}{X^{2\alpha}}$ with $C_{oi} = \frac{1}{n_{oi}}\sqrt{\tan(\beta_i)}$ where : n_{oi}- Manning's roughness coefficient $\tan(\beta_i)$ - ground slope (β_i) tangent X – horizontal DEM dimension	$\alpha = \alpha_o = {}^{5}/_{3}$
Channel	$b_i = \frac{C_{ci}W_i}{(XW_i)^{\alpha}}$ with $C_{ci} = \frac{1}{n_{ci}}\sqrt{\tan(\beta_i)}$ where: W_i – channel width n_{ci} – Manning's roughness coefficient $\tan(\beta_i)$ - ground slope (β_i) tangent	$\alpha = \alpha_c = {}^{5}/_{3}$

Evapotranspiration (ET) is a crucial process in any hydrological balance estimation. This process describe conversion of water to water vapour from the soil, open water surfaces as well as vegetation cover. Evapotranspiration can be grouped into actual evapotranspiration (ET$_a$) which describes all the processes by which liquid water in open surface becomes atmospheric water vapour and reference evapotranspiration (ET$_r$) which is maximum rate of evapotranspiration from a vegetated catchment under conditions of unlimited moisture supply (Xu et al., 2006). Weather conditions, water availability, vegetation properties and environmental constraints are major components in estimating evapotranspiration rate (Zanetti et al., 2007).

PyTOPAKPI requires evapotranspiration data either estimated or available historical data in its model computation. Actual evapotranspiration is used in the model evapotranspiration module formulation. In this way, the evapotranspiration is extracted in a channel at the rate of the reference evaporation from a free water surface. On each cell i, the actual evapotranspiration ET$_a$ is computed by multiplication of the reference crop evapotranspiration ET$_r$ with a constant crop factor K$_c$ and the current saturation of the reservoir computed at each time-step t (ratio of the effective (V$_s$) and maximum (V$_{max}$) soil water content) (Théo Vischel et al., 2008). The mathematical formulation for PyTOPKAPI actual evapotranspiration is,

$$ET_{ai}(t) = K_{ci} \frac{V_{si}(t)}{V_{s\,max\,i}} \; ET_{ri} \qquad\qquad 3\text{-}6$$

where ET$_a$ is the actual evapotranspiration, K$_c$ is the crop factor, V$_s$ and V$_{max}$ are effective and maximum soil water content, ET$_r$ is the reference evapotranspiration while t is the time .

It has been argued that estimation of evapotranspiration is difficult in some regions such as semi-arid and arid due to the large amount of low and sporadic precipitation returning into the atmosphere via evapotranspiration (Ayyoub et al., 2017, Kiafar et al., 2016). The formulation of PyTOPKAPI evapotranspiration allows the process to be highly dynamic over time, variable in space while also gives a precise estimate of evapotranspiration in regions where it is difficult to estimate.

Conclusively, though the model has not been tested on an ungauged catchment, it has been reported that the model may have high potential in simulating hydrological characteristics in an ungauged catchment considering its robust model formulation which reflect physical reality (Sinclair and Pegram, 2013). Thus, it is imperative to investigate the potential of PyTOPKAPI in modelling ungauged catchment. The model setup will be described in the following chapter.

CHAPTER 4

METHODOLOGY

This chapter describes research methodological approach used in this study. It starts with an overview of data preparation and model input requirements. It was then followed by the approach used for continuous streamflow time series. Finally, it gives details of the method used for the model setup and calibration.

4.1 Input data

In any physically based hydrological model, two major types of input data, namely; static and dynamic are required. Topography (DEM), soil-type, and land use data are typical static inputs while precipitation and evapotranspiration are typical dynamic input data (Parak, 2007). Depending on the scope of the project, the PyTOPKAPI model requires a minimal amount of data. This data can be available from field measurements or remotely sensed observations. Preparation of the data is time-consuming process and the most important aspect of this study.

In PyTOPKAPI model, runoff production is routed through grid cells. The model use seven important parameters that are necessary for runoff production. These parameters are obtained from soil characteristics, and land use components (Vischel et al., 2008a). Five of these parameters relates to the catchment soil characteristics. They include: L (thickness of the surface soil layer, in m), K_s (the saturated hydraulic conductivity of this layer in m/s), θ_s (saturated moisture content of the soil), θ_r (residual moisture content of the soil), α_s (pore-size distribution for the transmissivity of the soil). While n_o and n_c (surface and channel roughness coefficients respectively) are related to routing of runoff, over the channel and hill-slope (see model equation in section 3.4). These parameters may be source from direct field measurement or from the literature.

The DEM is the most important data in the model. It describes the topographic and geomorphologic element of the catchment from which the surface slopes, drainage area, flow pathways identification and drainage network/stream networks detection can be generated. Each pixel of a DEM results in the primary unit of the processing cells in the model. The generation entails the use of GIS techniques in manipulating, analyzing and preparing the data.

Figure 4-1 shows the processes involved in analyzing the terrain data for PyTOPKAPI input. These are further explained in the sub-sections below.
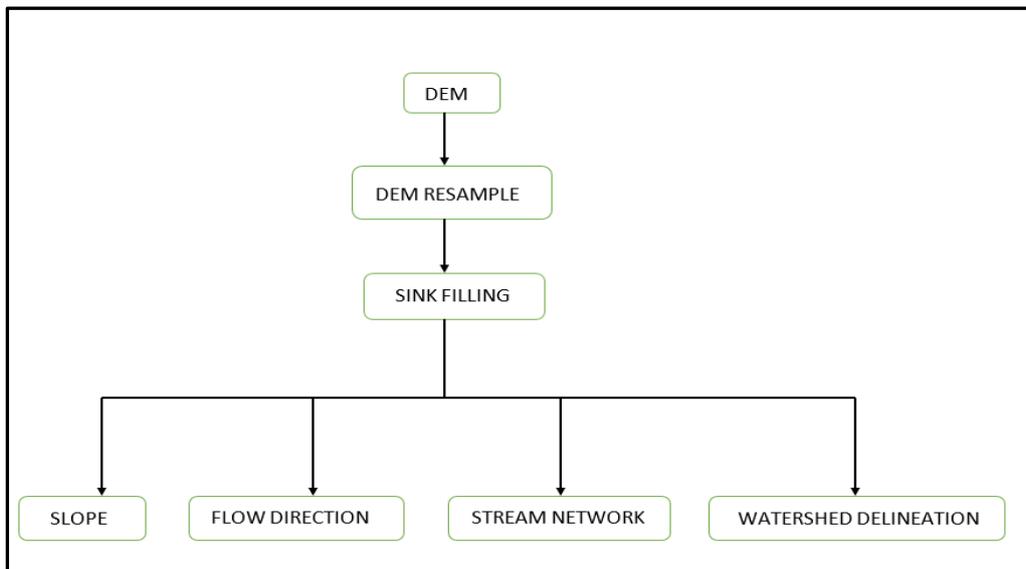
Figure 4-1: The terrain data process flow chart.

4.1.1 DEM application in the PyTOPKAPI model

Digital elevation data derived from the Shuttle Radar Topography Mission (SRTM) was used in this study. The data was obtained from the geographic database of the United States Geological Survey (USGS) with a resolution of 1 arc-second (30 meters). It is an open distribution of high-resolution global elevation data. The 30m resolution required about 6000 cells to cover the 80km² case study catchment since the PyTOPKAPI model is designed to estimate flow from each grid cell. The higher the grid cell count the longer the computational times. Following Pegram and Sinclair (2012), a compromise resolution of 500m was selected to reduce computational time while retaining sufficient details to accurately identify and resolve the flow pathways and detect the stream networks. Other resolutions (30m to 1000m) were tested before settling on 500m as an appropriate choice for this study. Following Théo Vischel et al. (2008), the spatial scale for grid models is valid up to 1000m.

Sinks occurrence (local low points) are common problem faced in using DEM data in hydrological models. These are areas that do not drain out at a specific point due to higher elevation than the neighboring surroundings (Zhu et al., 2013). The DEM obtained was therefore treated to allow downslope routing of water where the drainage network provides a

flow path for every cell. Figure 4-2 shows the re-sampled DEM from 30m pixel resolution to 500m pixel resolution.
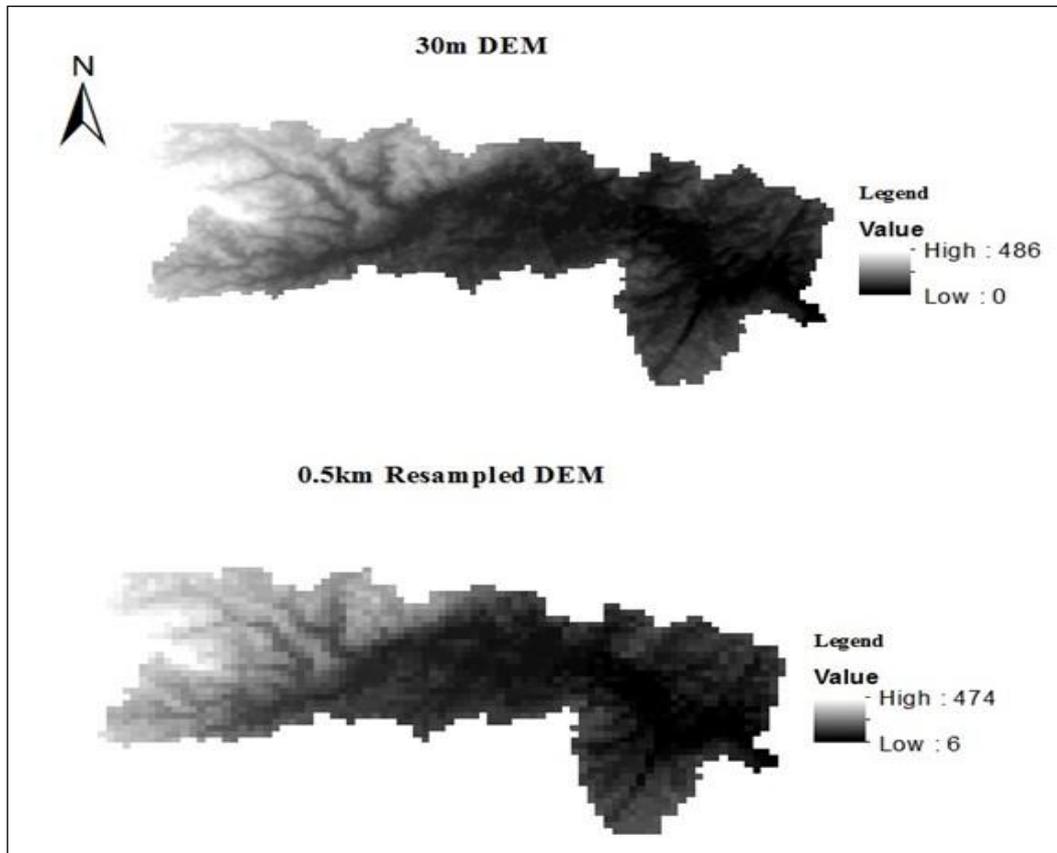
Figure 4- 2: DEM of Mhlanga catchment: 30m resolution (upper) & re-sampled to 0.5km resolution (lower)

4.1.2 Flow direction

The direction of flow in any hydrologic modeling shows the direction at which the landscape drains. The elevation data is used to represent the direction of flow for each cell in such a way that for every cell in the surface grid, the direction of steepest downward descent is located. Thus, for accurate representation of flow direction, DEMs free of sinks as discussed in section 4.1.1 must be used.

 Parak (2007), O'callaghan and Mark (1984) suggest a procedure that can be widely used for this purpose. The process is referred to as D8 flow model. In this process, pixels are in the center of the DEM grid point and each pixel spills into one of its eight surrounding cell (the one in the direction of the steepest flow). A code is assigned to each cell showing the direction

which each cell drains (shown on the top right of Figure 4-3) based on the direction codes shown in the bottom of the panel of Figure 4-3. These codes are different from elevations, rather, depends on the direction of greater slope calculated as the greater difference in elevation divided by the horizontal expanse from the Centre of the active cell to the centre of the eight neighboring cells. Figure 4-4 shows the flow direction raster calculated on ArcGIS for Mhlanga catchment.
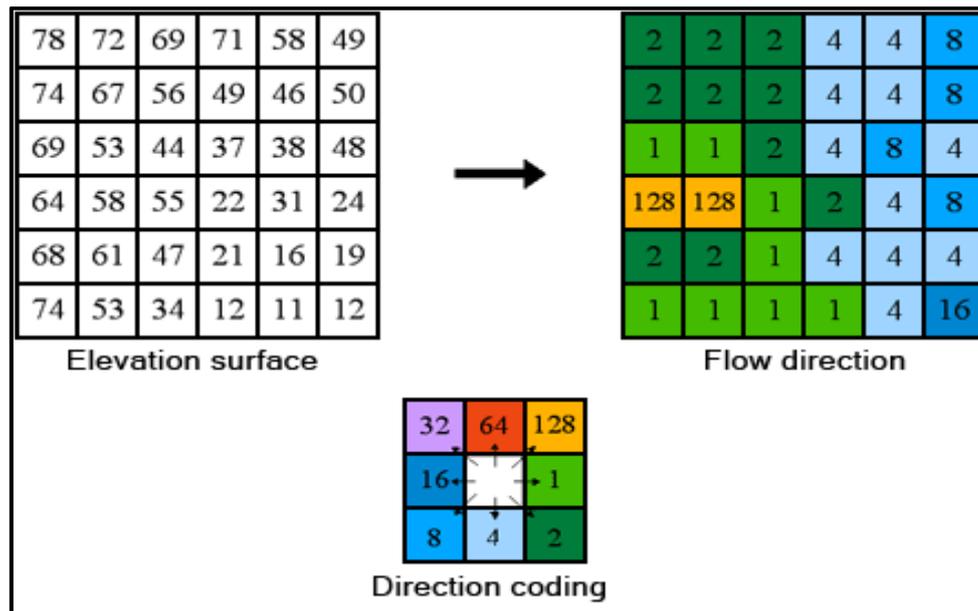
Figure 4- 3: The D8 flow model adapted from Parak (2007). Given a DEM (on the top left of Fig. 4-3), a drainage direction code is assigned to each cell (shown on the top right of Fig. 4-3) based on the direction codes which are shown in the bottom panel.
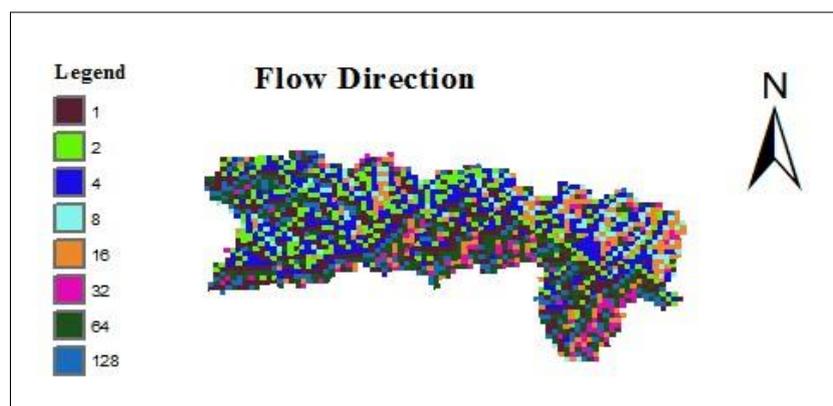
Figure 4- 4: The Flow direction raster for Mhlanga catchment. The codes in the legend explain the flow direction in each cell.

4.1.3   Flow accumulation

Flow accumulation determines the number of cells that accumulate flows into each cell. The flow accumulation is utilized to generate stream network following the flow direction of each cell. A cell that has the highest accumulated flow is selected based on the stream channel. Figure 4-5 shows the accumulation raster of the study area.
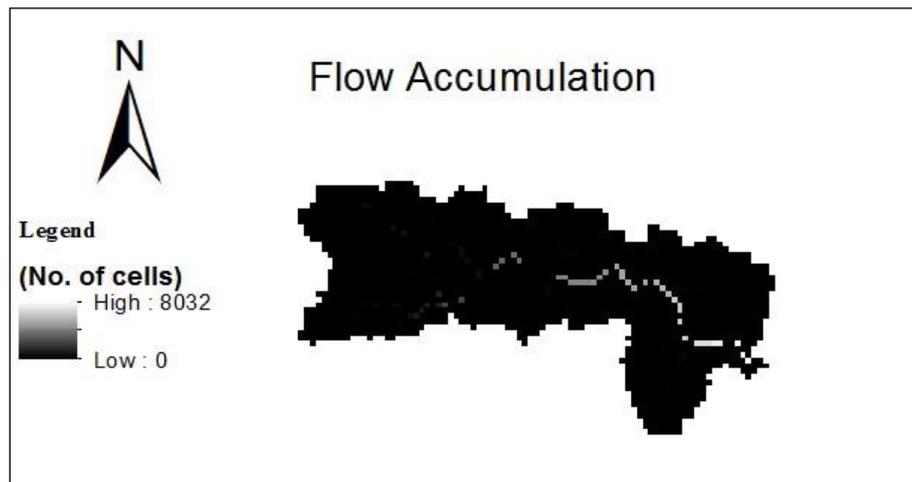
Figure 4- 5: The Flow accumulation raster map of Mhlanga Catchment. The values in the legend indicate the number of upslope cells that feed each cell.

4.1.4 Stream network

The stream network is generated by selecting cells with high flow accumulation and defining a threshold area (total number of upslope cells that creates flow to each cell). The approach explained by Parak (2007) to determine a threshold value is utilized. This approach extract channel network from a topographic map. In Figure 4-6, the comparison of the delineated stream network is shown on the left and a digitized stream network from a topographic map which can be seen on the right of Figure 4.6.
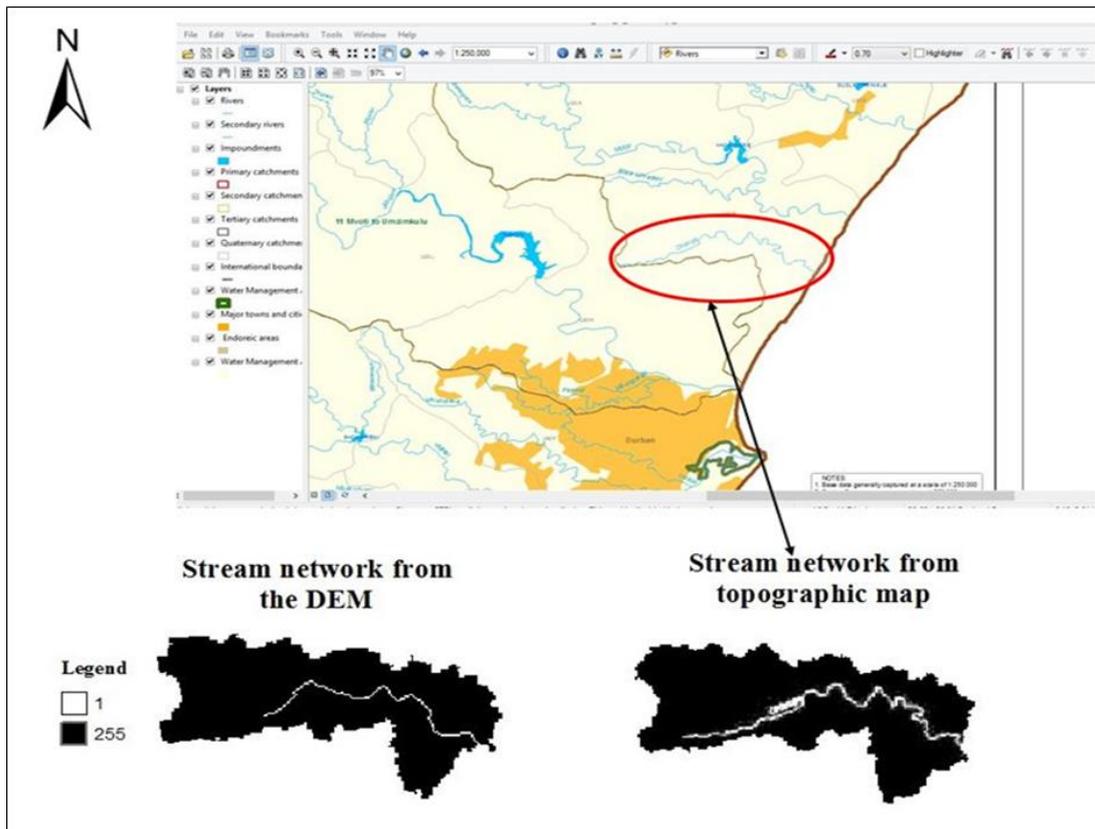
Figure 4- 6: The delineated stream network. The top map represents the base map used to obtain the stream network (topographic map) at a spatial scale of 1:250000 sourced from WR2005 study (Middleton and Bailey, 2008). The down left raster shows the stream network obtained from the DEM at 200 cells threshold value.

4.1.5 Watershed

Watershed is a boundary that represent the contributing area. The purpose of watershed delineation is to show where surface water within the watershed drains. Before watershed can be delineated, pour-point must be selected (watershed outlet) from a stream network. Water within the watershed must drain to one point. This point is located downstream of the grid close to the center of cells. Figure 4-7 shows the pour point interface in ArcGIS.
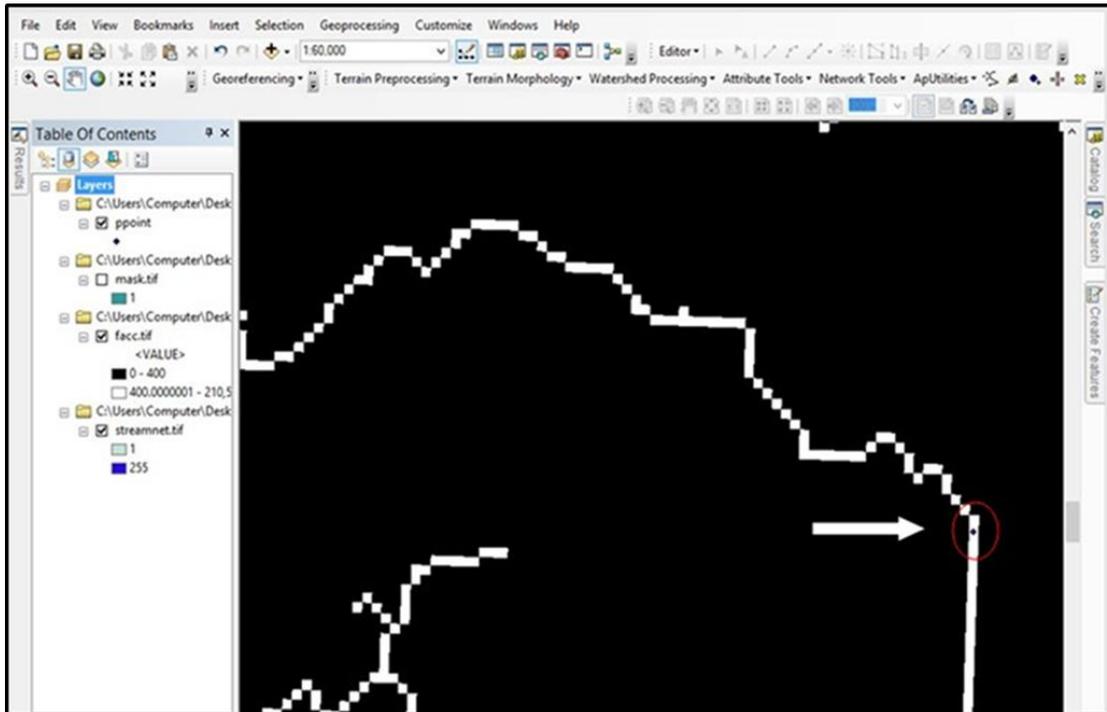
Figure 4- 7: Watershed Outlet. The black dot shows the watershed outlet from the stream network.

The next step in delineating the watershed is to snap pour-point. This method selects high accumulation of flow point when delineating watershed. The snap point locates the cell of highest accumulated flow and shifts the pour point to that location. Figure 4-8 shows the snap point. After selection of outlets point(s), the watershed can now be drawn with the aid of flow direction raster and the direction of flow as its input. Figure 4-9 depicts the delineated Mhlanga Catchment in ArcGIS environment.
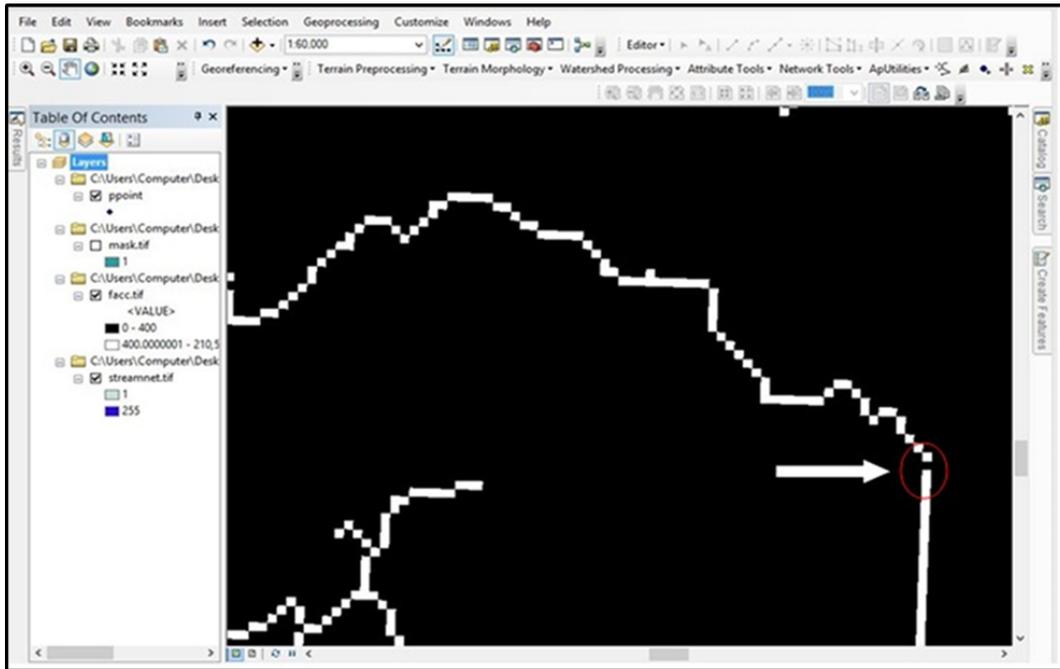
Figure 4- 8: The snapped pour-point. The black point in the circle indicate the shifted pour-point to the cell of highest accumulated flow in the outlet of the watershed along the stream network.
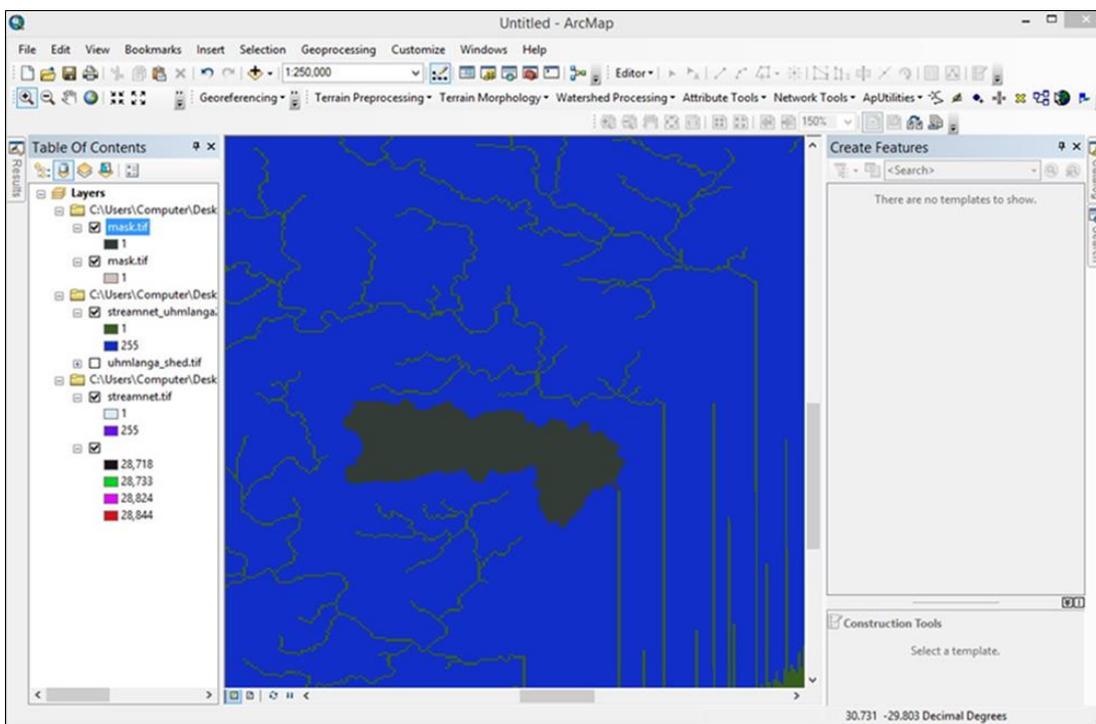
Figure 4- 9 : The delineated watershed. The brown region represent the watershed for Mhlanga Catchment.

4.1.6 Surface slope

Surface slope is one of the topographic characteristics utilized to explain watershed characteristics in any hydrological systems (Wu et al., 2008). It reveals the orientation (steep or flat) of a terrain. Steep slopes are very common in mountainous areas, rolling hills terrain has moderate slopes and flats slopes are common in plains and on plateaus (Fombe and Tossa, 2015, Brand et al., 2011). The surface slope raster for Mhlanga Catchment was generated from the DEM at 500m resolution. The output gives a slope value in either degrees or percentage. However, PyTOPKAPI requires slope in degrees. The lower value of the slope depicts a flat terrain while higher slope value represent steep terrain. Surface slope raster for the Mhlanga catchment is shown in Figure 4-10.
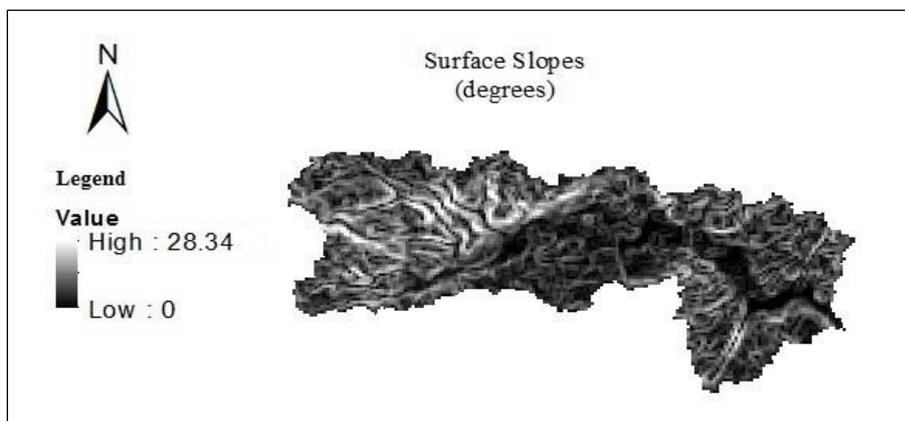
Figure 4- 10: A surface slope raster for the Mhlanga catchment. The values in the legend represent the slope in degrees.

4.1.7 Soil

Soil data map for Mhlanga Catchment was generated from the harmonized world soil database (HWSD). The HWSD is freely available for all continent of the word at 1000m spatial resolution. The resolution of the soil map was downscaled to 500m. The reason for the downscale is to align the soil map with another input map for the PyTOPKAPI model parametrization. Figure 4-11 shows the soil map of the catchment.
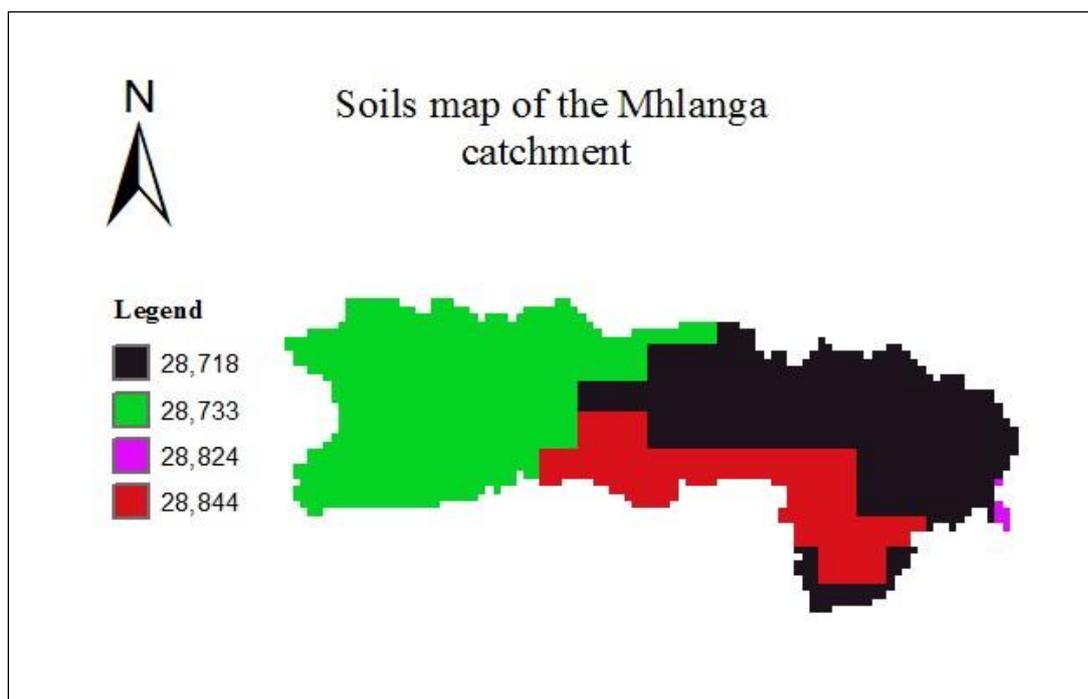
Figure 4- 11: A raster-based soil map of the Mhlanga Catchment sourced from Fao and Isric (2012).

The raster-based soils map legend for the Mhlanga catchment shows a particular code. This code relates to its properties rather than soil type. The related soil properties information is reported in Table 4.1.

Table 4- 1: The soil properties of Mhlanga catchment.

SOIL TYPE CODE	DEPTH(cm)	USDA TEXTURE CLASS
28718	100	10
28733	30	5
28824	10	5
28844	100	11

Source : Fao and Isric (2012)

The U.S department of agriculture (USDA) has grouped soils into classes and are represented by codes. The classes are based on soils texture which defines soil property used to represent the relative proportion of different mineral particle grain sizes in the soil. These particles are grouped according to their size into different soil types. The soil texture classes relate to a particular range of soil type fractions. For further details see harmonized World Soil database documentation (Fao and Isric, 2012). Figure 4-12 shows the soil ID that relates to the soil

texture. Table 4-2 shows the link between USDA texture class codes to their descriptive classes.

Table 4- 2: The relationship between the soil class code to its texture

SOIL TYPE CODE	SOIL CLASS CODE	TEXTURE CLASS
28718	10	Sandy clay loam
28733	5	Clay loam
28824	5	Clay loam
28844	11	Sandy loam
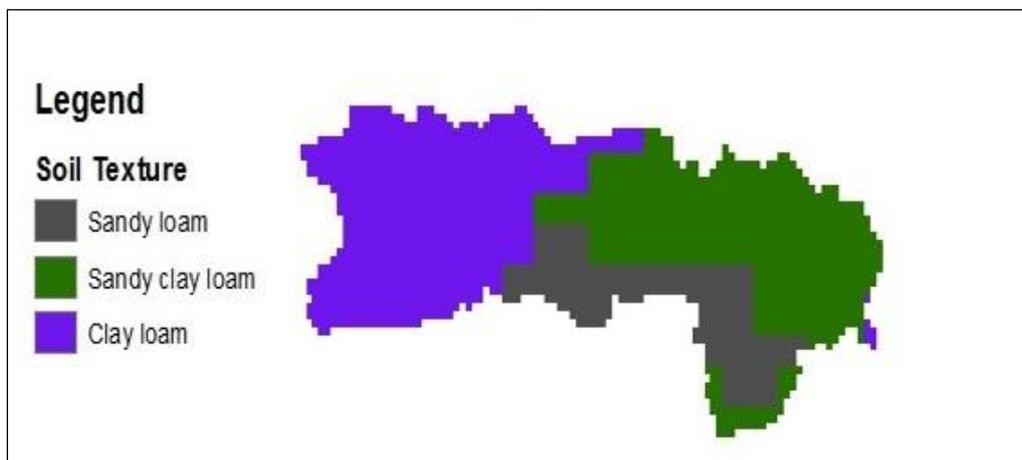
Figure 4- 12: Map that relates soil ID to its texture for the study area

PyTOPKAPI model requires soil parameters such as the soil depth, saturated hydraulic conductivities, moisture contents (saturated and residual), bubbling pressures and pore sizes. The parameter are related to its textural characteristics which can be obtained from literatures. In the study, the parameters was obtained from Rawls et al. (1982) which are summarized in APPENDIX II.

4.1.8 Land cover

 Adequate information on landuse is necessary to accurately represent the watershed hydrology. Information on landuse contains natural and anthropogenic features (Lafontaine et al., 2015). It is used to estimate Manning's roughness coefficients that influence the velocity of the overland water flow (Ayele et al., 2016). Studies show that satellite imagery have now

become an effective method for land cover acquisition. They provide valuable spatially distributed information (Nitze et al., 2015, Netzband and Stefanov, 2004).

Most global land cover maps are produced with minimal concern for their quality (Foody, 2002). Information on their qualities is often time not properly communicated to the users (Chen et al., 2017, Foody, 2002). Land use classification accuracy are needed to give users information on the degrree to which a landuse maps are accurate. In hydrology, watersheds are regarded as containing four major land use classes: water, soil, vegetation, and built-up (Ibrahim and Rasul, 2017, Solomon and Harvey, 1986). This serves as the basis for generating good quality land cover maps using satellite imagery techniques. Similarly, any error in the landcover maps may result in incorrect hydrological response and may lead to misinterpretation and wrong conclusions. In this study, there is dire need to generate a good quality land cover for PyTOPKAPI model.Figure 4-13 shows the classification process flow chart that is further explained below.
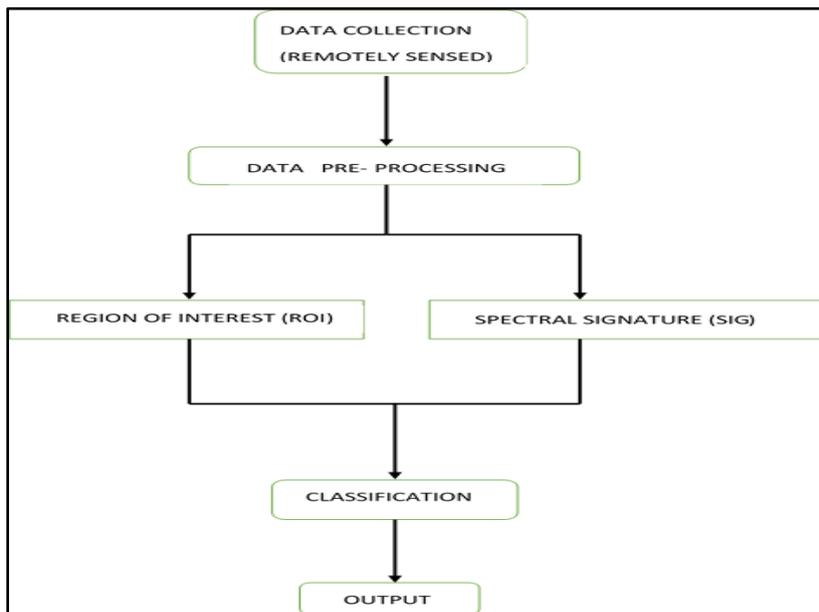
Figure 4-13: The land cover classification process flow chart.

4.1.8.1   Land use data collection

The satellite information for Durban (path/row: 168/81) on August 01, 2015 was procured from United State Geological Survey (USGS). Data from Landsat 8 information was utilized as a

part of this study. Landsat satellite 8 information is chosen because of its high accuracy (high resolution and minimal cloud cover).

4.1.8.2   Data pre-processing

The Landsat data often comes with generic pixel value called the digital number (DN). It is commonly used to describe pixel values that have not yet been calibrated into physically meaningful units. The top of atmosphere reflectance (TOA) is used to convert the pixel values to the real physical reflectance values of a specific land-use/land cover. This was done in ArcGIS application.

4.1.8.3   Spectral signatures for land use classification

A supervised land use classification was done by creating Regions of Interest (ROIs). ROIs are user-defined polygons drawn over similar areas of the image that represent land cover classes. The ROIs are drawn manually which accounts for the spectral variability of land cover classes. Selected ROIs are stored as a spectral-specific polygon shapefile, which serves as a source of spectral signature creation. The SCP will automatically count spectral signatures created from ROIs on the same land use classification which will consider pixel values define on each ROIs. After creating the land cover map for the whole Durban, the mask of the Mhlanga Catchment was used to extract land cover map for the area of interest. This is shown in Figure 4-14.
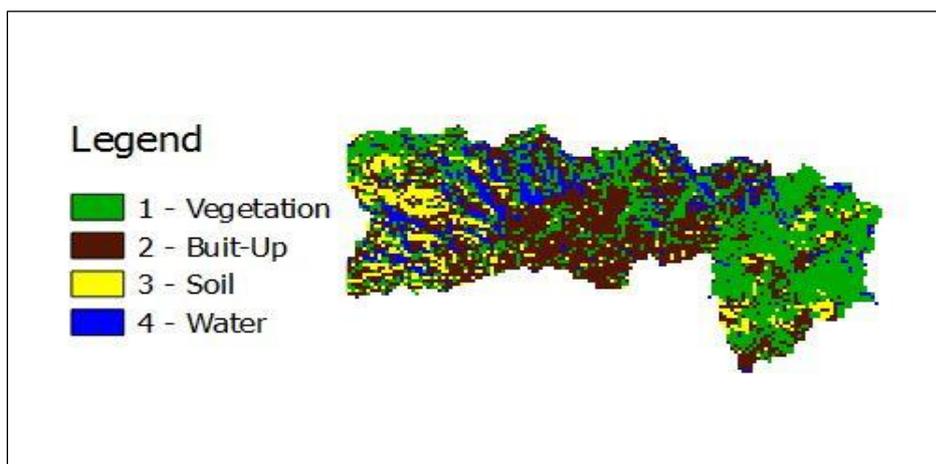
Figure 4-14: Land map classification of Mhlanga Catchment extracted.

PyTOPKAPI model requires the manning's roughness for the overland store. This is used to represent the surface roughness in the model formulation. The land use legend in Figure 4.14 shows the land use type of each pixel. This was used to obtain Manning's roughness coefficient of the catchment (see Table 4-3).

Table 4- 3: Manning's roughness value for each land use class.

Classification	Description	Manning's Roughness
Vegetation	Mixed shrubland/Grassland	0.05
Urban	Urban and Built-Up Land	0.03
Soil	Barren/Sparsely Vegetated	0.03
Water	Water Bodies	0.035

Source: Asante et al. (2008)

4.1.3.4 Land use classification assessment

Land use classification is incomplete until an estimate of its accuracy is obtained. Estimating the accuracy of land use classification often done by comparison with reference data. Such reference data includes high resolution satellite images and map derived from aerial photo which are believed to reflect true land cover. There are four standard matrices used to estimate accuracy following Congalton (1991), namely;

User's accuracy: It shows the probability that the prediction represent reality. It is calculated by dividing the correctly classified pixels in each category by the total number of pixels that were classified in that category.

Producer's accuracy: It indicates the quality of the classification of training set pixels. This can be calculated by dividing the correctly classified pixels in each category by the number of training set pixels of the corresponding category.

Overall accuracy: It indicates the quality of the map classification. It is the ratio ratio of total number of correctly classified pixels to total number of reference pixels.

The Kappa Coefficient: This is a statistical test used to evaluate how well the classification is performed. As the Kappa Coefficient value tends to unity, it indicate that the classification is significantly better than random.

4.2   Hydro-meteorological data

Hydro-meteorological data including rainfall, wind speed, maximum temperature, minimum temperature, and sunshine-hours, at a daily time-step was obtained from the South African Weather Services (SAWS) and South African Sugar Research Institute weather web (SASRI). Monthly hydrological data was collected at U30B quaternary catchment WR90 study from WR2012 website (Midgley et al., 1994). Table 4-4 lists the relevant weather stations.

Table 4- 4: Information about rainfall stations in the catchment

S/N	Station Name	Station ID	Coordinates		Years
1	Mandini (SAWS)	02716992	-29.1580	31.4020	25 (1986-2009)
2	Virginia (SAWS)	02410766	-29.7720	31.0550	15 (1995-2009)
3	Mount Edge combe (SAWS)	02410729	-29.7060	31.0460	30 (1980-2009)
4	Mount Edge combe (SASRI)	29	-29.7060	31.0460	14 (1996-2009)

Meteorological data is important in any hydrological investigation. However, this data is prone to errors such as missing data or inconsistencies that may not be communicated to users. Thus, it is imperative to ensure the data obtained is reliable. Missing data can be patched using data from other meteorological stations.

The Normal Ratio Method (NRM), which has been successfully applied by various users to patch missing data, was utilized in this study for patching purposes (Sattari et al., 2016, Suhaila et al., 2008, Paulhus and Kohler, 1952). This method is based on a weighted average of precipitation at various stations by the ratios of normal annual or monthly precipitations, namely

$$\text{Px} = \sum_{i=1}^{n} \frac{NR(x)}{NR(i)} * P(i) \qquad\qquad 4\text{-}1$$

where P(i) is rainfall from surrounding stations, NR(x) is the normal rainfall at station x, NR(i) is the normal rainfall at station i, and N is the number of surrounding stations whose data is used for calculation. Rainfall data was subjected to consistency test using double mass curve analysis as shown in Figure 4-15.
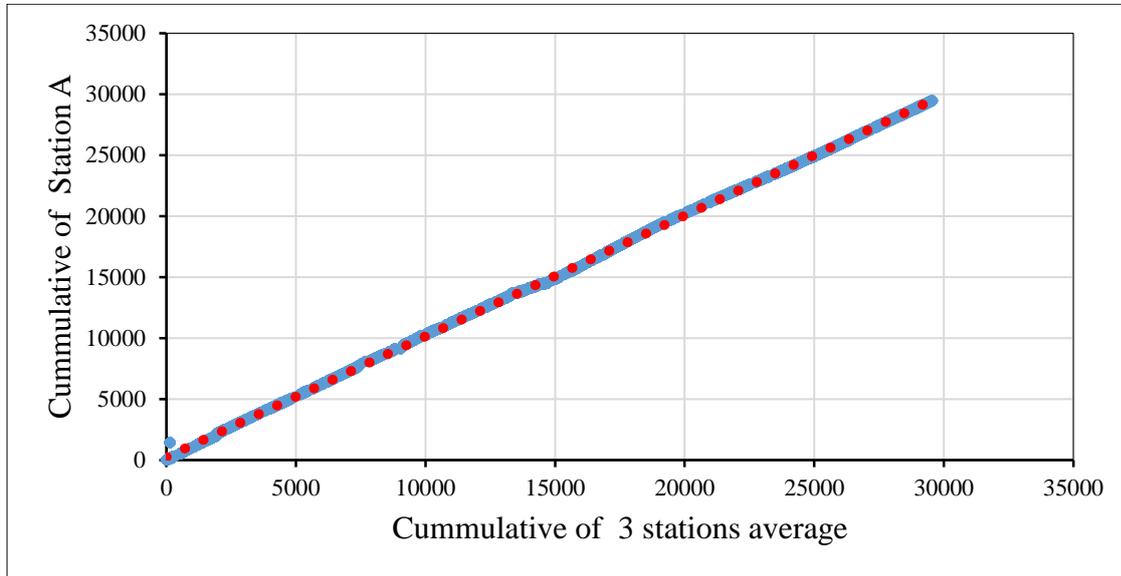
Note: Station A = Mount Edgecombe (SASRI).

Figure 4- 15: Consistency plot of Cumulative rainfall at station A and average of 3 rainfall stations. The red dot represent the trend line. The blue lines represent the rainfall data.

4.3   Evapotranspiration

Evapotranspiration is important in any hydrological model including PyTOPKAPI for proper estimation of water balance. In this study, the FAO Penman-Monteith equation was used for determining reference crop evapotranspiration (ETo). This method was selected because it incorporates wind speed, max/min temperature, relative humidity and sunshine hours data (R. Allen et al., 1998). The input data required wind speed, air temperature (maximum and minimum), sunshine hour, and relative humidity. The data was obtained from the South African Weather Services (SAWS) for a period of 30 years. Equation 4-2 express the reference crop evapotranspiration ET_o given by R. G. Allen et al. (1998)   .

$$ET_o \qquad = \qquad \frac{0.408\Delta(R_n-G)+900\gamma U_2\,(e_s-e_a)/(T+273)}{\Delta+\gamma(1+0.34U_2)} \qquad\qquad 4\text{-}2$$

where ET_o is reference evapotranspiration [mm day-1], Rn is the net radiation [MJ m-2 day-1], G is the soil heat flux density [MJ m-2 day-1], T is the mean daily air temperature at 2 m height [°C], U_2 is the wind speed at 2 m height [m s-1], e_s is the Saturation vapour pressure [kPa], e_a is the actual vapour pressure [kPa], Δ is the slope of the vapor pressure curve [kPa °C-1] and γ is the Psychometric constant [kPa °C-1].

PyTOPKAPI model requires actual evapotranspiration (Et$_a$) in its model setup. The reference crop evapotranspiration ETa described by FAO-56 R. G. Allen et al. (1998) was used. Equation 4-3 shows the relationship.

$$ETa = K_s K_c ET_o$$
<div align="right">4- 3</div>

where K_c is the crop factor and K_s is the Function of soil water availability.

Following T Vischel et al. (2008), PyTOPKAPI was setup to use a crop factor of one for computation of actual evapotranspiration.

4.4   Datasets trending

To analyse the long-term climatic trends in the region, the hydro-meteorological datasets obtained were used. This was done in order to check for the quality for the quality data obtained. Monthly average of rainfall, evapotranspiration, and streamflow for the study period is shown in Figures 4-17 and 4-18. It can be deduced from the plot, that the evapotranspiration and rainfall follow a similar distribution pattern regardless of their different values. Likewise, the streamflow pattern shares similar characteristics with rainfall and evapotranspiration. All these datasets experienced an increase between the months of October and February following a downward trend until a minimum point is reached between June and July. This shows that both rainfall and evapotranspiration contribute to the magnitude of streamflow in the river. Moreover, Figures 4-19 and 4-20 show plot of annual stream flow against annual rainfall and evapotranspiration respectively. However, in an anomalous behavior of the annual streamflow from the year 1982 is evident.
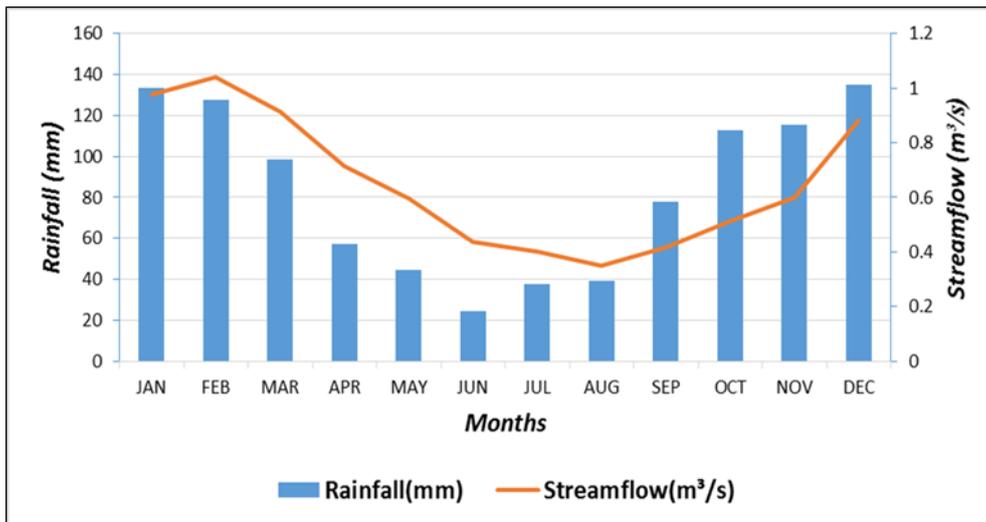
Figure 4- 16: Plot of average monthly rainfall and average monthly streamflow (U30B Quaternary) for 30 years period (1980-2009)
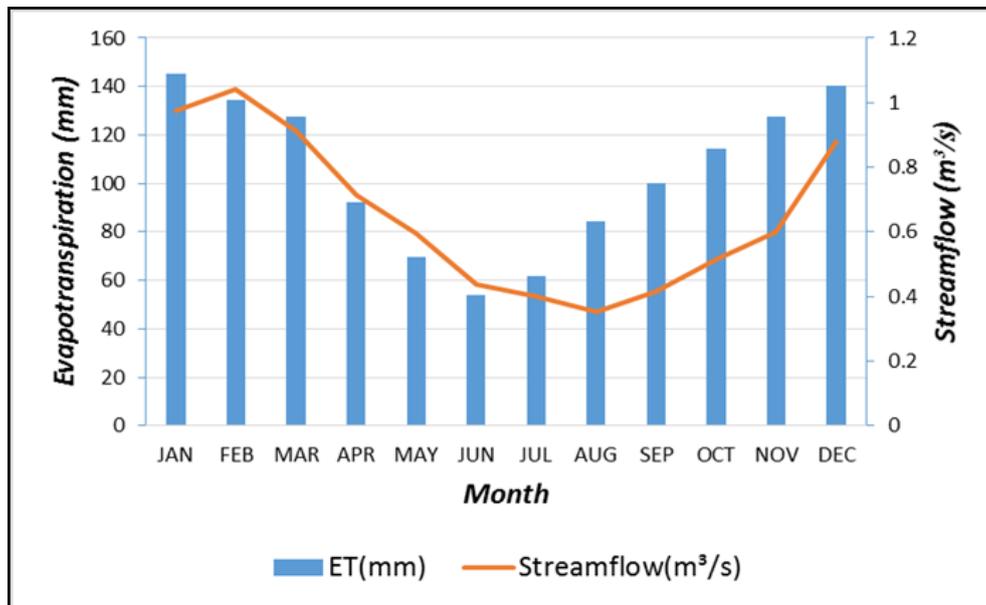
Figure 4- 17**:** Plot of average monthly evapotranspiration and average monthly streamflow (U30B Quaternary) for 30 years period (1980-2009).
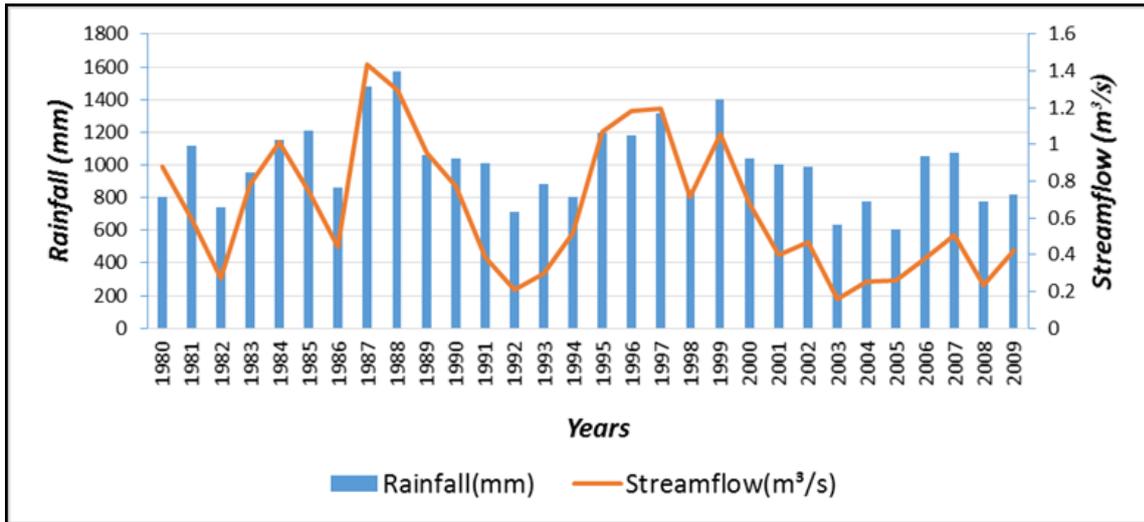
Figure 4- 18: Plot of average annual rainfall and total streamflow (U30B Quaternary) for 30 years period (1980-2009).
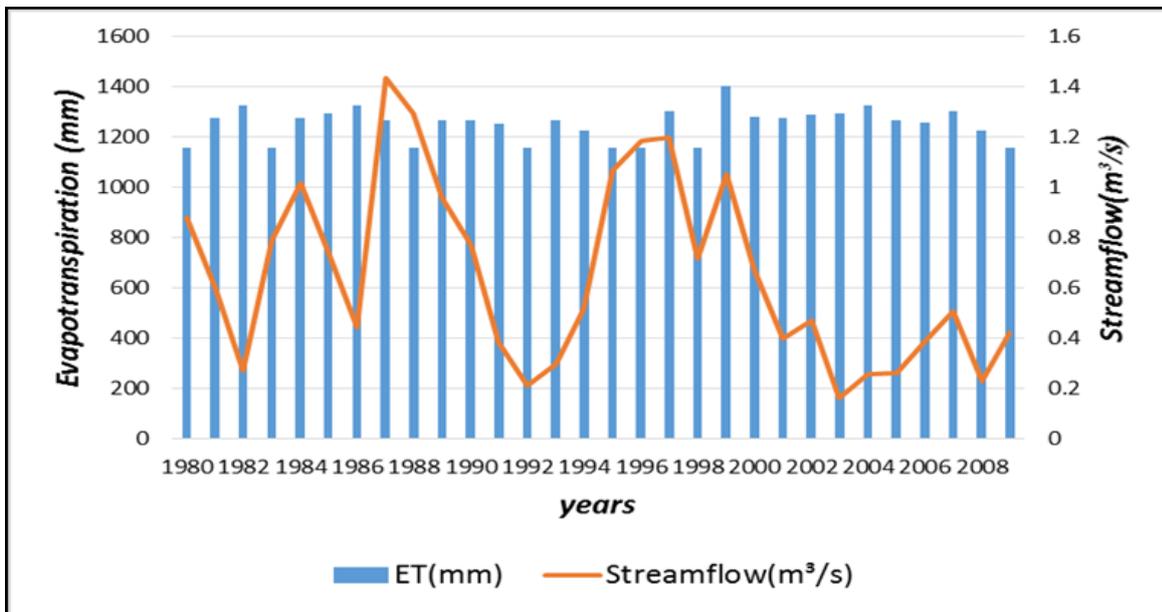
Figure 4- 19: Plot of average evapotranspiration and total streamflow (U30B Quaternary) for 30 years period (1980-2009).

4.5   Disaggregation of monthly streamflow to daily

In South Africa, catchments are grouped into primary, secondary and tertiary hydrological units called quaternary catchments (Maherry et al., 2013). Well trusted 70 year monthly naturalized flow are available at quaternary level across the country (Hughes, 2004). The naturalized flows are generated from Pitman (1973) hydrological model. The model has been widely used in

South Africa for various research and practical water resources assessment and has form the foundation of some water resources development strategies (Hughes and Slaughter, 2015, Pitman, 2011, Middleton and Bailey, 2008, Hughes, 2004, Hughes and Metzler, 1998). The flow are often used as an observed in most cases where there are no gauging stations (Hughes, 2013).

One of the objectives of this study was to show pragmatic steps in generating daily time series streamflow from available monthly streamflow which can be used for various hydrological purpose that require daily streamflow data. Similarly, to compare with the results from PyTOPKAPI hydrological model selected in this study. To achieve this objective, a 30-year monthly streamflow for the U30B quaternary catchment was obtained from the WR90 study (Midgley et al., 1994). The quaternary U30B has a total area of 221km². This includes 80 km² area for Mhlanga Catchment (Hansford, 2003). The disaggregated streamflow can thus be compared with the model results.

The following methods were used in the disaggregation approach:

1. Scaling of monthly flow based on the area is used to calculate the proportion of flow at a quaternary level to the study area. This method is called Drainage area method (DAR). The method performs best when the proportion of source to interested site drainage area is within the range 0.5-1.5 (Fry et al., 2013). In this study, the proposed method by Mohamoud (2008) which addresses the limitation of DAR (accounts for area ratio less than 0.5) was used. This method are expressed as

$$Q_{ungauged} = Q_{gauged} \left(Area_{ungauged} \Big/ Area_{gauged} \right)$$

For ratio between 0.5 & 1.5   4- 4

$$Q_{ungauged} = Q_{gauged} \tan \left(A_{ungauged} \Big/ A_{gauged} \right)$$

For ratio < 0.5   4- 5

2. Spatial interpolation techniques method suggested by Smakhtin and Masse (2000) and Smakhtin (2004) was adopted to generate daily streamflow time series from monthly.

The technique uses flow duration curves constructed from the available monthly flow and current precipitation index generated from daily rainfall data to calculate the exceedance probabilities. Equation 4-6 shows the expression used to generate continuous time series of daily CPI.

$$CPI_t = CPI_{t-1} * K + R_t \qquad\qquad 4\text{-}6$$

where CPI is a current precipitation index (mm) for day t, R_t is the precipitation for day t and k are the daily recession coefficient. Once the CPI is generated, the required CPI duration curve may also be established. The flow of that day is read off from the FDC by matching its exceedance probability with the CPI. Recession coefficient value of 0.92 suggested by Lawrie et al. (2010) was used for this study.

3. Volume adjustment

Having described the practical approach to convert the CPI time series into simulated daily streamflow time series using FDC, it has been argued in section 2.4 that the technique is prone to overestimation of high flows (Smakhtin, 2004, Smakhtin and Masse, 2000, Smakhtin, 2000). Moreover, the final daily time series disaggregated does not equal to its original monthly values when aggregated. A non-linear volume correction method proposed by Slaughter et al. (2015), was used to address these limitations. In this study, the volume correction approach was used to mitigate this limitation namely;

$$DC_i = D_i + \left(M_j - \sum_{i=1}^{n} D_i\right) * \left(\frac{D_{i2}}{\sum_{i=1}^{n} D_i}\right) \qquad for\ \sum_{i=1}^{n} D_i < M_j \qquad 4\text{-}7$$

$$DC_i = D_i * \left(\frac{M_j}{\sum_{i=1}^{n} D_i}\right) \qquad for\ \sum_{i=1}^{n} D_i \geq M_j \qquad 4\text{-}8$$

where D_i and DC_i are the initial and corrected daily simulated volumes for day i and month j, M_j is the month volume for month j i.e. the monthly flow obtained from WR90 study at U30B quaternary catchment.

4.6 Model calibration approach

Rainfall-runoff models explain hydrological processes happening in a catchment. Though most models try to describe all the processes in totality, they give an approximation of real word processes (Ampadu et al., 2013, Seibert and Mcdonnell, 2002, Abbott et al., 1986). In order to simulate the relationship between rainfall and runoff, hydrological model parameters need be determined.

In principle, physically based hydrological model requires no calibration, reason being that its parameters are estimated a *priori* from catchment information such as morphology and hydraulic catchment properties, soil, and vegetation (Liu and Todini, 2002). However, a *priori* information can not sufficiently give an adequate representation of processes being modeled such as spatial variability of catchment characteristics. This is because most of these parameter values are derived by laboratory experiments, average values from different sources or over a region and field observation (Kuchment et al., 2009). These values reflect the assumptions or uncertainties made in generating them (Kuchment et al., 2009).

Uncertainties in model parameters are dominant source of error for hydrologic models (Shi et al., 2014). Hydrologic model parameters nearly always require calibration for specific watersheds before they can produce realistic responses to environmental inputs. Some of these parameters are adjusted by matching streamflow generated by the model with observed streamflow. In most cases, this observed discharge is limited or not available in the exact location of interested study site(s). In such circumstances, models need to be fine-tuned. Thus, the accuracy of runoff simulation is still challenging.

A standout amongst the most fundamental issues in hydrology is to depict and clarify the spatial and temporal variability of the water balance, which is the apportioning of precipitation into runoff (Wolock and Mccabe, 1999). Understanding the water balance component gives a relationship between climatic and hydrologic variables. Since, the hydrological model estimate effects of climate on mean hydrological conditions, knowledge about factors responsible for annual water balance is required. The main factor responsible for the annual water balance is the runoff. Climatic factors have been established to be the dominant control of the spatial variability of annual runoff (Huang et al., 2016, Blöschl, 2013, Wolock and Mccabe, 1999). Hydrological models input largely depend on precipitation. Precipitation is one of the climatic

factors governing spatial variability of runoff. In what way can the climatic signature be used to calibrate a model? Here under focused on how to get a reasonable physically-based PyTOPKAPI model setup using the integral calibration approach as oppose the conventional use of historical streamflow data for the model calibration.

Integral calibration approach

Runoff ratio (%) is proposed as an alternative to streamflow for PyTOPKAPI calibration. It is the ratio of mean annual runoff (flow volume rescaled to catchment area) to mean annual precipitation (in terms of volume). This ratio reveals the water balance in a basin and serves as an indication of how well a model simulates the water balance in a basin given an input information as the ratio represents catchment response to dynamic changes in climate, soil, vegetation among others in the basin. Thus, it offers the same advantage as short or long streamflow data in calibration exercise.

In this study, a method proposed by Schreiber (1904) which shows the percentage of precipitation that appears as runoff in a basin or region was used. It characterizes the natural rainfall-runoff chain in terms of relative excess rainfall, which represents the fraction of water unused in a basin compared to the total water supply (Fraedrich, 2010). This fraction is termed runoff ratio. This method also uses the aridity-runoff relationship as equilibrium solution of the rainfall-runoff chain. The aridity is a ratio of evaporation to precipitation. The aridity describes the degree of dryness of a region or catchment such that if aridity is low, runoff exceeds evapotranspiration for a given precipitation and if aridity is high, water supplied by precipitation evaporates and exceed runoff (Blöschl, 2013). This can be regarded as refers to water surplus and evaporation surplus respectively in the catchment. The model is easy to use and requires two parameters which are precipitation and evaporation or temperature of any site of interest. Equations below describe the Schreiber formula, namely

$$Q = P \, exp(-D) \qquad\qquad 4\text{-}9$$

$$\frac{Q}{P} = exp(-D) \qquad\qquad 4\text{-}10$$

$$D = \frac{ET_o}{P} \qquad\qquad 4\text{-}11$$

where Q - Runoff (mean annual), P-precipitation (mean annual), D-Aridity index, ET_o-Potential Evaporation or Net radiation. The new method of model calibration procedure utilized in this study is the runoff-ratio proposed by Schreiber. On this basis, the runoff ratio was estimated to be 16% for the study area (see Table4-5). Stretch and Zietsman (2004) also reported a similar runoff ratio value from their study in the catchment. Likewise, in water resources of south Africa 2009 and 2012 report (Middleton and Bailey, 2008, Midgley et al., 1994), the runoff ratio for the catchment was reported to be 16%(0.16). This agrees with the scriber runoff ratio estimate. This value was used as a reference for the model calibration (see section 4.7.2). This approach is a new method proposed in this work and was used to calibrate the model as an alternative model calibrating procedure for stream flow generation in ungauged catchments.

Table 4- 5: Information on the Schreiber equation

Schreiber Equation	$Q = P\ exp(-N/P)$
Mean annual precipitation (P)	1000mm (Stretch and Zietsman, 2004)
Mean Annual Potential Evapotranspiration (ET$_o$)	1888mm (present study)
Runoff ratio (Q/AR)	0.16

4.7   PyTOPKAPI model set-up

The model was setup by using the required input data which was prepared for the catchment (described in section 4-1). The data consists of topography, soil characteristics, land use, and other data obtained from the literature. The model set up requires spatial pattern of parameter maps global and forcing files as parameters. These entails catchment boundary, spatial maps of, DEM, soil depth, surface slope, and moisture content (saturated and residual), soil conductivity, manning overland, pore size index and bubbling pressure. These parameters constitute the cell parameters required for PyTOPKAPI (Sinclair and Pegram, 2013). Figure 4-20, 4-21, and 4-22 shows the spatial distribution maps for the model input.

The global parameter file entails geometric characteristics of the channel or grid cell values in the model. These parameters include lateral dimension of the grid cell (x), model time step (Δt), pore size distribution(α_s), power coefficient from manning equation (α_o & α_c) and area with which the cell initiates a river channel ($A_{threshold}$) as well as its maximum and minimum channel width (W_{min} & W_{max}). The forcing file contains rainfall, reference and actual evapotranspiration data in an HDF5 binary file. This is stored in a 2D array, each row representing a single time step and each column a single model cell.
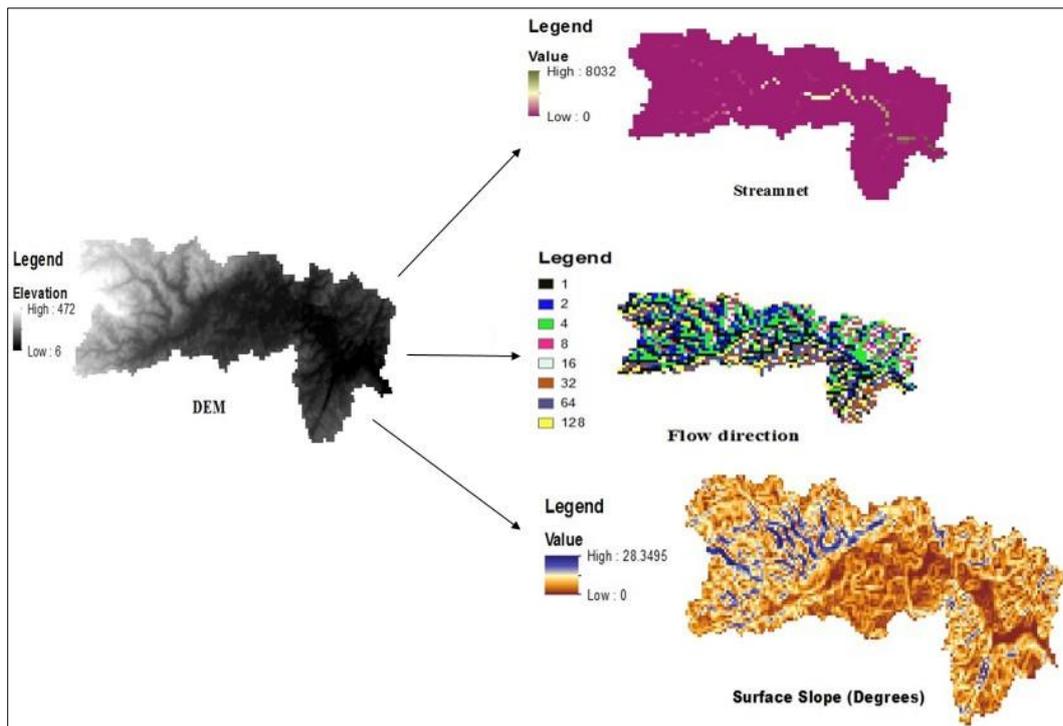
Figure 4- 20: The topographic maps for PyTOPKAPI model input.
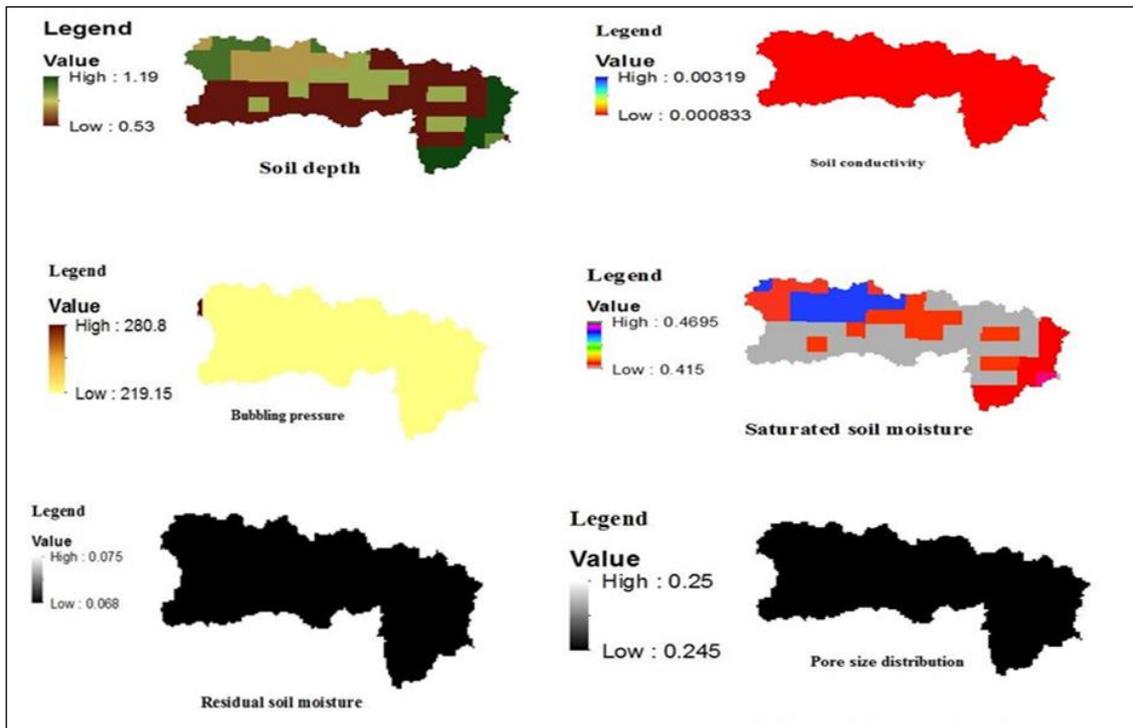
Figure 4- 21: The soil maps for PyTOPKAPI model input.
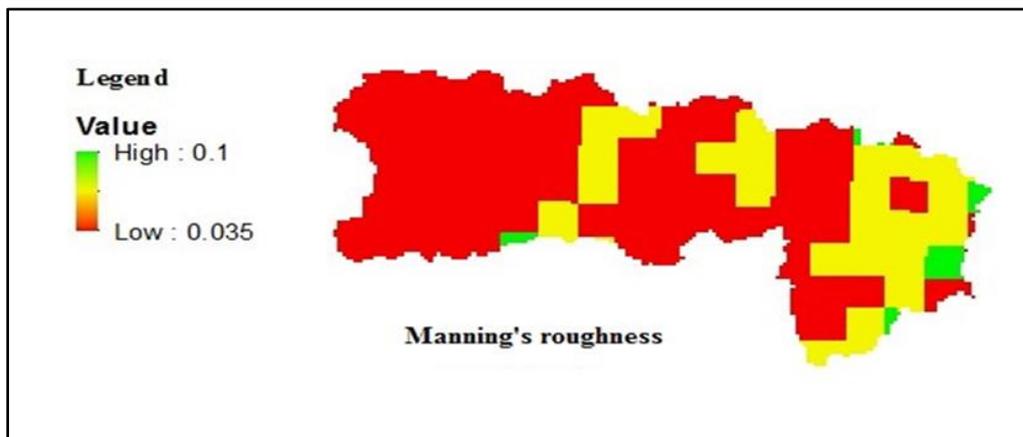
Figure 4- 22: Land cover manning's roughness map.The values in the legend represent manning's coeeficient for different land class.

4.7.1 Sensitivity Analysis

After completing the model setup, the next step is to run the model and analyze the simulation results. The model's appropriateness is then assessed through sensitivity analysis calibration and validation. It is difficult to know which parameter need to be calibrated whilst retaining the physical representation processes being modeled. Sensitivity analysis helps to identify those factors that yield the greatest change in model output. In PyTOPKAPI, Liu et al. (2005)

identified the most sensitive parameters that control the generation of runoff, namely, soil depth, soil conductivity, channel, and overland coefficient.

4.7.2 PyTOPKAPI model calibration

PyTOPKAPI model is a physically distributed model whose parameters represent physical meanings. These parameters can be obtained by direct measurement or through the use of RS and GIS especially in a catchment that is not easily accessible or ungauged. Often time, the model parameters obtained are not of sufficient quality, therefore the model parameters are difficult to define. In light of this, it should be calibrated accurately enough to be used as a default parameter for modeling exercise (Liu and todini 2002).

The spatial pattern of the parameter maps is relevant information that was chosen to be conserved in the calibration procedure by using a multiplicative scaling factor applied uniformly in space to the maps of the a *priori* parameters. For our application the 4 multiplicative factors to be applied were F_L (for the soil depth), F_K (for the hydraulic conductivity), Fn_o (for the overland roughness) and F_{nc} (for the channel roughness). Amongst the model parameters, soil conductivity and soil depth are the most significant in terms of sensitivity in such that slight changes in these parameters affects the model output. Other parameters such as manning roughness coefficient of channel and overland are of less significance to model output. This was set to its default values.

Accurate model parameters gives a better understanding of the catchment behavior. In this study, the dataset obtained for the period of 30 years was divided into two periods (15 years each) namely period 1, 1980-1994 and period 2, 1995-2009 (. Datasets in period 1 (1980-1994) was used to obtain the model parameters using the approach described in section 4.6. The choice of 15 years was adopted to accommodate the span of wet and dry season conditions in the area. Foglia et al. (2009) and Li et al. (2010) also suggest that calibrating data series with a span of at least 8 years is sufficient to give more consistent optimal parameter values in a more consistent simulation. The first year (1980) of the simulation was used as a warm-up period to obtain initial soil water storage. This ensures that the initial value at the beginning of the simulation period is representative of average conditions in the watershed. The mean annual runoff to the mean annual precipitation were estimated from the PyTOPKAPI model result and precipitation input respectively. This ratio was then compared with the reference ratio (runoff

ratio estimated from Schreiber). The model parameters was adjusted by trial and error until an appreciable agreement was reached between the simulated runoff ratio and the target runoff ratio (Schreiber). The optimal model parameters were obtained values without losing its real physical representation. Table 4-3 summarize the model initial estimated parameters post calibration multiplying factor values and retained.

Table 4- 6: PyTOPKAPI parameters initial values from literature and post calibration multiplying factor values of the retained after calibration**.**

Spatially distributed parameters		Parameter range	Source	Post-calibration Multiplying factor value	
Ground Slope tangent	$tanβ$	0.0018-0.1717	DEM(USGS)		
Channel slope tangent	$tanβc$	0.00044-0.024	DEM(USGS)		
Soil layer depth (m)	L	1-0.1	Soil type map (Fao and Isric, 2014)	Fac_L	1.0
Saturated hydraulic conductivity (m/s) Ks		6.38E-4 – 7.19E-3	Soil texture map (Rawls et al., 1982)	Fac_K	0.68
Residual soil moisture content (cm³/cm³) $θr$		0.41 -0.75	Soil texture map (Rawls et al., 1982)		
Saturated soil moisture content (cm³/cm³) θs		0.33-0.412	Soil texture map (Rawls et al., 1982)		
Manning's surface roughness coeff.	no	0.03 – 0.12	Landuse map(Asante et al., 2008, Glcc, 1997)	Fac_{no}	1.0
Manning's channel roughness coeff.	nc	0 – 0.05	(Théo Vischel et al., 2008)	Fac_{nc}	1.0
Soil pore size	λ	0.194 - 0 .32	Soil texture map (Rawls et al., 1982)		
Soil bubbling pressure	$psib$	146.6 – 280.8	Soil texture map (Rawls et al., 1982)		
Global parameters					
Horizontal Dimension of cell(m)		500	DEM		
Max. Channel width at outlet(m)		25	Aerial photograph		
Min. Channel width(m)		5	-		
Area required to initiate channel(m) A *threshold*		25000000			
Pore size distribution	$αs$	2.5	(Théo Vischel et al., 2008)		
Power coefficient	$αo$ & $αc$	1.667			
time step	Δt	86400	-		

4.8 Efficiency Criterion

In order to determine the potential of a developed model, its performance is usually appraised against one or more criteria. In this study, The Nash and Sutcliffe (1970) and coefficient of determination, a statistical method, widely used to evaluate the predictive accuracy of hydrological models will be used. The Nash coefficient is expresses as one minus the sum of the absolute squared differences between the simulated and observed values normalized by the variance of the observed values during the period under investigation. It is given by;

$$\text{Nash} = 1 - \frac{\sum_{i=1}^{n}(Obs - Sim)^2}{\sum_{i=1}^{n}(Obs - \overline{Obs})^2} \qquad \text{4-12}$$

Where Obs is the observed flow while, Sim is the simulated streamflow while $\overline{Obs}$ Sim is the mean of observed flow. The values of Nash range from $-\infty$ to 1(perfect agreement).

The coefficient of determination r² is defined as the squared value of the coefficient of correlation according to Bravais Pearson. It is calculated as:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(Oi - \bar{O})(Pi - \bar{P})}{\left(\sqrt{\sum_{i=1}^{n}(Oi - \bar{O})}\right)\left(\sqrt{\sum_{i=1}^{n}(Pi - \bar{P})}\right)} \right) \qquad 0 \leq R^2 \leq 1 \qquad \text{4- 13}$$

with O observed and P predicted values

It estimates the combined dispersion against the single dispersion of the observed and predicted series. The range of r² lies between 0 and 1 which describes how much of the observed dispersion is explained by the prediction. A value of zero means no correlation at all whereas a value of 1 means that the dispersion of the prediction is equal to that of the observation.

CHAPTER 5

RESULTS AND DISCUSSION

This chapter presents key results from the study focusing on landcover, the model calibration and validation. It ends with concluding remarks.

5.1 Land use/cover map result

Based on the satellite image classification and ground based (google earth image) observation of the current land cover situation, four major land use types were identified in this study. These includes: built-up area, vegetation, bare-soil and water. The land cover classification of the area shown in Table 5-1 reveals that majority of the study area is covered by built-up areas up to 32.1 km², which contributes 40% of the total area. The aerial coverage of the vegetation covers 31.1 km² (39%) of the total catchment area. Furthermore, soil and water classification covers an area of 8.4 km² (10%) and 8.5 km² (11 %) respectively.

The dense built-up area in the watershed indicates that as urbanization catch-up with the watershed, the vegetation/bare soil is replaced by impervious surfaces, which may lead to rapid runoff. This can result to an increase in frequent flooding in the watershed. The dense vegetation cover reveals the potential degradation of the river water quality due to the potential washing down of the excess agricultural land nutrient from the watershed down into the river in the study area. Moreover, runoff might be affected by the presence of vegetation through rainfall interception and evapotranspiration in the catchment.

Table 5- 1: Information about the land cover area

S/N	Land cover class	Area (km²)
1	Built-up area	32.1
2	Bare-soil	8.4
3	Vegetation	31.1
4	Water	8.5

Classification accuracy assessment report presented in Table 5-2 described how well the classification represents the real world when compared to ground-based data. Standard accuracy measures were utilized as explained in section 4.1.8. The high percentage values of the producer's accuracy reveal how well the land classes are classified. The high percentage values of the user's accuracy depict the reliability of a pixel class on the map, which represents the category on the ground. The overall accuracy of land use/land cover (97.8%) is determined by calculating the sum of values in the diagonal positions and dividing them by the total number of pixels that were assessed. The kappa statistics value of 0.967 shows a good agreement between classification map and reference map (ground-truth).

Table 5- 2: Classification accuracy assessment report

Land cover class	2015	
	Producer's accuracy	User's accuracy
Vegetation	98.6%	92.2%
Built-up area	96.4%	95.5%
Bare soil	95.8%	99.8%
Water	99.8%	99.4%
Overall accuracy	97.8%	
Kappa statistics	0.98	

5.2   PyTOPKAPI Simulation results

All the model default parameters were preserved except for initial soil moisture volume, soil conductivity and soil depth (see Table 4-6). In absence of quantitative information of the soil moisture, the initial soil moisture volume was adjusted during the warm-up process and set at a practical value of 60 %.

As discussed in section 4.7, the model parameters (soil conductivity and soil depth) was obtained by adjusting the parameters until an agreement was reached between the model runoff ratio and estimated Schreiber runoff ratio taking into consideration that the parameters must represent physical meaning. PyTOPKAPI runoff ratio was estimated by the ratio of the mean annual runoff generated by the model to its corresponding mean annual precipitation (in m³).

The datasets in period 1 was used to obtain the model parameters. It was observed that several combinations of the PyTOPKAPI parameters produced runoff ratios comparable to Schreiber's estimate (16% ± 1%). However, there is a need to select an optimal combination of the model parameters in which its physical meaning will be well represented. To this end, a statistical measure – the coefficient of variation (CV) - was used as an additional matching criterion to determine the optimal combination of calibration parameters. Studies have shown the effective use of CV for model parameter selection to reproduce temporal variability in runoff (Berhanu et al., 2015, Kuzuha et al., 2009, Bárdossy, 2007). Bárdossy (2007) applied CV to identify unique parameters for the HBV model for an ungauged catchment.

Figure 5-1 shows the different combination of the model parameters (with scaling factors F_L and F_K) and their corresponding runoff ratios. It can be observed that the model estimated the runoff ratio (Q/AR) to be 0.16(16%) (See Figure 5-3) at $F_K = 0.68$ and $F_L = 1.0$. This runoff ratio corresponds to the estimated using Schreiber equation. Figure 5-2 shows the different combinations of the model parameters and their corresponding CVs. The CV of 5.0 was obtained at $F_K = 0.68$ and $F_L = 1.0$. Similarly, the model result from this combination was further compared with the monthly disaggregated flow for the same period, 1980-1994. These model parameters also produced a CV (5.0) comparable to the CV obtained (4.83) for daily time step flow obtained from disaggregated monthly flows for the catchment. Therefore these parameters ($F_K = 0.68$ and $F_L = 1.0$) were chosen for the PyTOPKAPI's model used in this study.

Similarly, a MAR (mean annual runoff) of 0.38 m³/s was estimated by the PyTOPKAPI model upon using the model parameters estimated as above. Previous studies have reported a MAR of 0.4 m³/s for the catchment area (Stretch and Zietsman (2004). This further confirms that an appropriate set of calibration parameters have been selected for use in this study.
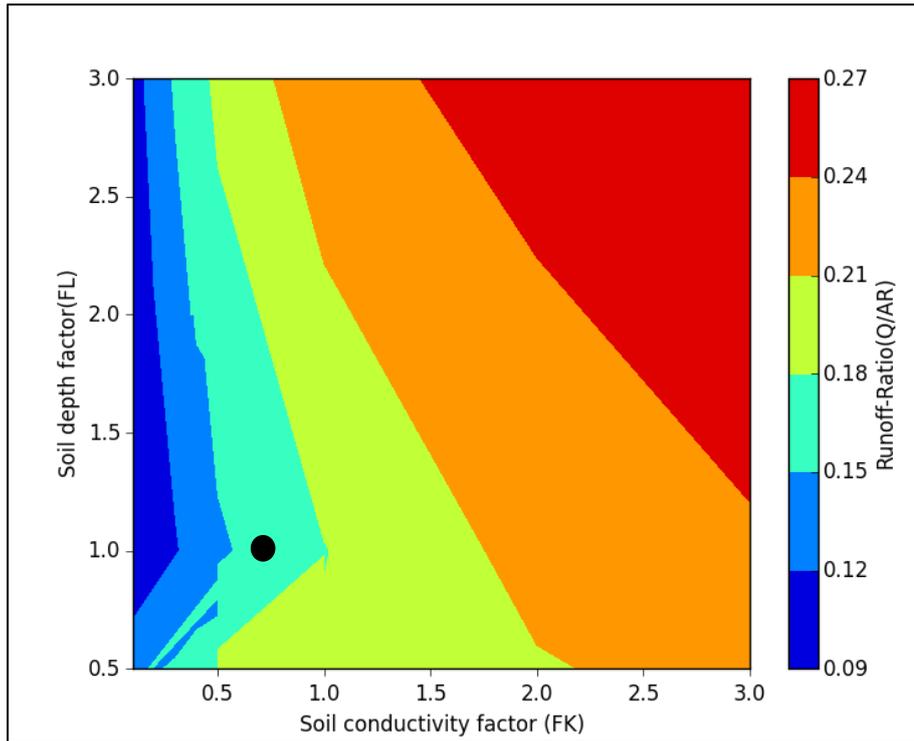
Figure 5-1: Contour plot of different combinations of the model parameter with their runoff ratio estimated. The black dot indicate the combination that gave a satisfactory runoff ratio compared with target value.
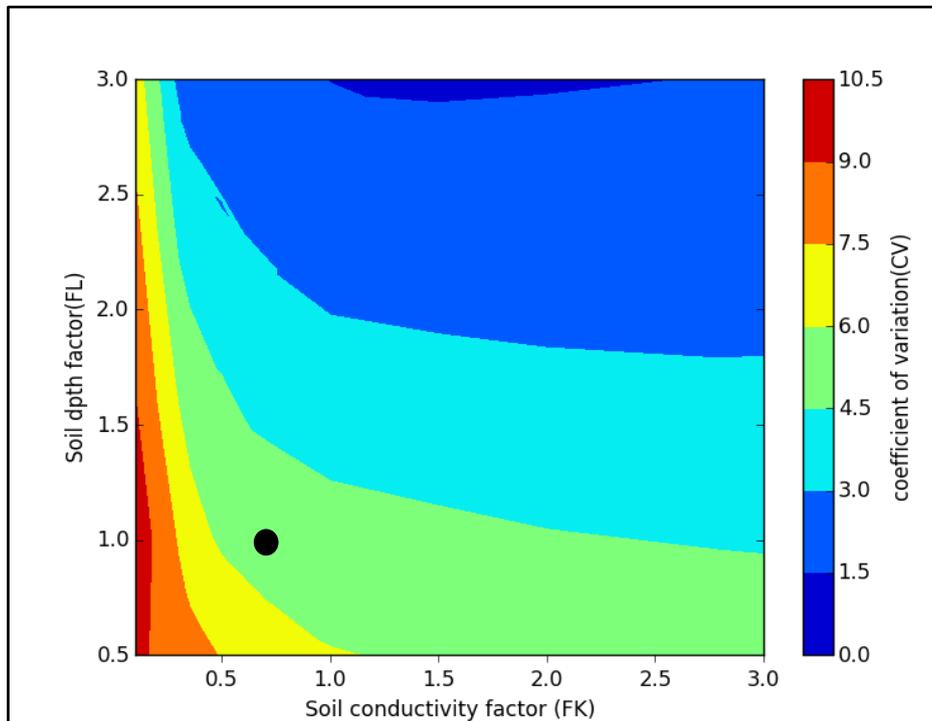
Figure 5- 2: Contour plot of different combinations of the model parameter with their corresponding CVs. The black dot indicate the CV of the combination that gave satisfactory runoff ratio.

Simulation was run for the datasets in period 2 (1995-2009) using the parameter set obtained during the calibration process in period 1, the simulated runoff ratio was 15.5% as shown in Figure 5-4. The runoff ratio and coefficient of determination (R^2) for both period 1 and period 2 period are 0.16, 0.99 and 0.154, 0.96 respectively. The high R^2 value indicate that there is a close agreement. According to Golmohammadi et al. (2014) R^2 value greater than 0.5 is considered acceptable. In general, the simulation results for both periods both agree well with the Schreiber runoff ratio value of 16%.
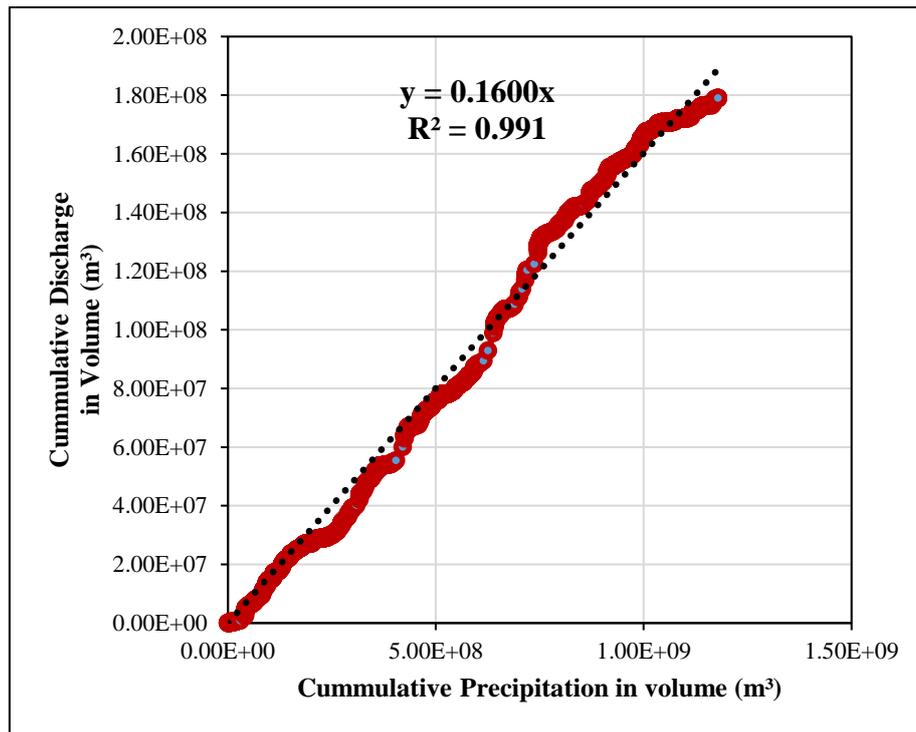
Figure 5- 3: The cumulative plot runoff ratio for model calibration. The red line depict the cumulative discharge and precipitation. The black dotted line shows the line of best fit.
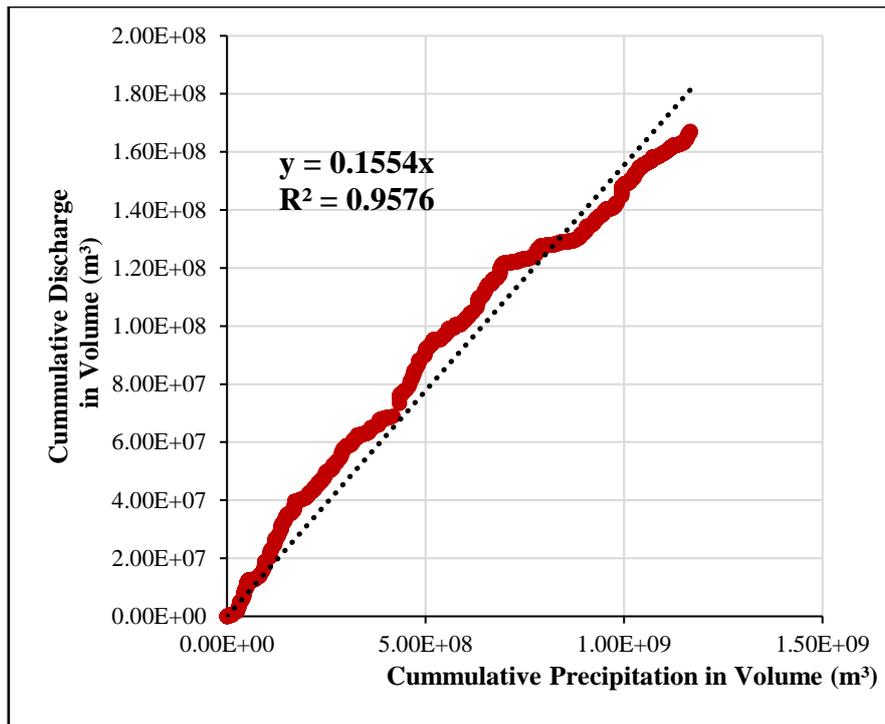
Figure 5- 4: The cumulative plot runoff ratio for model validation. The red line depict the cumulative discharge and precipitation. The black dotted line shows the line of best fit.

The model results from each periods were further compared with the disaggregated monthly flow. As described in section 4-5, the monthly flows were generated from a well-tested hydrological model developed by Pitman (1973) for South Africa's catchments. Hughes (2013) opine that Pitman (1973) model has contributed enormously to the practice of water resources assessment in South Africa. Studies have shown that the Streamflow information generated from this model can used as observed data for hydrological purposes within the country (Middleton and Bailey, 2008, Smakhtin, 2000, Smakhtin and Watkins, 1997). Since the monthly flow serves as observed flows in some cases, the monthly flow was disaggregated to daily time step and further compared with PyTOPKAPI model results. The summary of the disaggregated daily flow compared with simulated is shown in Table 5-3.

Table 5- 3: Results summarizing comparisons with daily streamflow (from disaggregated monthly data) for the datasets periods.

	Period 1 (1980-1994)		Period 2 (1995-2009)	
	Monthly to daily Disaggregated	PyTOPKAPI	Monthly to daily Disaggregated	PyTOPKAPI
Runoff-ratio (%)	16.8	16.00	15.3	15.5
CV	4.8	5.03	3.23	3.63

68

The information in Table 5-3 shows that the PyTOPKAPI model with the selected parameters producers reasonably consistent results in both periods. It was observed that the average runoff ratios and CV values for the period 2 are somewhat lower. This can be attributed to the generally drier conditions in the later period. Nevertheless PyTOPKAPI model reflect similar coefficient of variation when comparably.

Figures 5-5 and 5-7 show time series comparisons between the disaggregated streamflow and PyTOPKAPI streamflow for period 1 and period 2. The performance was expressed using the Nash-Sutcliffe efficiency. The Nash coefficient for period 1 and period 2 was 0.78 and 0.81 respectively. As noted by Pachepsky et al. (2016), model performance is very good if the Nash value is greater than 0.75. Figure 5-6 and 5-8 shows the projected segment of period 1 and period 2. Furthermore, there is an agreement between the simulated and disaggregated flow in terms of timing of peaks coupled with peak value as well as the rising and recession limbs of the streamflow hydrographs.
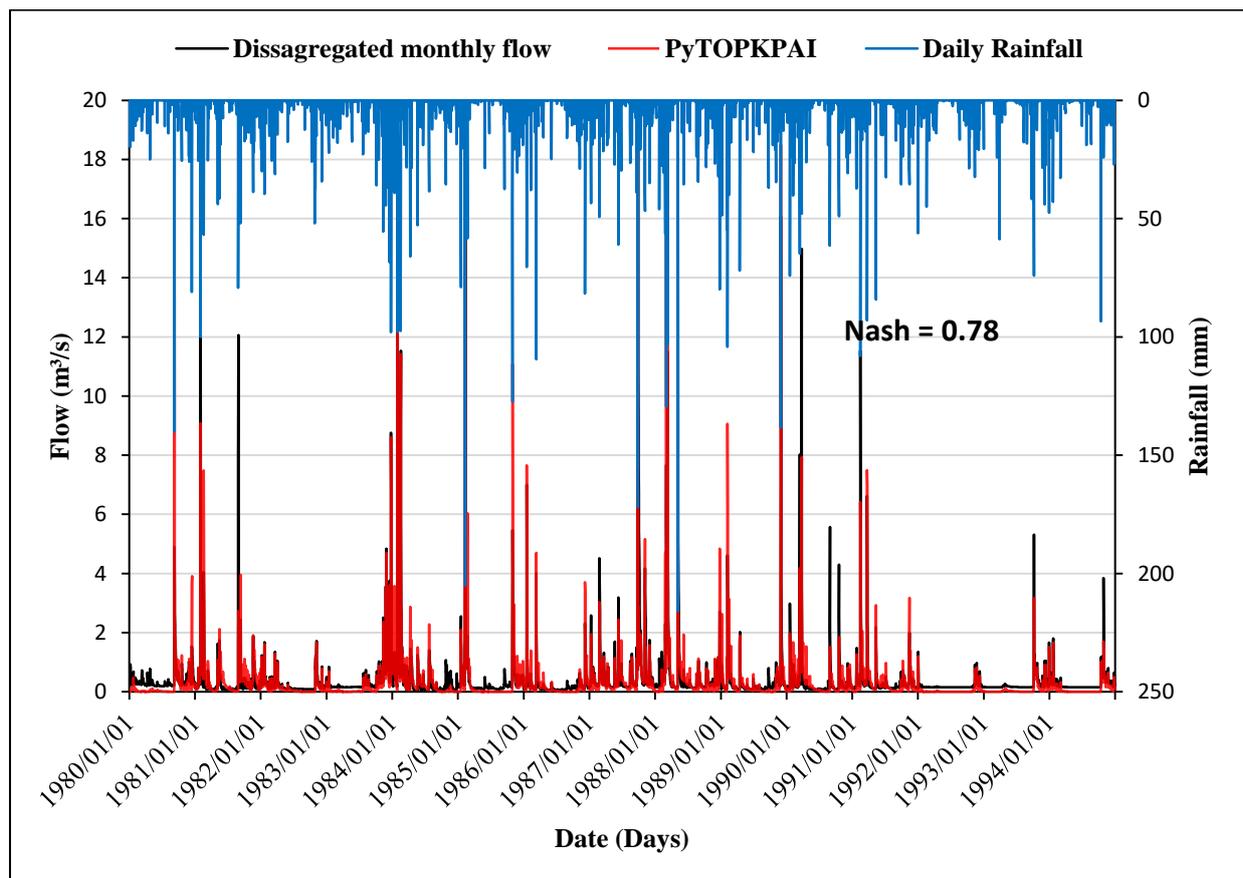
Figure 5- 5: Comparison between simulated flow and daily time series from monthly flow with rainfall pattern for period 1.
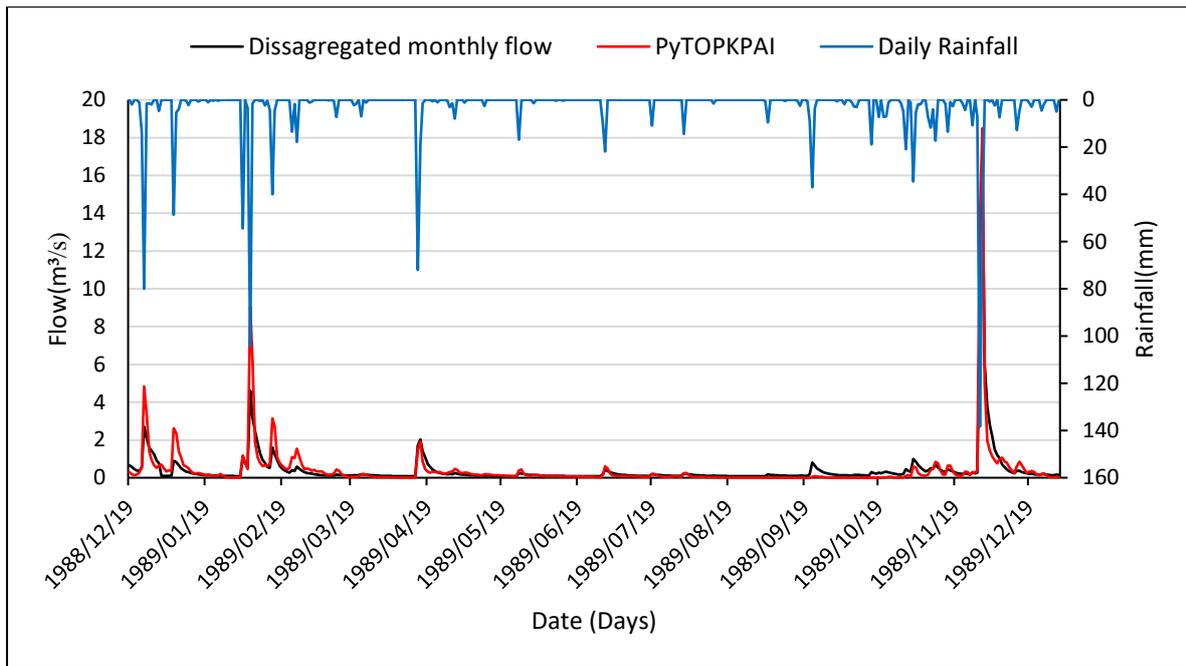
Figure 5- 6: Projected segment of figure 5-5 for 1989/01/01 to 1989/12/31.
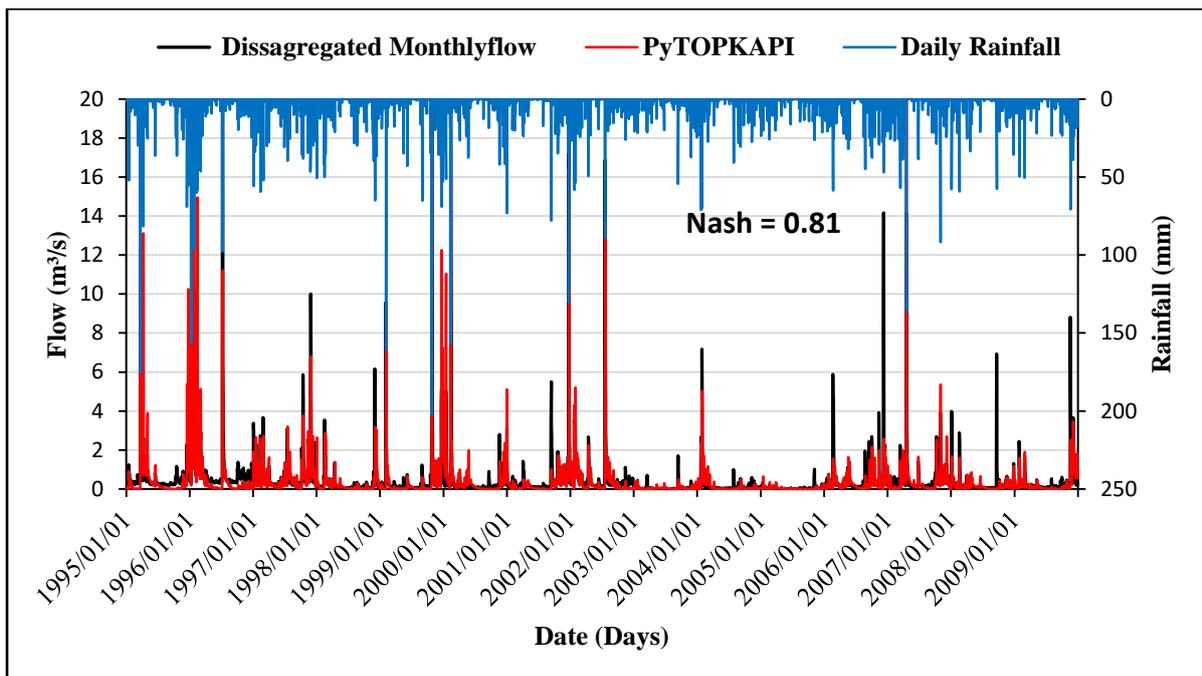
Figure 5-7: Comparison between simulated flow and daily time series from monthly flow with rainfall pattern for period 2.
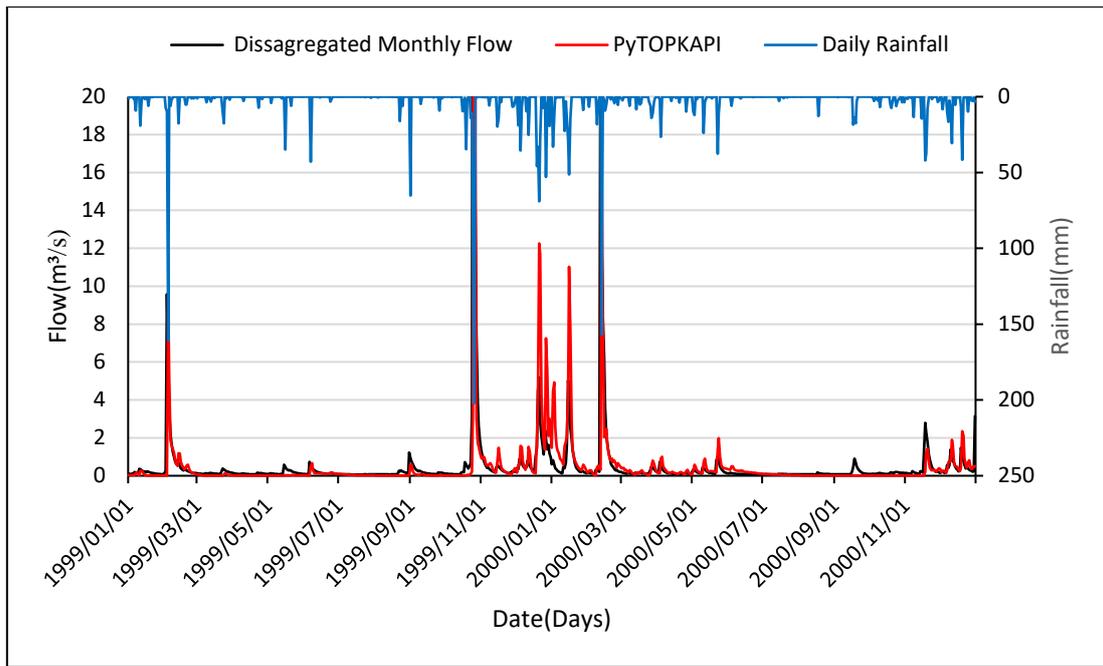
Figure 5- 8: Projected segment of Figure 5-7 for 1999/01/01 to 2000/12/31

Similarly, Figures 5-9 and 5-10 show the comparison between the PyTOPKAPI results and disaggregated monthly flow using flow duration curves (FDC) and scatter plots. The FDC relates flow to the percentage of the time that it is exceeded in the record. The FDCs are widely used for the assessment of the general quality of simulations throughout the range of flows (Blöschl, 2013, Smakhtin and Masse, 2000, Smakhtin and Watkins, 1997). Thus, this was used to visualize the differences and consequently to identify the deficiency of the model.
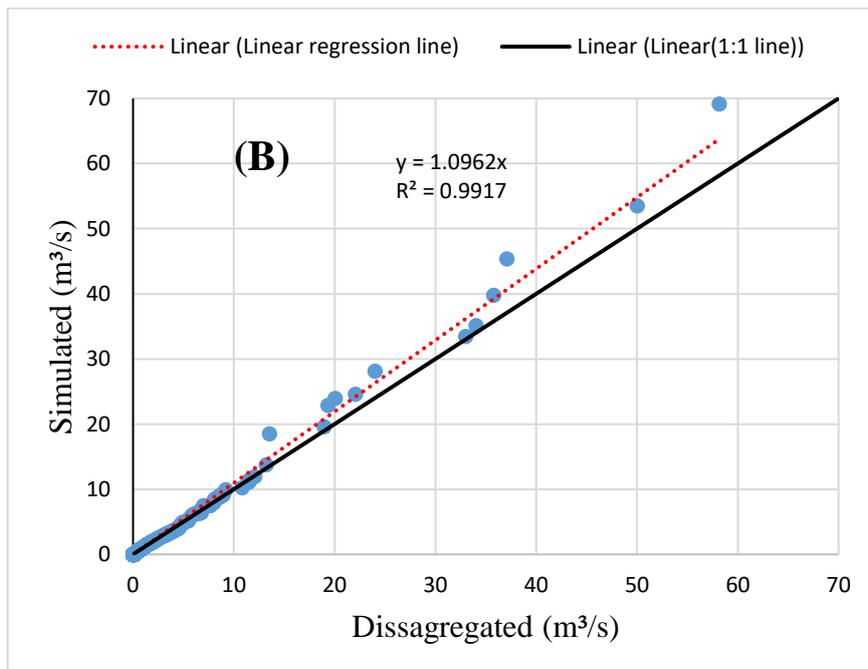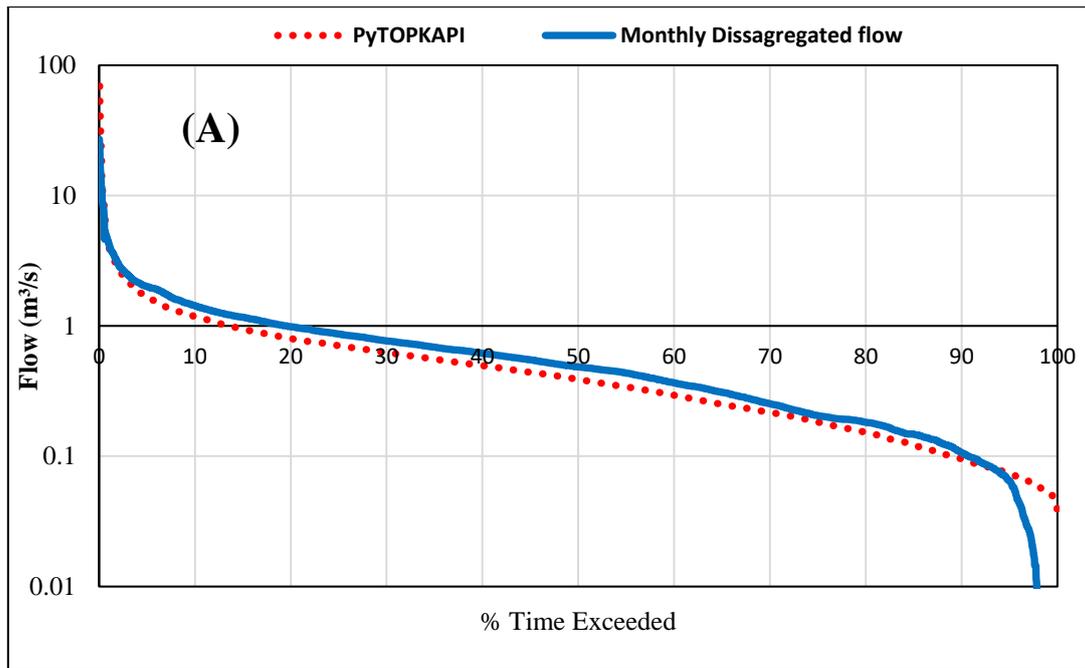
Figure 5- 9: Comparing flow characteristic for period 1: *(A)* Flow duration curve (FDC) of disaggregated and simulated flow, and (B) scatter plot of simulated and disaggregated flows. In A, the red dotted line indicate simulated flow while the blue line indicates daily disaggregated flow. In B, the black line represent 1:1 (predicted=disaggregated) line while the dotted red line represent line of best fit.
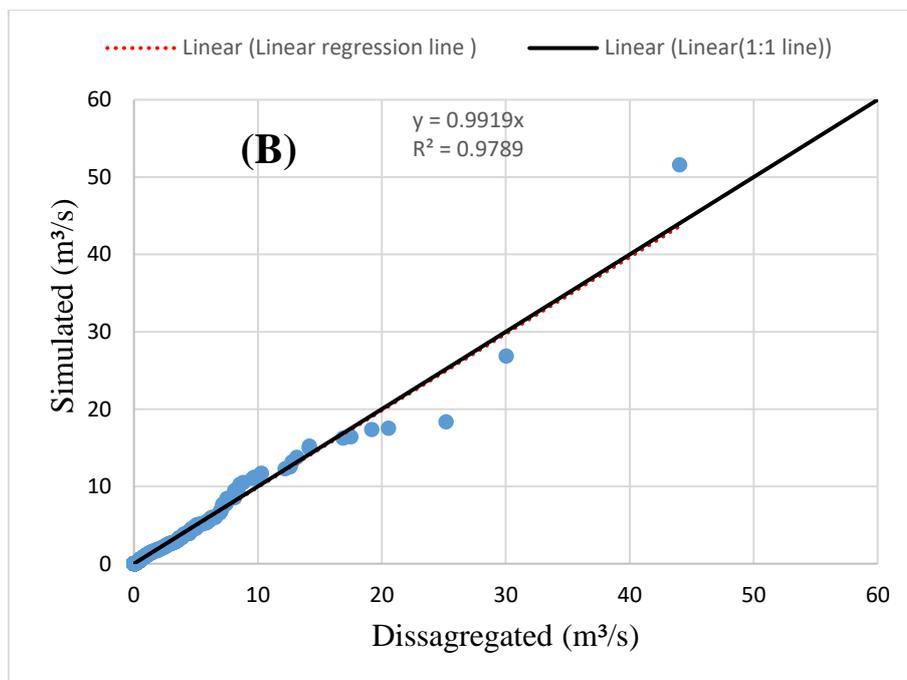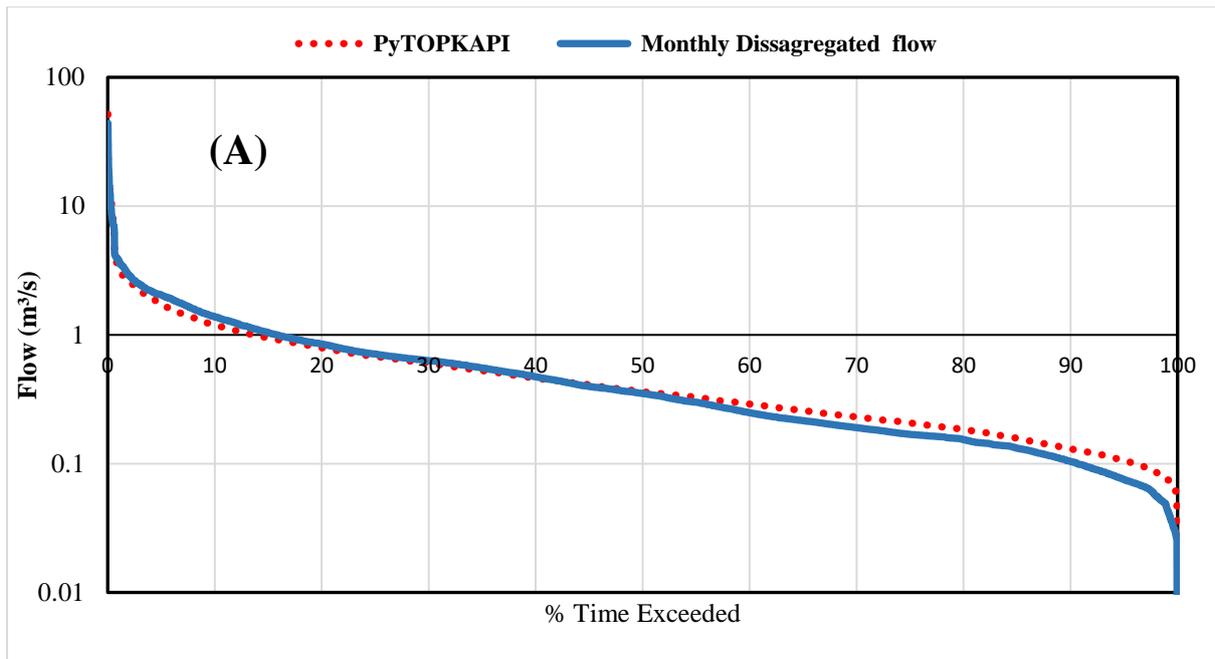
Figure 5- 10: Comparing flow statistics for period 2: *(A)* Flow duration curve (FDC) of disaggregated and simulated flow, and (B) scatter plot of simulated and disaggregated flows. In A, the red dotted line indicate simulated flow while the blue line indicates daily disaggregated flow. In B, the black line represent 1:1 (predicted=disaggregated) line while the dotted red line represent line of best fit.

In Figure 5-9 (A) and 5-10(A), it can be observed from the FDC that PyTOPKAPI predicted peaks higher compared with the disaggregated flows. This is also evident in scatter plots presented in Figure 5-9B and 5-10B respectively. The low flows predicted by the model in both periods (at 95-100% exceedances) was higher compared with the disaggregated flow. However from the FDC, the simulated and disaggregated flows exhibit similar properties as there was a close agreement. In Figure 5-9(B) and 5-10(B) the flows are closely fitted with the 1:1line. The close agreement between the model and the disaggregated monthly are evident with high R^2 value of 0.98 and .99. Thus, simulated results were well results were well represented comparable to the disaggregated monthly flows.

PyTOPKAPI results for period 1 and 2 were also aggregated into monthly time series which was further compared with the area-scaled monthly U30B quaternary flows. Figure 5-11 and Figure 5-12 shows the FDC and scatter plots of the monthly time steps for the aggregated PyTOPKAPI results and the area-scaled U30B quaternary monthly. In Figure 5-11(A) and 5-12(A), upon aggregating the daily time series to monthly for both periods, the magnitude of peaks simulated by PyTOPKAPI model was higher comparable to the area-scaled U30B monthly streamflow. The higher magnitudes of peaks and low flows simulated by the model was evident in daily time steps plots in Figure 5-9 and 10. However, PyTOPKAPI gave a satisfactory results in the monthly comparison with R^2 values of 0.93 and 0.95 for period 1 and period 2 respectively.
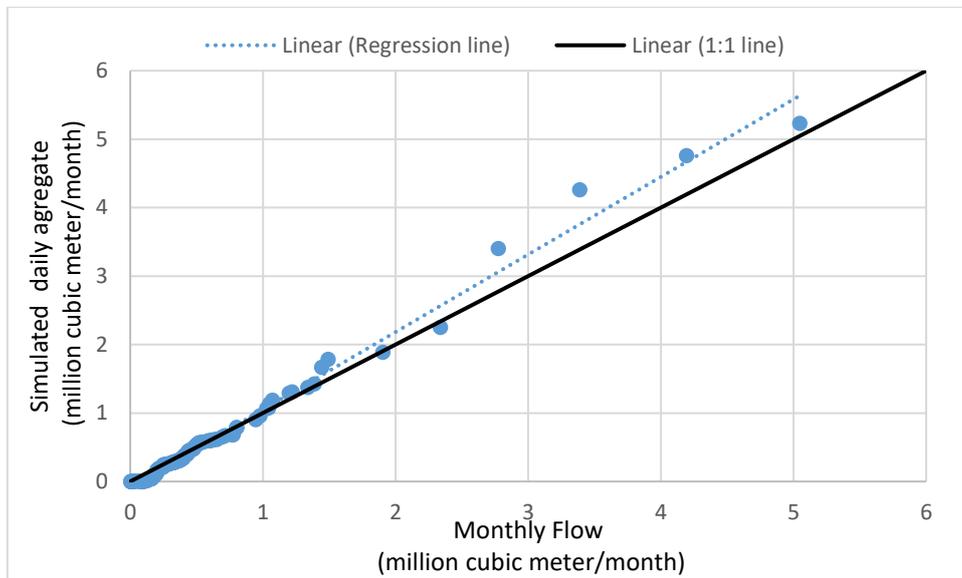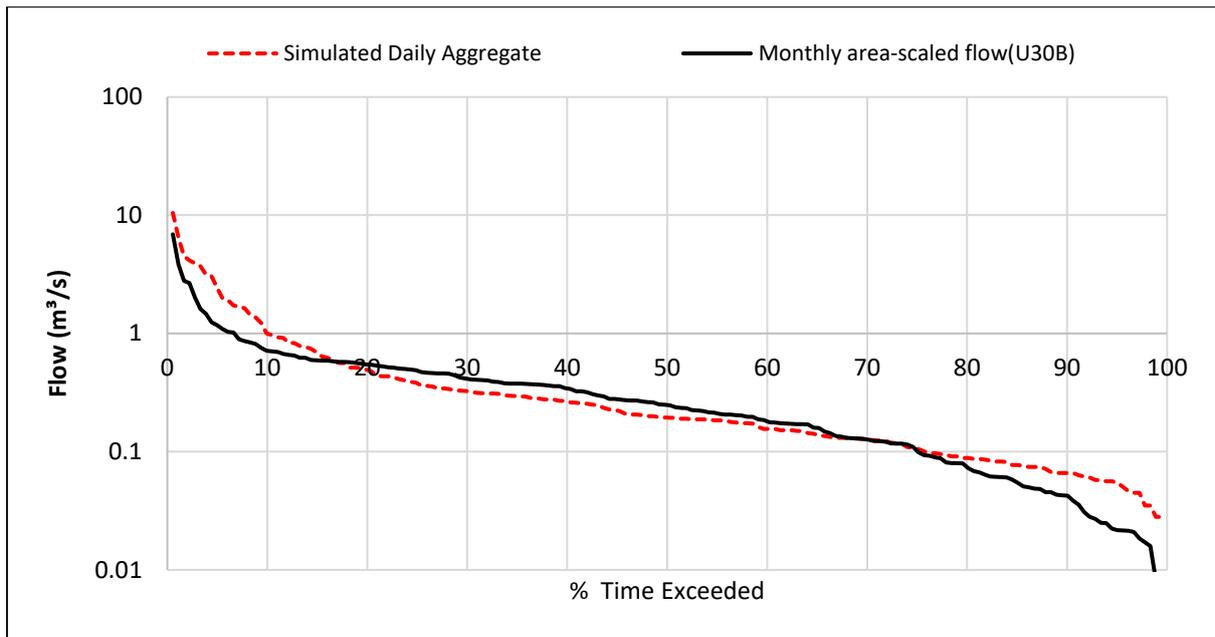
Figure 5- 11: Comparing flow statistics for the validation period: Figure 5-9 (11) shows FDC for the calibration period while Figure 5-11 (B) show the scatter plot for the calibration period. The red dotted line indicates U30B area-scaled monthly flow while the blue line represents the simulated flow. In B, the black line represent 1:1 line while the dotted blue line represent line of best fit.
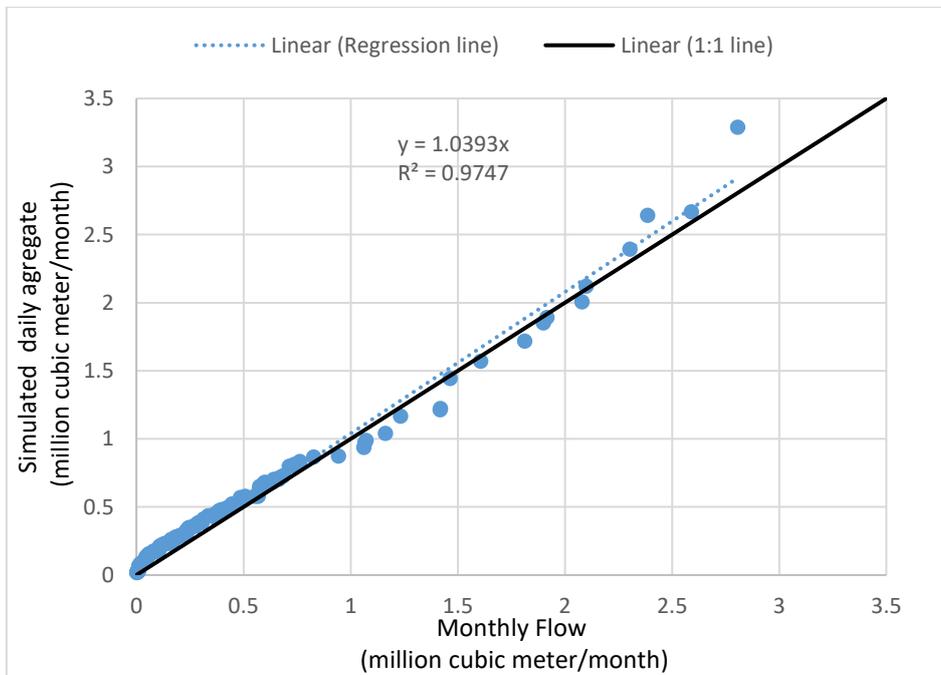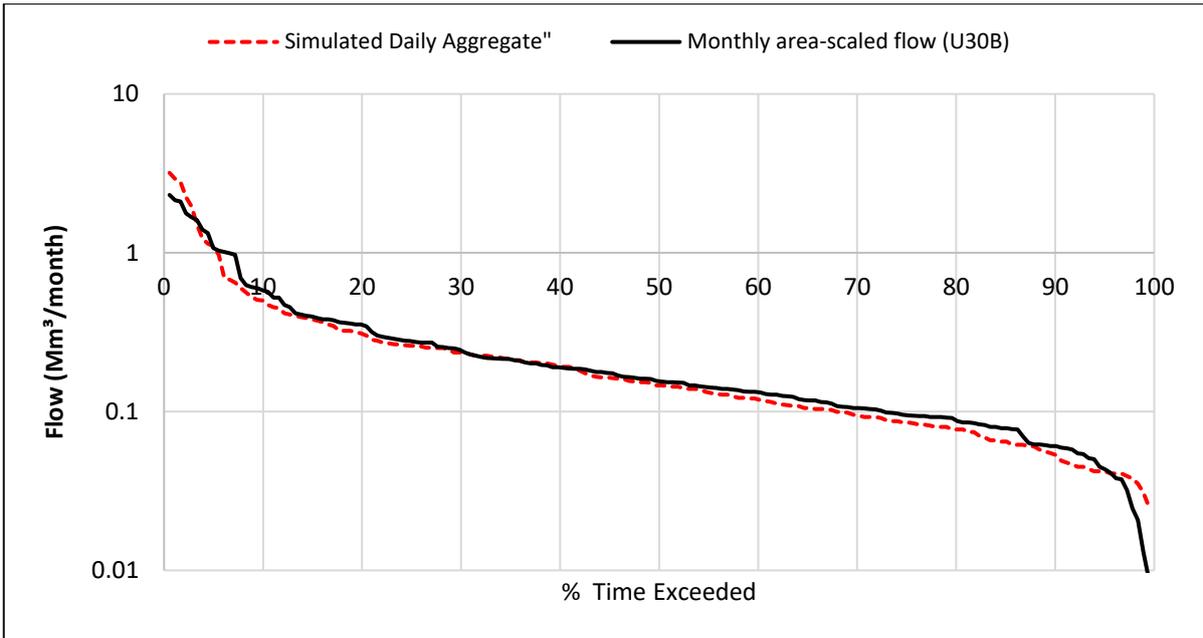
Figure 5- 12: Comparing flow statistics for period 2: Figure 5-12 (A) shows FDC for the calibration period while Figure 5-12 (B) show the scatter plot for the validation period. The red dotted line indicates U30B area-scaled monthly flow while the blue line represents the simulated flow. In B, the black line represent 1:1 line while the dotted blue line represent line of best fit.

Although PyTOPKAPI peaks and low flows predicted were higher compared with the monthly area-scaled U30B flows and the daily time step disaggregated from monthly, it cannot be concluded that PyTOPKAPI over estimate high flows and lows flows. This is because the flow data used to compare with PyTOPKAPI results was generated from pitman hydrological model. Flows generated from Pitman model are tested, trusted and are often serve as observed flows for hydrological purposes in south African catchments, nevertheless there might be uncertainties in the Pitman hydrological model results. Such uncertainties might be from the assumption made in pitman model setup. On the other hand, simulation results that PyTOPKAPI gave comparable satisfactory results.

Moreover, the disaggregation approach gave satisfactory results. The success of the disaggregation approach is largely due to the volume correction process, which is relatively insensitive to uncertainties (Slaughter et al., 2015).

Generally, PyTOPKAPI results exhibit similar pattern compared with the disaggregated daily flow. Likewise, the model results when aggregated to monthly gave a satisfactory results comparable. The magnitude and frequency of high and low flow events are reasonably represented by the model. This is generally adequate for studies involving the analysis of flood magnitude and frequency. This further ascertain the ability of PyTOPKAPI in modeling hydrological processes in an ungauged catchment.

5.3 Concluding remarks on the results

Sequel to the land use/cover classification results, it was noted that the catchment is characterized by dense built-up and vegetation areas. The high built-up area in the watershed indicates that more storm water runoff may likely be experienced due to impervious surface. Also, the dense vegetation cover in the watershed implies that runoff from agricultural land/vegetation cover is expected to carry excess nutrients into the river. Studies have also shown that dense vegetation and built up prevent water infiltration into the soil, resulting in increased runoff generation affecting the hydrological condition of a watershed (Hameed, 2017, Cadaret et al., 2016, Loch, 2000).

The simulated mean annual runoff and runoff ratio of both period 1 and period 2 are 0.38 m³/s, 0.16(16%) and 0.35 m³/s, 0.155(15.5%) respectively. The mean annual runoff for both periods

are approximately equal to the natural mean annual runoff of the catchment 0.4 m³/s as indicated in Stretch and Zietsman (2004). Likewise, the runoff ratios gave a satisfactory results comparable to the Schreiber estimate. The calibration procedure demonstrated a satisfactory level of performance desired in hydrological modeling as it is capable of representing the hydrological processes within the catchment based on the mean annual runoff, runoff ratio and coefficients of variation.

The area scaling regionalization approach used in this study described how streamflow data can be generated from nearby gauging station to an ungauged catchment. More so, disaggregation technique was employed in generating reasonable daily streamflow time series from available monthly streamflow; allowing for hydrological modelling studies especially in data scarce regions.

The runoff ratio for monthly disaggregated flow in period 1 (1980-1994) was higher compared to the target value (16%) while lower in period 2. This is because period 2 experienced a dry condition compared to period 1.

Overall, the calibration procedure guarantees that simulated runoff gives better performance for low, moderate and peak flows, the absolute amount and timing of streamflow are well reproduced. The results indicate that the PyTOPKAPI model is an effective catchment management tool that can be applied to ungauged catchments. Its ability to reproduce high and low flows will be useful in flood and drought alert applications. Thus, water managers can effectively predict runoff at ungagged rivers for various purposes using PyTOPKAPI model.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the general conclusions of the study. It also addresses the specific objectives set in this study, presents research findings, and its contribution. Lastly, it offers a summary of future recommendations resulting from the study.

6.1 General conclusions

The development of accurate and reliable hydrologic models for irrigation, planning, hydrological systems and other simulation studies, have been the subject of extensive past research. Water scarcity in the semi-arid regions of the world such as South Africa, requires rapid assessment of catchment water yields for better planning, management and sustainable use of water resources. Several hydrological models, with varying degrees of complexity, have been widely used for water resources problems. In South Africa, as for most developing countries, most catchments are ungauged so that observed flow data is limited. This is a concern in the management of limited water resources.

The aim of this study was to develop and investigate the applicability of the physically based distributed hydrological model, PyTOPKAPI, for simulating runoff in the ungauged Mhlanga Catchment of South Africa. The parameters of the model were obtained from various data sources such as hydro-meteorological data from SAWS, DWS and SASRI, and soil and land-cover data from literature and remotely sensed satellite data prepared with the help of GIS. The PyTOPKAPI model was run at a daily time step with 30 years hydro-meteorlogical data divided into 2 periods (Period 1 and Period 2, 15 years each). The model was calibrated by matching the average runoff ratio estimated from the formula proposed by Schreiber (1904). This facilitate applications to ungauged catchments in general.

6.2 Research findings

This study has three specific objectives.

   a. To identify and generate the relevant model parameters using a geographic information system (GIS) and remotely sensed (RS) data.

b. To generate daily streamflow data from available monthly time series in the Mhlanga River Catchment.

c. To investigate the calibration and validation of the PyTOPKAPI model for ungauged catchments using the Mhlanga River as case study.

This study provides an overview of existing physically based hydrological models which are being used for rainfall-runoff modelling in ungauged basins. In setting up the PyTOPKAPI model, a number of important datasets and files were established. To do so, the remotely sensed data, land cover, DEM, and soil map were prepared using GIS. This addresses objective (a) and (c) above.

Precipitation is the major factors that drives hydrologic modelling. There are missing rainfall data in the datasets obtained which may be due to limited rain-gauge distribution or human error. However, the rainfall data used was patched with nearby rainfall gauging stations which gives a consistent and reliable data.

In South African catchments, a 70 years monthly streamflow data generated from a well trusted hydrological model Pitman (1973) are available at quaternary level. The monthly flow used in this study was obtained from U30B quaternary catchment under which the study area is situated. Drainage area ratio method of regionalization was employed to scale available monthly streamflow to an ungauged Mhlanga catchment. The scaled monthly streamflow was further disaggregated to daily streamflow which was further compared with the PyTOPKAPI model results. The disaggregation approach is a parsimonious method for generating daily time series from existing monthly streamflow data. This approach addressed objective (b) which gives a clear method to generate streamflow time series in an ungauged catchment.

The runoff ratio, which is a novel approach for calibrating the PyTOPKAPI model, was used as an alternative calibrating procedure rather than the conventional matching of available observed streamflow in calibrating hydrological models. This approach addressed objective (c).

It was observed during the calibration process that the soil conductivity, and soil depth were the most sensitive model parameters. Different combinations of these parameters gave similar

result when compared with the reference runoff ratio. A statistical approach - coefficient of variation (CV) was subsequently used to select a unique parameter set for the system. This addressed objective (c).

The overall results answered the research questions which are; can PyTOPKAPI model be applicable in ungauged catchments for simulating stream flows? How can the PyTOPKAPI be calibrated in ungauged catchments where there are no observed stream flow data? The result shows that the research objectives were achieved by setting up and calibrating PyTOPKAPI model to generate streamflow in an ungauged basin. Also, the calibration method used presents a new tool that hydrological modelers and water resources managers can adapt to semi-arid and arid regions for the proper management of water resources.

6.3   Novelties and contribution

The following novelties and contributions to the community of hydrologist have been accomplished.

1. The implementation of PyTOPKAPI model in an ungauged catchment.
2. The runoff ratio proposed by Schreiber for calibration of PyTOPKAPI model. Thus, modelers can then use this approach in calibrating hydrological models in regions in the world characterized by data scarcity and where the Schreiber model is applicable.

6.4   Recommendations and future research

The following are the summarized future recommendations resulting from the study.

- Groundwater has been recognized as an essential asset in any catchment. It is recommended that the linkage between ground and surface water should be incorporated into the model.
- PyTOPKAPI simulation results indicate that the model can be used in ungauged catchments with simple calibration approach if need be.
- PyTOPKAPI has shown ability to simulate high, moderate and low flows. The model will be a promising tool for predicting flood. This is suggested for future research

- Beside the use of CV for selecting a unique calibration parameter combination, other criteria should be examined.

- Missing data in the meteorological datasets obtained from the DWS is a genuine source of concern. Observed information of good quality is a significant necessity of all modeling exercise. Modelers should ensure good quality of data is used.

- Although data scarcity introduces a dimension of uncertainty, notwithstanding, the uncertainty associated with input data seem to be generally less of a constraint than expected, considering the accuracy of the results that were obtained. Nevertheless, this does not eliminate the need for intense basic data collection.

- The model use point rainfall data which may not fully capture the rainfall spatial distribution. This is suggested for future research.

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APPENDICES

Appendix 1: Rainfall and Evapotranspiration forcing file script

```
import h5py

import numpy as np

import os
```

#Rainfall

```
x=np.loadtxt ('rainfalldata.dat') #path to rainfall data#

y=np.empty((3650,319)) # specify the time step versus cell size#

for i in range(319):

    y[:,i] = x

h=h5py.File('rainfield.h5','w')

group=h.create_group('sample event')

dset=group.create_dataset('rainfall',(3650,319),chunks=True,compression="gzip",compression_opts=9,data=y)

h.close()
```

 # Evapotranspiration

```
a=np.loadtxt('Et warmup.dat') #path to rainfall data

b=np.empty((3650,319)) # specify the time step versus cell size
```

```
for i in range(319):

    b[:,i]=a

h=h5py.File('ET2.h5','w')

group=h.create_group('sample_event')

dset=group.create_dataset('ETo',(3650,319),chunks=True,compression="gzip",compression_opts=9,data=b)

dset=group.create_dataset('ETr',(3650,319),chunks=True,compression="gzip",compression_opts=9,data=b)

h.close()
```

Appendix 2: The hydrologic soil properties classified by soil texture

Texture class	Sample size	Total porosity (θ), cm³/cm³	Residual saturation (θ_r) cm³/cm³	Effective porosity (θ_e), cm³/cm³	Bubbling pressure (ψb) Arithmetic, cm	Bubbling pressure (ψb) Geometric,† cm	Pore size distribution (λ) Arithmetic	Pore size distribution (λ) Geometric†	Water retained at -0.33 bar tension, cm³/cm³	Water retained at -15 bar tension, cm³/cm³	Saturated Hydraulic Conductivity‡ (K_s) cm/h
Sand	762	0.437** (0.374 0.500)	0.020 (0.001 0.039)	0.417 (0.354–0.480)	15.98 (0.24–31.72)	7.26 (1.36–38.74)	0.694 (0.298–1.090)	0.592 (0.334–1.051)	0.091 (0.018 0.164)	0.033 (0.007–0.059)	21.00
Loamy sand	338	0.437 (0.368 0.506)	0.035 (0.003 0.067)	0.401 (0.329–0.473)	20.58 (0.0 45.20)	8.69 (1.80–41.85)	0.553 (0.234–0.872)	0.474 (0.271 0.827)	0.125 (0.060 0.190)	0.055 (0.019–0.091)	6.11
Sandy loam	666	0.453 (0.351–0.555)	0.041 (0.0 0.106)	0.412 (0.283–0.541)	30.20 (0.0–64.01)	14.66 (3.45–62.24)	0.378 (0.140–0.616)	0.322 (0.186 0.558)	0.207 (0.126 0.288)	0.095 (0.031–0.159)	2.59
Loam	383	0.463 (0.375–0.551)	0.027 (0.0 0.074)	0.434 (0.334 0.534)	40.12 (0.0 100.3)	11.15 (1.63–76.40)	0.252 (0.086–0.418)	0.220 (0.137 0.355)	0.270 (0.195–0.345)	0.117 (0.069 0.165)	1.32
Silt loam	1206	0.501 (0.420 0.582)	0.015 (0.0–0.058)	0.486 (0.394 0.578)	50.87 (0.0 109.4)	20.76 (3.58–120.4)	0.234 (0.105–0.363)	0.211 (0.136 0.326)	0.330 (0.258–0.402)	0.133 (0.078 0.188)	0.68
Sandy clay loam	498	0.398 (0.332–0.464)	0.068 (0.0 0.137)	0.330 (0.235 0.425)	59.41 (0.0 123.4)	28.08 (5.57–141.5)	0.319 (0.079–0.559)	0.250 (0.125–0.502)	0.255 (0.186 0.324)	0.148 (0.085–0.211)	0.43
Clay loam	366	0.464 (0.409 0.519)	0.075 (0.0 0.174)	0.390 (0.279–0.501)	56.43 (0.0–124.3)	25.89 (5.80 115.7)	0.242 (0.070–0.414)	0.194 (0.100–0.377)	0.318 (0.250–0.386)	0.197 (0.115 0.279)	0.23
Silty clay loam	689	0.471 (0.418 0.524)	0.040 (0.0 0.118)	0.432 (0.347–0.517)	70.33 (0.0 143.9)	32.56 (6.68–158.7)	0.177 (0.039–0.315)	0.151 (0.090–0.253)	0.366 (0.304 0.428)	0.208 (0.138–0.278)	0.15
Sandy clay	45	0.430 (0.370 0.490)	0.109 (0.0 0.205)	0.321 (0.207 0.435)	79.48 (0.0 179.1)	29.17 (4.96–171.6)	0.223 (0.048 0.398)	0.168 (0.078–0.364)	0.339 (0.245 0.433)	0.239 (0.162–0.316)	0.12
Silty clay	127	0.479 (0.425 0.533)	0.056 (0.0–0.136)	0.423 (0.334 0.512)	76.54 (0.0 159.6)	34.19 (7.04 166.2)	0.150 (0.040–0.260)	0.127 (0.074–0.219)	0.387 (0.332 0.442)	0.250 (0.193 0.307)	0.09
Clay	291	0.475 (0.427 0.523)	0.090 (0.0 0.195)	0.385 (0.269 0.501)	85.60 (0.0 176.1)	37.30 (7.43 187.2)	0.165 (0.037–0.293)	0.131 (0.068 0.253)	0.396 (0.326 0.466)	0.272 (0.208 0.336)	0.06

Source: Rawls et al. (1982)