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Regionalisation of AWBM Hydrological model parameters for humid catchments in Kenya

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CERTIFICATION AND APPROVAL

Regionalization of AWBM Hydrological model parameters for humid catchments in Kenya

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DEDICATION

To God Almighty, I give all the credit.

I could never find the exact action to honour my late father, ALFA Tchalla, who laid the foundation of my first steps into the academic journey, my loving mother KPANAKE Tchilalo,

To all my siblings.

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STATEMENT OF THE AUTHOR

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ABSTRACT

Water resource management is critical to economic development in Africa, but surprisingly lack of data and its quality undermines decision making in the water sector. Hydrological simulation is a powerful tool providing timely and useful information about streamflow, but requires streamflow data for model calibration and validation. The lack of data required for model calibration has brought the practitioners and scientists to come up with alternative methods namely regionalisation techniques. In this study, 17 catchments selected in the humid part of Kenya, essentially located in the mountainous areas, were calibrated in order to derive a regional model for calibration of ungauged catchments in the area. CHIRPS rainfall estimates and PET estimated from NASA POWER meteorological data have been harnessed to calibrate AWBM, the model selected for the study. Multiple linear regression was used to develop regional models relating defined catchments soil, topography, land use/cover based attributes and the model parameters obtained from calibration. Three models were developed including those for the average surface storage and the baseflow parameters BFI and Kbase. The surface recession constant's model could not be established and default values were adopted. The successfully estimated parameter values and the default values, were used to simulate the daily streamflows. The average of the determination coefficient R^2 were comparable, with R^2 values of 0.64 and 0.65 over the calibration periods and 0.62 and 0.60 over the verification periods, respectively for calibrated and estimated parameters. Better quality data will substantially improve the method, however, in context of strict data scarcity, this method can be recommended for estimation of streamflow in ungauged catchments.

Key words: PUB, CHIRPS, regression method, data-scarcity, complex landform.

Resumé

La gestion des ressources en eau a été clairement reconnue comme essentielle au développement économique de l’Afrique, mais il est surprenant de constater que la valeur des données sur lesquelles reposent les décisions est moins bien valorisée, la collecte et la gestion des données ayant diminué ces dernières années. La simulation hydrologique est un outil important fournissant des informations opportunes et utiles sur le debit de cours d’eau. L’absence de données nécessaires à la calibration des modèles a amené les praticiens et les scientifiques à proposer une méthode alternative, à savoir les techniques de régionalisation. Dans cette étude, 17 bassins versants ont été sélectionnés dans la zone humide du Kenya, essentiellement situés dans les régions montagneuses, et ont été calibrés afin de créer un modèle régional pour la calibration des bassins versants non jaugés de la région. Les estimations des précipitations de CHIRPS et l’evapotranspiration poteniel estimées à partir des données météorologiques de la base de données NASA POWER ont été utilisées pour calibrer le modèle sélectionné pour l'étude ; l'AWBM (Model Australien du Bilan de L’Eau). Des régressions linéaires multiples ont été utilisées pour développer des modèles régionaux associant les characteristeristiques définis pour les bassins versants liées a leur sol, leur topographie et leur utilisation/couverture des terres aux paramètres du modèle obtenus à partir de la calibration. Trois modèles ont été développés, notamment le resevoir moyen de surface, les paramètres de l’écoulement de base IEB et Kbase. Le modèle de la constante de récession des ruissellements n’a pas pu être établi. Les estimations des paramètres jugées acceptables et les valeurs par defaut ont été utilisées pour simuler le débit journalier. Les moyennes du coefficient de détermination r^2 sont proches, avec des valeurs de R^2 de 0,64 et 0,65 obtenus sur les périodes de calibration et de 0,62 et 0,60 sur les périodes de vérification, respectivement pour les paramètres calibrés et estimés. Des données de meilleure qualité amélioreront considérablement la méthode. Toutefois, dans un contexte stricte de manque données, cette méthode peut être recommandée pour l'estimation du débit dans les bassins versants non jaugés.

Mots clés: PUB, CHIRPS, Regression , Manque de données, Relief accidenté.

ABBREVIATIONS AND ACRONYMS

AWBM	Australian Water Balance Model
CHIRPS	Climate Hazards Group InfraRed Precipitation with Stations
DEM	Digital Elevation Model
FAO	Food and Agriculture Organization
GIS	Geographic Information Systems
IDWM	Inverse Distance Weighted Method
NIB	National Irrigation Bureau
PUB	Prediction in Ungauged Basins
SDG	Sustainable Development Goal
CAs	Catchment Atributes
MPs	Model Parameters
WRA	Water Resources Authority

Tables of Contents

Tables of Figures

Liste of Tables

1 Introduction
1.1 Background of Study
Sustainable management of river basins requires a variety of tools that can generate runoff predictions over a range of time and space scales (Blöschl, Sivapalan, Wagner, Viglione, & Savenije, 2013). The applications of runoff prediction are so diverse and extremely important wherever communities are established, for research and practical applications. Some of those applications are water supply, water allocation and planning, hydropower potential, engineering design, water quality control, and ecological purposes. Viewed at global scale, is not possible to properly work toward SDGs achievement, integrated disaster management or adaptation and mitigation to climate change and variability without good information about streamflow prediction. At regional level, one of the priority of the Agenda 2063 is water in its several aspects, including water management, water and food security, hydropower production, water for environment and water governance that cannot be achieved without a sound level of mastery of streamflow prediction. Knowledge about surface water resources and the complex processes underlying its availability form the occurrence of precipitation to the routing, storage and depletion across the hydrological system is important for flood risk management, water supply, food production, hydropower production and adaptation to climate change among others. Most of the reliable methods of runoff prediction are data-driven, which means they require historical streamflow records to produce better estimations. And the more accurate are the records, better the predictions. The common method for streamflow data acquisition is measurements of water levels at a river gauging station that is converted into flow rate using a rating curve. Unfortunately, in most catchments around the world runoff is not measured. According to Blöschl et. al. (2013) in any given region, in any part of the world, only a small fraction of the catchments possess streamflow gauging station where runoff is measured. If the high cost of installation, maintenance and operation of river gauging station is the main issue of lack of data or poor quality data (with gaps and inconsistencies) for most of the catchments, especially in developing countries, other reasons for lack of reliable streamflow data enumerated by Gibbs, Dandy, & Maier, (2008) are the significant modifications to catchment characteristics, or long periods of unseasonable rainfall producing unrepresentative relationships.

The problem of streamflow data availability is so acute that it has been recognized worldwide, prompting the International Association of Hydrological Sciences (lAHS) to adopt the Prediction in Ungauged Catchments, as a decadal research agenda for the period 2003-2012, the principal objectives being to further develop methodologies for predictions in ungauged basins and to reduce uncertainties associated with model prediction (Blöschl et al., 2013).

Nevertheless, for its important applications, streamflow data is a necessity at any location, where communities are established, or of interest for implementation of any project involving surface water. This need of streamflow data is crucial today more than ever, as such information is needed to support decision-making to alleviate the pressure of increased population on water resources quantity and quality and one the other hand, to design engineering structures such as dams, reservoirs and any other infrastructure for water management or to face the increasing frequency and magnitude of floods due to the combined effect of climate change and land use change.

Hydrological rainfall-runoff modelling and simulations are a key component of water-related projects management. Hydrological rainfall-runoff models are based on mathematical equations representing in a simplified way the different complex processes underlying the runoff generation in the catchment area. Hundreds of such models are available today and classified in many ways. One of the most important classifications according to Devi et al, (2015) distinguish them into empirical models, conceptual models and physically-based models. Rainfall-runoff models are able to translate under certain precision the rainfall into runoff at few minutes, hourly, daily up to yearly time increments. Most of them use as inputs, climate data and catchment area, but some very sophisticated, require more detailed catchment physical characteristics information across the catchment area. There are many processes underlying runoff generation grouped into routing, storage and loss processes. In the rainfall-runoff models, only the dominant processes in the context of the model development and application are taken into account. Each process is represented by a parameter that quantifies the magnitude of the process. Finding the optimal values for each of the parameters of a particular model applied to a particular catchment is known as model calibration. This step in the modelling process requires concurrent climate data, mainly precipitation, evaporation or temperature and catchment physical characteristics according to the model, and the historical record of streamflow which is the rare commodity. Another constraint, is that the changes in the catchment characteristics, defining its hydrological behaviour, should be minimal unless the model is able to allow for important changes if those changes have been measured. The Lack of data, the availability of poor quality data for model calibration and validation, and unmonitored changes of the catchment physiography are the major problems that can face a hydrological rainfall-runoff modeller. Nevertheless, simulations are a very important source of information for water forecasting and long term water balance. Historical records of climatic data, most of the time longer than streamflow data, and stochastic rainfall predictions are available, allowing to fill the gaps of non-recorded periods and water forecasting.

Water resource management has been clearly recognized as critical to economic development in Africa, but surprisingly, the value of the data on which decisions are based is less well appreciated, with a decline in data collection and management in recent years (Houghton-Carr & Matt, 2006). In Kenya, even though big efforts have been done to implement a relatively high-resolution network of streamflow gauges, it is reported a decline in the number of stream gages in recent years. According to Mwangi, (2008) the number of river gauging stations declined by 78% between 1990 and 2001. Let alone this decline, there are still many catchments that are ungauged and for some catchments having a river gauging station, the data quality is poor. Some alternative methods have to be applied to satisfy this need for streamflow data for any kind of application.

Many approaches are available for this purpose. In general, they consist of transferring hydrological information from gauged catchment(s) to an ungauged catchment based on their spatial proximity or physical similarity. The underlying assumption for the similarity-based regionalisation is that catchments having similar catchment properties are hydrologically similar. This is done by using statistical regressions or a rainfall-runoff model regionalisation. The statistical regressions consist of establishing equations linking concurrent catchment physical characteristics and climatic variables to the observed streamflow of the same time span. These equations can be then used to estimate streamflow for ungauged catchment as catchment physical characteristics and climatic data can be obtained. The hydrological rainfall-runoff model regionalisation consists of a panoply of techniques used to estimate the set of optimal parameters values of a rainfall-runoff model for calibration of an ungauged catchment from optimal parameters obtained for gauged catchments after calibration. This second approach of estimating streamflow in ungauged catchments has been employed in many studies (Mwangi (2008), Boughton et al., (2007) Xue, Rizzi and Xu, (2017) Ibrahim *et al.,* (2015)) and can be applied to many situations as good estimations can be achieved with sparser streamflow gauging stations networks and over larger areas compared to the statistical model, thus fitting well to this situation.

Generally, for estimations in ungauged catchments, it is desirable according to Gibbs et al., (2008) to implement a model with as few free parameters as possible, provided the model describes well the processes occurring in the catchment under consideration. This makes the lumped conceptual rainfall-runoff models suitable for the regionalization studies. The aim of this study is develop a method for estimation of streamflow in ungauged catchment in the humid area of Kenya.

Regionalisation studies are data intensive, especially for extended study areas. This is referred to as the paradox of PUB described by Bonell et al., (2006) as situation that requires data-rich cathments to solve a problem of data scarcity. For rainfall and evaporation data and catchment attributes information, estimates available from global remote sensing dataset will be explored.

1.2 Problem Statement and Justification

Kenya is a country with a surface area of 582,646 km2 square kilometres of which about 97% is the land and the remaining 3% is water. Approximately 490,000 km2 (more than 80% of the land area) of the land area, is classified as arid and semi-arid land (ASAL). The 81,000 km2 remaining is classified as non-arid and profitably usable lands, sustaining most of the Kenyan economy and human population. The country faces enormous challenges in the management of its limited water resources due to an increasing population estimated to 39 million in 2009 and projected to 52 million by 2030. The magnitude of the issues, challenges and the severity of the water crisis that face Kenya cut across most sectors of the economy hence, making water resources management a high priority (WATER RESOURCES SITUATION REPORT of July 2017 to June 2018). Water resources data collection and information generation has been highlighted in the same report as one of these challenges along with water scarcity and variability; water pollution; enforcement of water laws; catchment degradation; and climate change impacts.

Also, the country is classified as a chronically water-scarce country because the freshwater is limited by an estimated annual supply of 534m^3 per capita (2009) projected to decrease as population increase. Which is less than 1000m^3, threshold below which a country is considered as water scarce (World Bank, 2010). The uneven distribution of rainfall and population are the major reason for the water supply problems. The surface water contribute to 96% of the total available water resources while the rest is the groundwater component, this shows the importance of surface water resources for the country and the need of intensive monitoring (KARANI, 2005). The Water Act 2016 imposes an obligation on all public bodies to consider the requirements of the reserve when performing any statutory function in relation to the water resource concerned. For rivers, the amount of water available 95% of the time (Q95) should be established and assured at any given time, whereas for ground water a Q45 of ground water recharge is required. Reserve flow is determined using flow duration analysis. To do this, long term flow data is required(WARMA, 2017) . However, scarce water resource data exists and thus cannot be relied upon for purposes of planning; this is because the hydrometrological network data collection stations are not available within some catchments. It is reported in the WATER RESOURCES SITUATION REPORT of July 2017 to June 2018, 71.3% of the river gauging station are operational leaving 29.7% of the gauging network out of service. The intense rehabilitation and automation of many river gauging station reported in the same document confirms the need of streamflow data. Unfortunately such rehabilitation cannot satisfy the need since long term record are required for the management practices. Hence the increase of smallholder irrigations schemes facing the ambition of the country to ensure equitable access to water by the NIB (National Irrigation Bureau) requires reliable information about water availability (Karina & Mwaniki, 2011). An integrated water resources management relies on adequate water resources information that is acquired through continuous data collection, in combination with suitable analysis and assessment of the water-related information for water resources planning and development purposes (RIWSP, 2012) cited in (Abimbola *et al.*, 2017). There is need therefore for alternative methods of generating this data to enable proper assessment of the water resources potential of these basins which supports the importance of this study to develop regionalization techniques for streamflow estimation.

1.2 Objectives

General objective: To establish a method for estimation of stream flow in ungauged catchments using the lumped, conceptual AWBM hydrological model and regionalization techniques in humid areas of Kenya.

Specific objectives

i. To determine the hydrologically relevant geomorphometry soil, land use and climate characteristics of the selected catchments,

ii. To calibrate and validate AWBM model for selected catchments in the humid areas of Kenya,

iii. To establish statistical relationships between AWBM parameters and the defined geomorphometry, soil, land use and climate characteristics of the selected catchments,
iv. To derive from the established relationships, the regionalized parameters for ungauged catchments,
v. To estimate stream flows in the "ungauged" catchments in the humid areas of Kenya using regionalized parameters.

1.3 Research questions

i. What parameter sets of the AWBM give the best fits between observed and simulated stream flows in the selected in the humid areas of Kenya?
ii. What are the functional relationships between catchments' characteristics and the AWBM parameters?
iii. Can derived relationships between catchments characteristics values and AWBM parameters be used to regionalize the model for runoff estimation in ungauged catchments?

1.3 Limitations

The study was limited to rivers with sufficient data records and catchments with little land use change or dams over the recorded period as this study requires unimpaired catchment, as changes in land use and dams can alter the catchment response. The study targeted small and medium sized catchments (up to 1000 Km^2) where rainfall data can be considered relatively well distributed. No study has been done to take into consideration the effect of land use change.

2. Literature review

2.1 Regionalization method uncertainties

Predicting runoff in the mostly ungauged water catchment areas of the world is vital to practical applications such as the design of drainage infrastructure and flood defences, for runoff forecasting and for catchment management tasks such as water allocation and climate impact analysis (Blöschl et al., 2013). Runoff prediction in ungauged catchments has been the focus of many studies by hydrologists and a tangible fact is the worldwide initiative by International Association of Hydrological Sciences (IAHS), which established the Decade on Prediction in Ungauged Basins (PUB) program aimed at improving capability in estimating runoff from ungauged basins using the so-called regionalization techniques (Blöschl et al., 2013). The reason is that only few catchments in the world are gauged, and also it is reported that current measurement networks are declining and the impacts of anthropogenic changes and climate amplify this issue. The underlying assumption for the regionalization of hydrological parameters is that catchments having similar catchment properties are hydrological similar.

Despite all the efforts, there is still no single accepted approach for streamflow regionalization in river basins (Araujo, Mello, Gollin, Quadros, & Gomes, 2018a). For example Liew and Mittelstet, (2018) used three regionalization methods, the averaging, the nearest neighbour and donor approaches for estimating the SWAT model parameters of catchments in Nebraska. They found out that the regional average approach gave better results than the nearest neighbour or donor approaches. Xue, Rizzi and Xu, (2017) carried out a comprehensive assessment of the strengths and limitations of existing regionalization methods in predicting ungauged stream flows in the high latitudes, large climate and geographically diverse, seasonally snow-covered mountainous catchments of Norway, using the water balance model – WASMOD (Water And Snow balance MODeling system) on 118 independent catchment. They concluded that spatial proximity and physical similarity approaches, performed better than regression-based approaches, the combination the first approaches improved slightly the simulations, but classifying the catchments into homogeneous groups did not improve the simulations in ungauged catchments. Merz and Blöschl, (2004) worked on the regionalization of 308 catchments in Austria using a lumped conceptual water balance model involving 11 parameters calibration. They concluded that multiple regressions with catchment attributes produce better regionalization results, and local regressions gave better results suggesting the worthiness to take regional differences into account, whereas taking a regional parameter value gave the worst simulations.

A comprehensive evaluation of single-and multi-donors, simple benchmarks and more advanced regionalization methods using multi-models, two performance measures and their statistical evaluation indicated that the identification of regionalization methods is dependent on the models, the performance measures and their statistical evaluation (Hailegeorgis et al., 2015). The choice of the model makes the regionalization more diverse. Many studies have been carried out using lumped conceptual water balance models because of their simplicity, limited data sets and parameters number. Xu and Singh (1998) pointed out that less the number of parameters in the hydrological model, great the advantage for a more accurate prediction of the parameters for ungauged watersheds. Xue, Rizzi and Xu (2017) made the choice of a simple conceptual model on the basis that the influence of equifinality problems and the inter-dependence of model parameters will be reduced to a minimum, and also it will provide an objective comparison of the regionalization. Another important parameter to consider while discussing regionalisation uncertainties is the climate. Patil and Stieglitz (Patil & Stieglitz, 2011), showed that high runoff similarity among nearby catchments (and, therefore, good predictability at ungauged catchments) is more likely in humid runoff-dominated regions than in dry evaporation-dominated regions.

Many regionalization studies have been undertaken at the continental level. Ibrahim *et al.*, (2015) used Krigging and multiple regression method with GR2M and WatBal models in the Volta basin catchments. The results of the two models were similar and the water balance established for the basin over the years simulated agreed strongly with the results of other studies. Makungo *et al.*, (2010) used a modified nearest neighbour regionalization approach, and Mike 11 NAM and AWBM in the Limpopo river basin. He concluded that the results were satisfactory and the method can be used to fill the gap of data for the river streamflow. Mwangi (2008) carried out a regionalization study in the Upper Tana catchments, using the IHACRES lumped conceptual model. He found the calibration r^2 ranging from 0.57 to 0.85 while the simulation r^2 ranged from 0.55 to 0.77 for all catchments, the Nash-Sutcliffe efficiency ranged from 0.78 to 0.91 for calibration and from 0.77 to 0.88 for simulation. According to his findings, the stream flows simulated using the estimated parameters agreed well with the observed stream flow series with the R^2 values being of 0.21 and 0.67 and the Nash-Sutcliffe efficiency values being 0.21and 0.68 respectively.The importance of streamflow regionalization is not only due to its capacity for spatialising hydrological information, but also because it can identify those areas in need for hydro-meteorological network improvement, either by installing new stations or relocating the existing ones(Araujo et al., 2018b).

2.1.1 Methods of regionalization of rainfall-runoff models

Many methods of regionalization are found in the literature, each of them is specific depending on the approach but also on the model used. The methods of regionalization of hydrological model parameters are developed in three main ways (Susana, 2014). The ungauged catchment model can calibrated with the same parameter values as for a neighbouring gauged catchment, termed as spatial proximity method, or with the same parameters as a gauged catchment with similar physical attributes, termed as catchment similarity method. The other method knows as regression method is very similar to the catchment similarity. It consists of developing statistical relationships relating the model parameters to catchment characteristics. These relationships are then used to estimate the model parameters for the ungauged catchments (Gibbs et al., 2008). A more recent review has numbered five types of techniques consisting of regional averaging approach, nearest neighbour approach, regression approach, donor approach and kriging approach (Liew & Mittelstet, 2018).

The first method is referred to as regional averaging, whereby model parameters from calibrated catcments in a given region are averaged and then applied to ungauged catchments in that region. A second regionalisation method, called the nearest neighbor, is based on the spatial distance between an ungauged catchment of interest and nearby calibrated catchments, which are considered to have similar catchment attributes and same parameter values. A third regionalisation technique consists in estimating the model parameters independently from a linear regression analysis based on the attributes of calibrated catchments in a given region. A fourth method, commonly reported in the literature is the donor approach. The basis of this method is to identify a donor catchment in a given area that is most similar in terms of its catchment attributes and to transpose the calibrated set of parameters to that catchment. A fifth method of regionalization is kriging, which interpolates between spatially autocorrelated variables.

2.2 Data importance and availability

Most catchments around the world are ungauged; indeed, only a little proportion is gauged. For this reason, when runoff is needed at any ungauged river or catchment, it is estimated by means of some kind of extrapolation from a gauged location to that ungauged location, which is not straightforward. One way or another, this extrapolation requires data of many kinds since methods used through the process implicate models that can be legitimated only by observed data collected (Blöschl et al., 2013). The data needed for prediction in Ungauged are of three types: climate (input), runoff data (in gauged locations) data and catchment characteristics data. Moreover, data should not be just seen as model inputs for data have hydrological context and contains specific hydrological information. That is why some data from a certain location, relating to runoff, climate and catchment of that location, analysed and interpreted by a trained hydrologist, and informed by prior knowledge about evolvement of the physical state of the location, can reveal a lot about the hydrology of the place. It can direct on what type of model to choose and on the interpretation and the rejection of the predictions made by the model. According to Blöschl et al., (2013), the value of data becomes paramount when one begins to accept the notion that catchments are complex systems, reflecting the co-evolution of climate, soils, topography and vegetation, and the patterns one sees in the landscape structure and the runoff response (e.g., signatures) are emergent patterns and reflect more than the mere balance equations that are embedded in many of today's process-based models. Therefore the starting point for any regionalization study has to include an assessment of available data and the information that can be derived from this data based on the available database and the time frame of the study.

Data available for application in ungauged locations exist from diverse sources. Among others, we have national data sources that are of varying availability and accuracy, field observations or assessments of local system characteristics and global data sets that are of typically low resolution. Every country has some type of national hydrological network, even though the spatial coverage of such gauging networks might vary widely. According to Munishi-Kongo (2013) as quoted in (Näschen et al., 2018), data scarcity constitutes an obstacle in East Africa with regard to hydrological modelling. The main reasons being local water authorities facing numerous challenges, like accessibility of discharge stations (especially in the rainy season), limited staff, and insufficient equipment due to restricted funds. The field observations not only cannot provide data in the time span for such studies but are also costly. Hence field observations are important for hydrological assessment that could allow more skilled interpretation and reading of the hydrological landscape when coupled with other collected data (Blöschl et al., 2013). The remaining alternative is the global data sets despite the low resolution and subsequent uncertainties.

2.2.1 Observed streamflow data

Water resource management has been clearly recognized as critical to economic development in Africa, but surprisingly, the value of the data on which decisions are based is less well appreciated, with a decline in data collection and management in recent years (Houghton-Carr & Matt, 2006) despite the fact that the practical value runoff data is often much larger than their monitoring (Cordery & Cloke, 1992). The challenges associated with hydrological data assessed through field observations, hydrological analysis, gauge readers testaments in a typical developing region during a flood study has revealed poor maintenance of hydrological equipment and surrounding landscape, poor data management architecture (collection, transmission, storage and format), and floods events that destroy hydrological equipment, inundation of roads restricting access to data collection during peak floods, as factors that hamper sustainable data collection. This results in inconsistent hydrological time series and availability of shortened length of the historical hydrological data source of random uncertainty that propagates through flood modelling processes (Ekeu-wei, 2018). Assessment of data quality and estimation of data uncertainty are therefore important steps in any modelling exercise. In some cases, while long term data on water levels may be available,the water level-discharge rating curves may be innacurate mainly due to inadequate discharge measurement campaigns, especially during high flow events. In other cases, the water level recorders may be blocked by silt or the gauging station area may experience scouring or deposition thus interfering with the accuracy of measurements.A simple way to assess data quality is by plotting and examining trends and comparing the runoff coefficient with the estimate values from global climatic datasets.

2.2.2 Rainfall data

Precipitation is one of the primary controlling factors in the hydrological cycle and thus the reliability of hydrological simulations strongly depends on accurate representation of spatially distributed precipitation (Worqlul et al., 2014). In fact simulation of hydrological processes in river basins or catchments characterised by diversified landforms encounters the challenge of sparse and heterogeneous spatial distribution of rain gauges often cause weak simulation results (Cho et al., 2009). Precipitation is essential for prediction in ungauged catchments, be it in the streamflow gauged or ungauged location. Although the duration of rainfall data is usually longer than the duration of streamflow measurements in most tropical-equatorial countries it is not likely to have high coverage of rain gauge stations in location where the population are not settled. Precipitation data are available at the global scale as a modelled and remotely sensed product down to the point scale at rain gauges (Worqlul et al., 2014). The growing availability of high-resolution satellite rainfall products is an opportunity for hydrologists to obtain more accurate precipitation data, particularly in developing countries and remote locations where conventional rain gauges are sparse and weather radars are absent (Kidd, 2001).

2.2.3 Evaporation

Many rainfall-runoff need to estimate evaporation, and its estimation is often done on the basis of a potential evaporation PE. It is defined as the evaporation that would occur if there were no moisture constraint or if the system evaporated at full capacity. However, potential evaporation is never measured directly, it is either estimated using a number of other basic meteorological measurements or inferred from other meteorological data like pan evaporation data for example. There are several methods of estimation of potential evaporation. The Penman equation estimates PE on taking into account net radiation, air temperature, atmospheric humidity and wind speed values. The Priestley and Taylor equation is a simplified form of the Penman equation. It also requires the same data, except the humidity. The Penman-Monteith equation is an adaptation of the Penman equation that accounts for the effects of evaporation taking place from vegetated surfaces, resulting in a correction to the EP estimates based on the resistance of the plant canopy (stomatal resistance) to diffusion of water fluxes(Pereira et al., 2015). In this way, the Penman-Monteith equation can be used as a model for evaporation directly, or alternatively, if the stomatal resistance is taken at its minimum value, it can be used to estimate EP as well (Blöschl et al., 2013).

2.2.4 Catchments attributes that influence hydrologic behaviour

Catchment characterization is typically focused on assessment and quantification of the aspects of physical and ecological structure that influence the storage, movement and release of water to evaporation and runoff (Blöschl et al., 2013). Hydrologists have tried for many years to develop some metrics upon which catchments could be describe, expecting that their behaviour, which could be define as the way their internal processes translate rainfall into runoff, could be understood. These metrics are based on the catchments physical characteristics ranging from topographic, soil-based, vegetation-based and human activities-related (W. C. Boughton & Askew, 1968). The last two can be combined into land-use and land cover-based characteristics. Much have been achieved in the understanding of the link between the physical components of a catchments and the hydrological response within, but very less could be taken as granted when it comes to using them theoretically to depict the catchment hydrological behaviour.

Catchment with steep land scape will experience a sharp accumulation of overland flow resulting in high peak flows at the outlet. This is explained by the availability of high potential energy accelerating the routing of the water toward the stream channel. The high speed of the routing favours surface runoff and interflow at the expense of infiltration and percolation. The shape of the catchment also contributes to the quick accumulation of water and increased runoff. In this case it is explained by the shortening or lengthening effect of the shape configuration of the catchment defined by shape factors such as Gravelius index. Compact catchment will exhibit quicker response to storm than fan-shaped catchment. A greater density of a stream network favours the runoff for any given rainfall, because stream channels conduct runoff efficiently they lead to high, sharp peaks and rapid recessions. Antecedent soil moisture conditions strongly influence the rate at which rainfall infiltrates into the soil and contribute to the processes of runoff production. Natural vegetation can be very important in determining runoff amounts; in many instances it is the most important influence of all, after rainfall. Areas bare of vegetation can lose more than 40% of seasonal rainfall through runoff and for intense, individual storms the loss can be much greater. Areas with dense grass cover and tree canopy cover can retain as much as 99% of the rainfall that reaches the ground. Vegetation reduces the energy of raindrops making them less erosive and intercepts rainfall which is then re-evaporated. Thus natural vegetation works against the occurrence of runoff in several ways. The urbanisation increases the impervious areas and reduce the soil storage and infiltration capacity (Klungniam, 2016), it can also the catchment storage due to abstractions and rain water harvesting. Geological information can provide insight into deeper groundwater contributions to runoff, vegetation cover distribution can inform on runoff production mechanisms and the topography (slope) can in some extent explain flow routing patterns. For this reason, topography, soil characteristics, geology, land cover and land use are of primary interest for hydrological study.

Many catchment descriptive attributes (CAs) related to the soil, topography, land use and land cover and climate have been widely used in regionalization studies. Gibbs, Dandy and Maier, (2008) considered catchment area, average annual rainfall, average annual potential evapotranspiration (PET), location (in the form of drainage division, longitude and latitude), median elevation, average slope of the catchment, leaf area index, percentage of woody vegetation, plant water holding capacity (PWHC), and soil transmissivity as catchment description attributes. They found out that PWHC, median elevation, average slope, longitude average annual potential evapotranspiration and average annual rainfall has a significant relationship with baseflow index parameter of AWBM and average annual potential evapotranspiration, PWHC, latitude and longitude have significant relationships with baseflow recession constant of the same model. They recommended using as more descriptive attribute as possible for better results. Catchment area (km^2), Perimeter (km), Mean Elevation (m), Minimum Elevation (m), Maximum Elevation (m) Range Elevation (m) Slope (%), Precipitation (mm), potential evapotranspiration (mm), River Density (km/km2) Forest (%), Shrubland (%) Grassland (%) Cropland (%), Salthardpans (%) Water bodies (%) have been considered in estimation of high, mean and low flow in Rwanda, the results showed that River density, mean catchment slope, minimum and maximum catchment elevation were among the dominant physiographical descriptors (Abimbola et al., 2017). In most of the studies, the choice of catchment attributes is done, based on the relevant data available. Today the availability of high-resolution terrain and land use/cover images from remote sensing database offers a great opportunity in data-scarce areas.

2.2.5 Remote sensing data resources opportunities for hydrological studies

Remote sensing gives an opportunity of observing land surface hydrologic fluxes and state variables over large areas particularly in regions where onsite stations networks are sparse. Over the last years, the study of land surface hydrology using remote sensing techniques has increased tremendously with the launch of NASA's Earth Observing System (EOS) and other research satellite platforms. In addition, developments in geographic information system (GIS) tools have enhanced the capabilities to produce and manage large databases describing the variability of land surface characteristics. Remote sensing techniques also can be used to obtain spatial information in digital form on vegetation and rainfall at regular grid intervals with repetitive coverage. The integration of a hydrological model with the spatial data analysis capabilities of a digital terrain model like a DEM provides information that helps to understand and monitor hydrological processes. Digital Elevation Models (DEM), meteorological data and land cover/use data are some sources available through remote sensing used for hydrological modelling nowadays which could be used as alternative or the only data source for a regionalization study. Catchment area and topographic characteristics such as slope, elevation, drainage density, length among others can easily be derived from a DEM of the study. There are many sources of global elevation datasets providing very fine resolution DEMs at near-global scale readily. The GTOPO30 (http://www1.gsi.go.jp/geowww/globalmap-gsi/gtopo30/gtopo30.html), NOAA GLOBE (The Global Land One-km Base Elevation project), The Shuttle Radar Topographic Mission (SRTM) Global Digital Elevation data, Space Borne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (http://srtm.csi.cgiar.org/) are some of them.

Another important type of information needed for regionalization studies is the state of land cover and land use over the catchments. Several satellite platforms equipped with specific imaging sensors are in operation have made available data sets of remote sensing imagery. LANDSAT, SPOT, IRS, IKONOS are some of the satellites platforms equipped with specific imaging sensors that are in operation. For modelling purposes, hydrologically relevant parameters need to be associated with the assigned land use classes. For modelling purposes, hydrologically relevant parameters (evaporation resistance, leaf area index etc.) need to be associated with the assigned land use classes (Blöschl et al., 2013). Considering the extent of the areas subject of hydrological investigations and the tediousness of digitizing, remote sensing is far better the method of acquisition of land/ use and land cover data. Some soil properties can be also acquired using remote sensing imagery.

The more crucial input data for hydrological modelling is the meteorological data. The growing availability of high-resolution (and near-real-time), long time series availability and public domain availability satellite rainfall products can help hydrologists to obtain more accurate precipitation results, particularly in developing countries and remote locations where weather radars are absent and conventional rain gauges are sparse (Dembélé & Zwart, 2016; Kidd, 2001). Satellite precipitation products are available at different timescale and spatial resolution. Some of these products frequently encountered in the literature are: the Tropical Rainfall Measuring Mission (TRMM), EUMETSAT’s Meteorological Product Extraction Facility (MPEF), Multi-Sensor Precipitation Estimate Geostationary (MPEG), the Climate Forecast System Reanalysis (CFSR), the NOAA/Climate Prediction Center morphing technique (CMORPH), precipitation estimation from remotely sensed information using artificial neural network (PERSIANN), the Naval Research Laboratory’s blended product (NRLB) (Luo, Wu, He, Li, & Ji, 2019; Worqlul et al., 2014) and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS). There is also a need to provide for water loss through evaporation. Depending on the model, wind speed, temperature, relative humidity, solar radiation, albedo might be required for evaporation estimates instead of direct estimate of evaporation. The Prediction of Worldwide Energy Resource (POWER) (https://power.larc.nasa.gov/#resources) and daily Climate Forecast System Reanalysis (CFSR) (https://globalweather.tamu.edu/) are some example of global datasets estimates of precipitation, wind, relative humidity, and solar can be accessed. The version 4 Global operational Simplified Surface Energy Balance (SSEBop) Actual ET (https://earlywarning.usgs.gov/fews/datadownloads) is an example of high resolutions actual evaporation estimates available at decadal, monthly and yearly time scale that can be freely accessed.

Although remote sensing data has been proven by some studies as an opportunity to improve hydrological simulation (Dembélé & Zwart, 2016; Luo et al., 2019; Satgé et al., 2019), there are some investigations (Bai et al., 2018; Dinku et al., 2018; Worqlul et al., 2014) that have highlighted poor correlations with rain gauges. Luo et al., (2019) performing the SWAT modelling of Lancang-Mekong river used the gauge observations, Inverse Distance Weighted (IDW)data, TRMM and CHIRPS estimates. In the order of performance TRMM and CHIRPS were better followed by the gauge observations and IDW. NSE values were 0.95, 0.93, 0.86 and 0.87 respectively for calibration, and 0.86, 0.84, 0.77 and 0.75 respectively for validation on mouthly time scale. Satgé et al., (2019) tested 12 satelite precipitation products to assess space-time consistency. They found out that six out of twelve (CHIRP v.2, CHIRPS v.2, CMORPH–BLD v.1, MSWEP v.2.1, PERSIANN–CDR, and TMPA–Adj v.7) could produce a realistic representation of regional precipitations despite recurrent spatial limitation over regions with contrasted emissivity, temperature and orography. Besides, when these products were used as forcing precipitation data in lieu of precipitation directely derived from the available observations gauge networks, in nine out of ten of the cases considered, streamflow was more realistically simulated (Satgé et al., 2019).

Dembélé and Zwart (2016), undertook a validation study at the national level in Burkina Faso. They investigated on seven satellite-based rainfall products including Africa Rainfall Estimate Climatology (ARC 2.0), Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS), African Rainfall Estimation (RFE 2.0), African Rainfall Climatology and Time-series (TARCAT), Tropical Applications of Meteorology using SATellite (TAMSAT) and Tropical Rainfall Measuring Mission (TRMM) daily and monthly estimates. They concluded that the choice of product depends on the specific application and recommended PERSIANN, CHIRPS, and TRMM daily for application in flood monitoring in Burkina fasso. In contrast to these studies, Worqlul et al., (2014) found TRMM estimates, also used in the above studies, poorly correlated to the ground observation in the hight land of Ethiopia. Such finds are backed by Dinku et al., (2018) while conducting the validation of CHIRPS estimates over Eastern Africa. The performance is diversified with exhibition of poor observesions over the mountainous areas of Ethiopia, Kenya and Tanzania, the costal area of Kenya and Tanzania and the locations around the lake Victoria. Bai et al., (2018) while comparing CHIRPS data with 2480 rain gauges found out that the satellite exhibits a diversified performance across the country. Nevertheless, given the currently available precipitation gauge network, satellite precipitations are attractive and efficient tools to monitor local precipitation and to force impact modelling, such as snow-hydrological models (Satgé et al., 2019).

2.3 Rainfall-Runoff Modelling

The main reason for hydrological modelling is our incapacity to measure in desired details over a wide range of space (Beven, 2012). The measurement capabilities available today are limited to cover the range of space and time we desire. For this reason, we require techniques of inferring from available measurements in both space and time, into the future to assess the likely impact of future hydrological change, particularly to ungauged catchments where measurements are not available and into the future. A runoff model can be described as a set of equations that produces estimations of runoff as a function of various parameters used for describing watershed characteristics (Devi et al., 2015). If many books describe the complex equations underlying hydrological processes, narrowing down these several equations into a few simpler ones that can still produce applicable result is the key task in hydrological modelling (Beven, 2012).

Those equations that involve inputs and state variables such as drainage area, meteorological and catchment characteristics. Rainfall, potential evapotranspiration, temperature are the main meteorological inputs. Watershed characteristics include soil properties, watershed topography, vegetation cover, characteristics of the groundwater aquifer. The hydrograph which is interpreted as the integral response function of all upstream processes due to rainfall is the main output from a rainfall-runoff model is a hydrograph. The interpretation of a hydrograph provides useful information for decision-making in water resource planning, flood management or any water abstraction scheme.

2.3.1 Types of models

There is a diverse classification of hydrological models based on a specific characteristic of the model. Based on the randomness we have the stochastic models and deterministic models. When the model describes the random variation and incorporates the description in the predictions of output, the model is a stochastic model and if all input, parameters, and processes in a model are considered free of random variation and known with certainty, then the model is a deterministic model. Deterministic models will give same output for a single set of input values whereas, in stochastic models, different values of output can be produced for a single set of inputs. It can be classified as lumped and distributed model based on the model parameters as a function of space. Lumped models, take the entire river basin as a single unit where spatial variability is disregarded, generating the outputs without considering the spatial processes. a distributed model, on the other hand, can make simulations that are distributed in space by subdividing the entire catchment into smaller units, usually square cells or triangulated irregular network, giving the possibility to the parameters, inputs and outputs to vary spatially (Moradkhani & Sorooshian, 2008). Continuous and event-based models are distinguished based on whether the model produces output only for specific time periods or produces a continuous output. According to Devi et al., (2015) a widely used classifications is empirical model, conceptual models and physically-based models.

2.3.1.1 Empirical models (Metric model)

These models are observation oriented. They take only the information from the existing data making no use of the features and processes of the hydrological system and hence are also called data-driven models (Devi et al., 2015). For this purpose, mathematical equations are not derived from the physical processes of the catchment but from concurrent input and output time series. These models are valid only in the context of their development. One example of this method is the unit hydrograph (Wheater et al., 2011). Statistically based methods use regression and correlation models and are used to find the functional relationship between inputs and outputs. Artificial neural network and fuzzy regression are some of the machine learning techniques used in hydro informatics methods (Devi et al., 2015).

2.3.1.2 Conceptual methods (Parametric models)

This model describes all of the component hydrological processes (Devi et al., 2015). It consists depending on the level of complexity of two, three interconnected reservoirs for simple structures and many more for highly complex, which represents the physical elements in a catchment. They are recharged by rainfall, infiltration and percolation and are emptied by runoff, evaporation and drainage among others. Semi-empirical equations are used in this method and the model parameters are assessed not only from field data but also through calibration which requires a large number of meteorological and hydrological records. The curve fitting involved in the calibration process makes the interpretation difficult. This is due to the induced problem of model parameters non-identifiability which causes the effect of land-use change difficult to be predicted with much confidence. For a given model, many combinations of parameter values may give similar output as indeed different model structures may do. Similarly, it is difficult to represent catchment change if the physical significance of parameters is ambiguous. This has given rise to two major limitations. Parameters cannot be linked to catchment characteristics if they cannot be uniquely identified, and here is a major problem in application to ungauged catchments (Wheater, 2002). Many conceptual models have been developed with varying degree of complexity. Wheater (2002) noted that “a simple model structure does not reflect the complexity of the rainfall-runoff response and a complex model structure is not always supported by the available data. A balance between the complexity of the model and available information is crucial for successful model identification”. Hydrological conceptual rainfall-runoff are widely used for practical purposes in gauged and ungauged catchments.

2.3.2 Physically-based models

These are mathematically idealized representations of the real phenomenon (Devi et al., 2015). They solve the governing equations for mass, momentum and energy in a spatially explicit way, drawing on as much laboratory-scale process understanding as possible (Blöschl et al., 2013). These are also called mechanistic models that include the principles of physical processes. It uses state variables which are measurable and are functions of both time and space. The hydrological processes of water movement are solved numerically using a finite-difference or a finite element spatial discretisation (Wheater et al., 2011). Their calibration does not require extensive hydrological and meteorological data but the evaluation of large number of parameters describing the physical characteristics of the catchment are required. Such models require large amount of data such as initial water depth, soil moisture content, topology, topography and dimensions of river network among others. Physically-based models can overcome many defects of the other two models because of their parameters having physical interpretation (Devi et al., 2015). It can provide large amount of information even outside the boundary and can be applied for a wide range of situations. However the huge amount of data required makes their use very limited for practical applications outside well documented catchments.

3 Methodology

3.1 Data and study area

The study area consists of the catchments located in the humid part of Kenya located essentially on the slopes of the Mount Kenya, The Mont Elgon and Aberdare. The CAs was based on landscape, land use/ land cover and soil attributes. The streamflow of these catchments has been purchased from the Water Resources Authority (WRA). The daily precipitation used in this study has been extracted from CHIRPS rainfall data using the appropriate packages from R software. For the evapotranspiration, it has been computed using INSTAT from NASA POWER minimum and maximum temperature, wind speed, relative humidity and solar radiation data. The catchments where selected based on their location, their size and data availability. Small catchments were targeted to minimize the effect of sharp heterogeneity that can occur across the big catchments' area on the modelling.

3.1.1 Study area

3.1.1.1 Presentation of the study area

The study area extends to 112136 KM^2, located between 37.818 and 34.44 longitude west and between -1.481 and 1.222 latitudes. It covers the humid part of the country, essentially located around the Mountains. It includes the headwaters of Kenya's five primary catchment areas, all arising in five indigenous mountain forest areas. These five forest areas are commonly referred to as Kenya's five Water Towers consist of the Mau Forest Complex, Mount Kenya, the Aberdares, Mount Elgon and Cherangani. The Mau Forest Complex is the source of Mara, Njoro and Sondu rivers. The Mara River sustains the Masai Mara Game Reserve and is key to the survival of wildlife in Serengeti National park in Tanzania and Masai Mara Game Reserve. The Sondu river runs the Sondu Miriu Hydropower complex. The Njoro River feeds the Lake Nakuru which is an important wildlife refuge and centre of tourism. The Tana River generates 70% of hydropower in Kenya and provides water supply to Nairobi Mt. Kenya is the source. It also supports agricultural development along the Tana Basin. Mt. Kenya supports numerous streams and springs that support commercial and subsistence farming on the lower slopes. Aberdare Ranges and Mt. Kenya water towers provide water to the significant horticultural and floricultural industries, which generate high export revenue. The Nzoia River, which drains into Lake Victoria, originates on Mt. Elgon (World Bank, 2006).

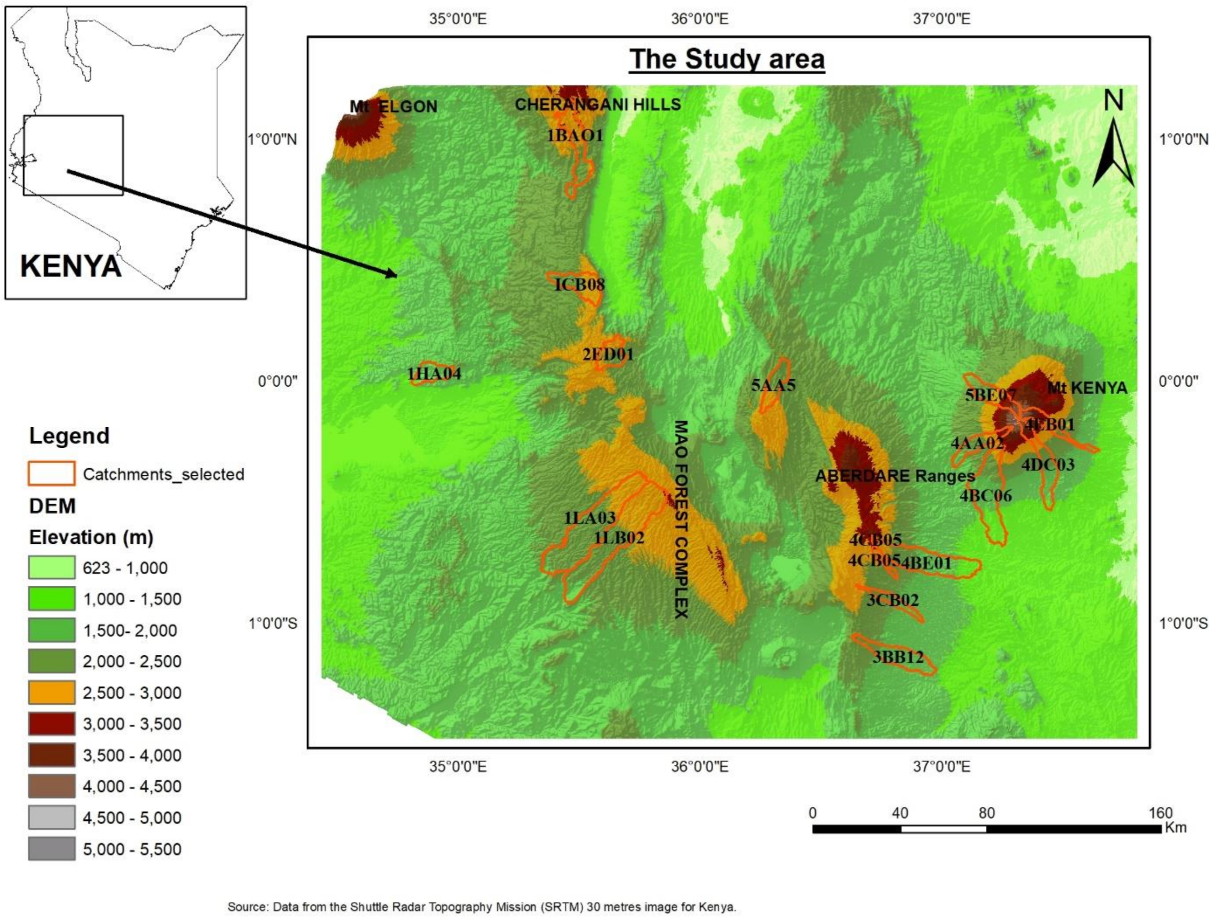


Figure 1: Study area

3.1.1.2 Climate and vegetation

The overall country's climate is controlled by the Inter-Tropical Convergence Zone (ITCZ). The climate and soils formations are highly correlated to the altitudes. The climate ranges from humid in the highlands to dry sub-humid in the midlands. The temperature ranges from less than -4 degrees centigrade at Afro Alpine High lands (more than 3050m) to 28 degrees centigrade in the midlands (1200-1500m). The mean annual temperature is less than 10 in the Alpine high lands and ranges from 20 to 22 in the Midlands. The annual precipitation reduces with the altitudes. In the high land excluding altitudes above 3050, the annual rainfall and annual potential evapotranspiration vary between 1100 and 2700 and between 1200 and 2000 respectively under a climate essentially classified as humid. The vegetation is moist forest with a very high plant growth potential. The midlands are dominated by sub-humid and dry semi-humid climates. The annual rainfall ranges from 1000 to 1600 mm and from 800 to 1400 respectively. For the potential evapotranspiration, it ranges from 1300 to 2100 in the sub-humid areas and from 1450 to 2200 in the semi-humid areas. Both subhumid and semi-humid areas are covered moist and dry forest and with dry forest and moist woodland respectively. The aridity index (P/PET) is very high (>80%) in the Afro Alpine high lands high in the sun humid zone just below (65-80%) and medium (50-65%) in the lower part of the midlands dominated by the semi-humid climate. The uppermost part, at the peaks of mountains is covered with typical vegetation called Mooreland.

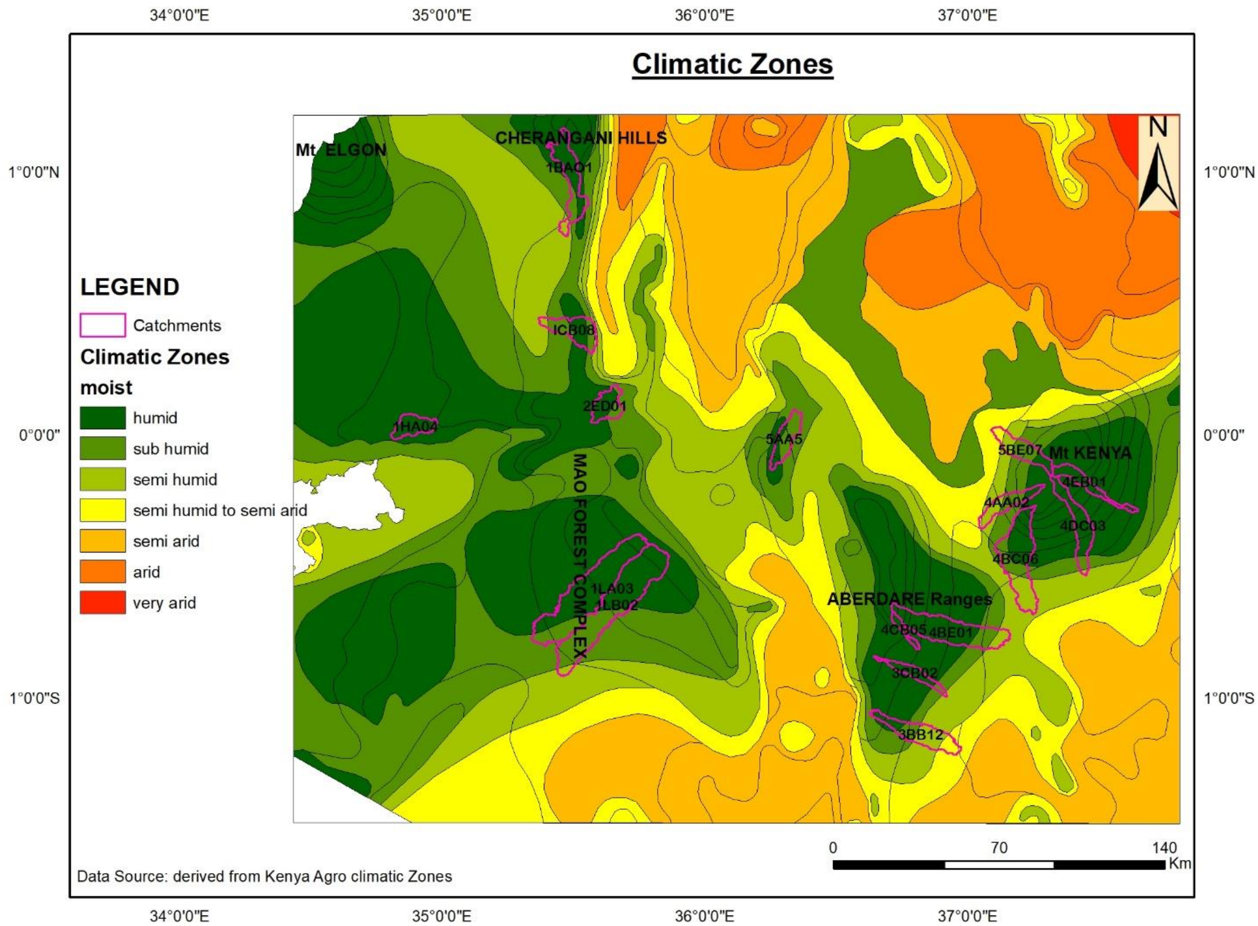


Figure 2: climatic zones

3.1.1.3 Soils

Most soils in the study area are volcanic in nature and have not only high infiltration rates but are also resistant to erosion and highly permeable. The higher parts such as mountains and escarpments comprise of histosols, humic andosols and lithic leptosols that are poorly drained and are developed on olivine basalts and ashes of major older volcanoes. On the hills and minor scarps at the eastern part, lies a very diverse type of soils dominated by nitisols forming a ring around the histosols and followed by luvisols and phazoems at the small extent in the decreasing order of the altitude. The soil types in the south-western part of the study area are andosols and nitisols occupying most part of the Mao forest complex. The gleysols, the ferrasols, the cambisols, the andosols and the nitisols are the most represented soil types in the north-western part of the study area. The majority of the study area is dominated by nitisol.

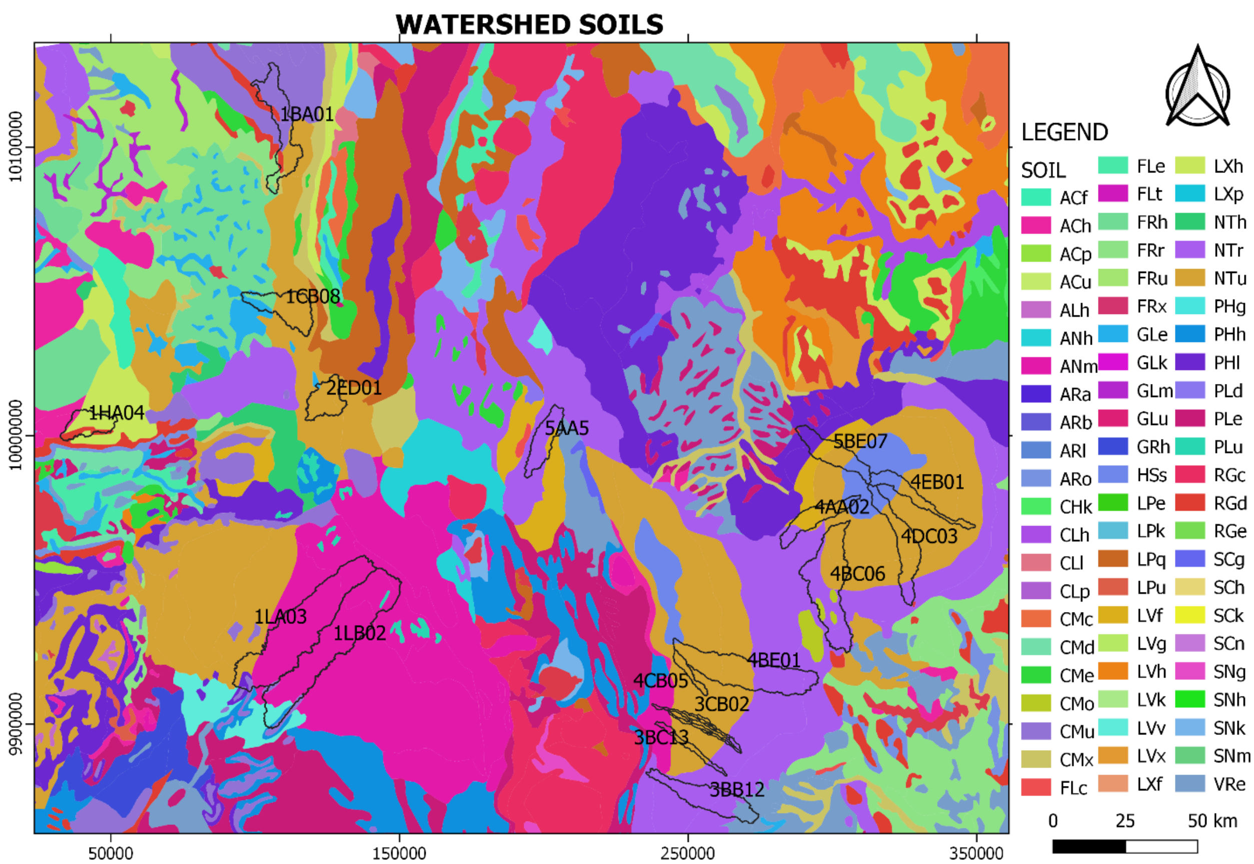


Figure 3: Soil map

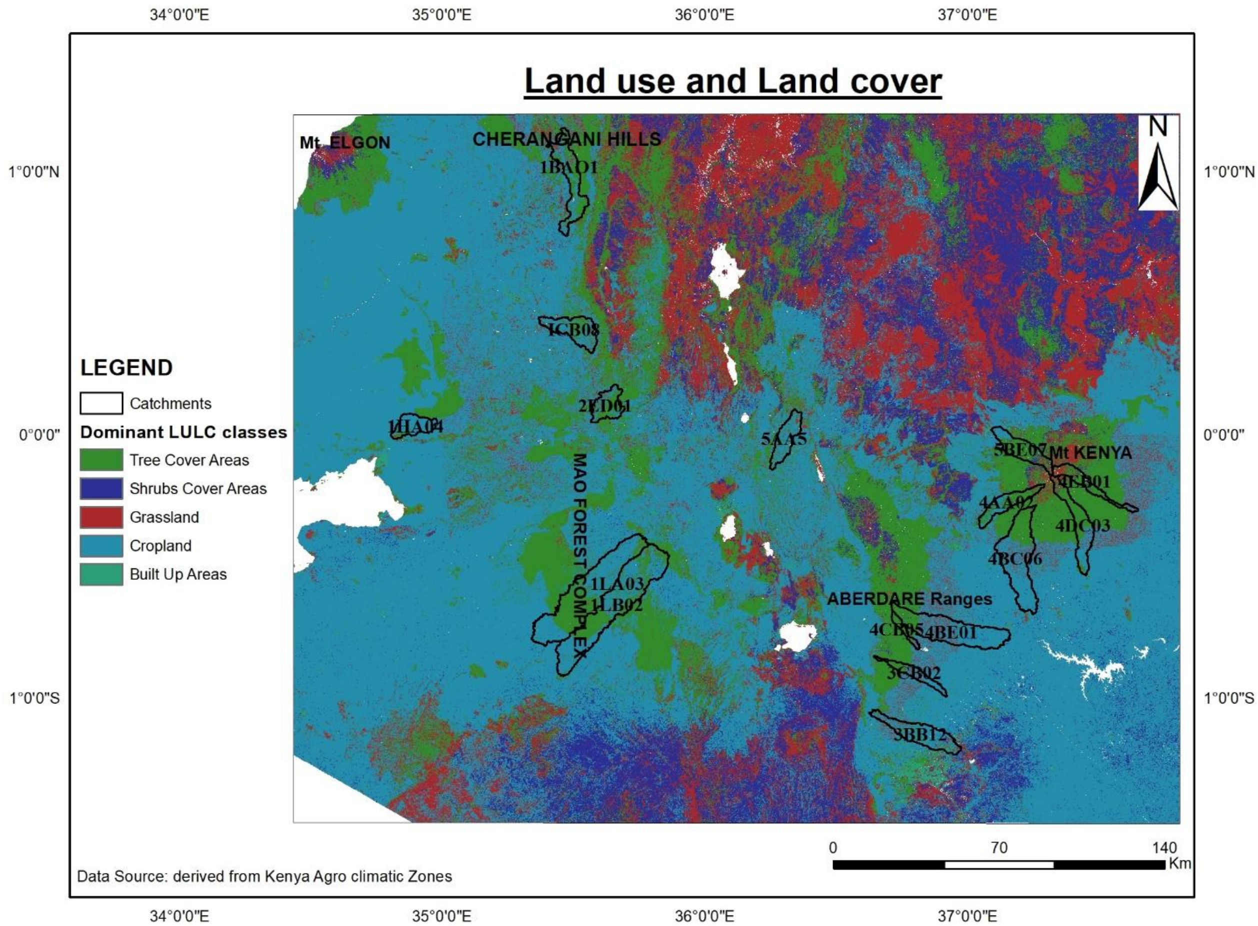


Figure 4: Land use/cover map

3.1.2 Data

The data gathered for this study is composed of:

Kenya Digital Elevation Model (DEM): The digital elevation model (DEM), was from global public data sets. The Shuttle Radar Topography Mission (SRTM) provides a high-resolution digital topographic database, and SRTM30 data, a 30 arc-second resolution global topography grid was selected.

The Harmonized continental SOTER-derived database of Kenya (KEN_SOTWIS) (Batjes et al., 1984): It is a GIS-based database which provides a harmonised set of soil parameter estimates for Kenya. The land surface of the country has been characterised using 397 unique SOTER units that correspond to 623 soil components. Soil parameter estimates are presented for each component soil of a SOTER mapping unit for depth intervals of 0.2 m up to 1 m depth. They include; organic carbon, total nitrogen, pH (H2O), CECsoil , CECclay , base saturation, effective CEC, aluminium saturation, $CaCO_3$ and $CaSO_4$ content, exchangeable Sodium percentage, electrical conductivity of the saturation paste (ECe), bulk density, sand, silt and clay content, content of coarse fragments (>2 mm), and available water capacity (-33 to -1500 kPa; cm/m).

Land use/ cover data: It is a prototype high-resolution Land Cover map over Africa, released in September 2017. It has been developed at 20m, based on 1 year of Sentinel-2A satellite observations from December 2015 to December 2016. The main objective to make public this prototype is to collect user's feedback for further improvements. The legend of the S2 prototype LC 20m map of Africa 2016 was built after reviewing various existing typologies (e.g. LCCS, LCML…), global (e.g. GLC-share, GlobeLand30) and national experiences (Africover, SERVIR-RMCD). The legend includes 10 generic classes that appropriately describe the land surface at 20m: "trees cover areas", "shrubs cover areas", "grassland", "cropland", "vegetation aquatic or regularly flooded", "lichen and mosses / sparse vegetation", "bare areas", "built-up areas", "snow and/or ice" and "open water".

National Aeronautics and Space Administration Prediction of Worldwide Energy Resource (NASA POWER) Agroclimatology data: It consists of daily minimum and maximum temperatures, wind speed and relative humidity at 2m and All-Sky Insolation Incident on a Horizontal Surface data. These data were obtained from the NASA Langley Research Center (LaRC) POWER Project funded through the NASA Earth Science/Applied Science Program.

CHIRPS daily rainfall data: Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a quasi-global rainfall dataset available over more than thirty-year. CHIRPS incorporates 0.05° resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring (Funk et al., 2015). The CHIRP/S algorithm combines three main data sources: (1) the Climate Hazards group Precipitation climatology (CHPclim), which is a global precipitation climatology at 0.05◦ latitude/longitude resolution estimated for each month based on station data, averaged satellite observations, longitude, latitude and elevation; (b) Thermal InfraRed-based Climate Hazards group Infrared Precipitation (CHIRP); and (c) *in situ* rain-gauge stations' measurements (Dinku et al., 2018; Funk et al., 2015). The particularity of CHPclim from other precipitation climatologies is its usage of long-term average satellite rainfall fields as a guide to deriving climatological surfaces. This improves its performance in mountainous countries like Ethiopia (Dinku et al., 2018).

Streamflow data: The streamflow data was purchased from the Water Resources Authority (WRA). The length of records spanned most between 1940 and 2018.

The version 4 Global operational Simplified Surface Energy Balance (SSEBop) Actual ET: It is a high resolution daily actual evaporation.

3.1 Methods

3.1.1 Topographic characteristics

The Kenya Digital Elevation Model (DEM) was used to delineate the selected catchments within the study and to identify their topographical characteristics using Arc SWAT and other tools from Arc map. The catchment delineation was done using the gauging stations as outlets.

3.1.2 Soil parameters

The Harmonized continental SOTER-derived database of Kenya (KEN_SOTWIS) Database has been used to derive the areal percentages of the different soils of the study area for each catchment. Using the individual parameter of each soil, areal values have averaged sand, clay and silt percentage, hydraulic conductivity, AWC and TOC have been defined.

3.1.3 Land use/ cover indices

Land use/cover data map was used to define the percentage of the dominant land use and cover classes including as Tree cover area, Built-up area, cropland, Shrub cover area and grassland area. This was done using the relevant tools in Arc-GIS.

3.1.4 PET

Daily values of potential evapotranspiration were estimated from solar radiation, wind speed, minimum and maximum temperatures and relative humidity using Penman-Montheit equation in the INSTAT 3.37 software. This data was downloaded from NASA POWER global dataset, using the centroid of each catchment as point location. It happened that there are missing values for solar radiation one few days, the values for the previous or next day was thus assigned to those days. The use of version 4 Global operational Simplified Surface Energy Balance (SSEBop) Actual ET has been attempted, since the time span of the availability is short and on monthly basis, long term ratio with the Penman-Montheit estimates has been calculated and affected to each month.

3.1.5 Rainfall

CHIRPS daily estimations of rainfall have been used for this study. Due to the high spatial resolution (0.05° × 0.05°) of the CHIRPS products (Africa daily precipitations in .tif format Raster files) downloaded from http://chg.geog.ucsb.edu/, stations were defined using coordinates of one point selected in every grid covering a catchment. Daily rainfall estimates were extracted for each station using the coordinates of the stations using the specific packages in R 3.5.4 software. The lumped daily precipitation was then estimated as the areal average over the catchment after estimation of the part of catchment that overlaps with each specific grid. The data is available from 1981 up to date.

3.1.6 Streamflow data

The streamflow data purchased was preliminarily analysed for patterns consistency using plotting. The length of records spanned most between 1940 and 2018. The data contains gaps. The value for missing data (-9999) was used to fill the gaps. The runoff coefficient Q/P was computed and analysed with respect to global annual water balance dataset available in the FAO's Local Climate Estimator (New_LocClim_1.10). This was done on the part of data available from 1981 since the CHIRPS rainfall estimates availability starts from that year.

3.1.7 Selection of the catchments

Thirty catchments were preliminary selected based on their size and availability of streamflow record for both calibration and simulation periods. The selection of the catchments considered also the need to cover a wide range of locations and morphological types and for each catchment to be less than $1000km^2$. The reason was to reduce uncertainties that could emerge from the occurrence of localised rainfall since the model uses lumped rainfall and to ease the abstraction of physical catchment descriptors. Since AWBM is a lumped model, spatial variability can result in poor model performance especially in very large catchments. The stream flows in the selected catchments were assumed to be unaffected by large scale abstractions, storages or effluents. In addition consideration was not given to land-use change since most of catchments are located in mountainous forested area. It suggests that the land cover/cover changes have not altered significantly the streamflow signature. Geographical proximity and landscape aspect were considered in order to make the catchments fairly homogeneous climatically, physiographically and hydrologically. The study catchments were of similar scale and were geographically spread across humid and sub-humid areas, hence they exhibited differences in land cover, topography, soil types and drainage density network structure. The study aimed at relating these different features to the variations in the hydrological responses of these catchments.

3.1.8 Characterization of the catchment

Let alone the distance-based regionalisation methods, other methods that can be put together into the similarity-based methods require the identification of some quantifiable physical features of catchments that would explain their hydrological response. A key choice when performing such methods is which of the catchment physical features are best for predicting model parameters. Unfortunately, it is frequently uncertain which landscape attributes will best explain each of the different rainfall-runoff model parameters. It is common therefore to initially consider a wide range of possible descriptors and then refine to a smaller subset using some form of statistical analysis and hydrological reasoning (Susana, 2014). Considering the time frame of the study, there is very little to expect from in-situ data collection, therefore the descriptors were limited to existing information on the physical catchment attributes. The major issue with that situation is the bias incurred in the quantification of CAs since it is tedious to achieve data concurrency for all the catchments. It has been thus assumed that changes in the study area did not alter significantly the hydrological behaviour of the catchments. Based on the literature, some CAs expected to be hydrologically relevant in the study area and which were available from existing data sources was defined and used in the study. For the seventeen catchments selected, 14 CAs (6 topography based, 5 land cover based and 4 soil type based) were therefore derived using the DEM, soil and land cover maps to represent topography, soil and land use.

3.1.9 Selection of the model structure

The rainfall-runoff model selected for use in regionalisation studies is usually a lumped conceptual model. Physically-based models require high-resolution catchment physical description, which can only be provided at experimental scale according current data collection capability. It could not hence satisfy the objectives of this study which is to come up with a simple technic for estimation of runoff in ungauged catchments. Very few studies have employed physically-based hydrological model for runoff estimation in ungauged catchments. The use of conceptual models has many advantages including the ease with which they can be constructed, time and information required for implementation and their computational efficiency (Susana, 2014). Examples of conceptual models used in the context of PUB mentioned in (Blöschl et al., 2013) include, among others, PDM Bulygina et al., 2009), HBV (Seibert, 1999), GR4J (Oudin et al., 2008), IHACRES (Post and Jakeman, 1999) and AWBM (Boughton and Chiew, 2007). This gives evidence that wide range of conceptual model is used to make estimations of streamflow in ungauged catchments. A large number of model structures and the fact that each modeller tends to praise his achievement makes it difficult to choose a particular model for a specific purpose. The number of arguments on which model selection is often justified includes the modellers' past experience with a given model structure or its structure and its good performance in a similar climatic zone or region and applications. The accessibility of the model whether it is open source or requires to pay for the license is also another reason for model structure choice. Other aspects to be taken into account in the process of the model structure selection encompass among others, input data requirement, hydrological realism and adequate model complexity.

A highly complex model with poorly constrained parameters due to limited data availability has as consequence high degree of freedom that causes models to behave like "mathematical marionettes" (Kirchner, 2006). Over-parameterisation of the model structure can compensate for data error and structural deficiencies, leading to many different parameter sets presenting similar good performance but that often incapable of producing good results for conditions where the model have not been trained in (Clark, Kavetski, & Fenicia, 2011). There are many situations where the model simulation fits the observed data well, but where the model structure does not reflect the essential hydrological processes observed in the catchment and thus lacks realism. In these cases, when the model is applied somewhere else (either in time or in space) large bias and uncertainties may be introduced. This makes hydrological realism and model structure very important in PUB context (Susana, 2014). Even if a model works well for certain catchment, it is possible that the same model might not perform well on another catchment in the context of prediction in ungauged catchments as the dominant runoff mechanisms are different. The AWBM model has been chosen for this research based on its simplicity, seven parameters most of which are available and accessible, its development to allow for runoff prediction in ungauged catchments and the good results compared to other models requiring more of parameters in humid catchments of Australia (Blöschl et al., 2013). Makungo *et al.*, (2010) used Mike 11 NAM and AWBM in the Limpopo river basin. He concluded that the results for both models were good and comparable and that the method can be used to fill the gap of data for the river streamflow.

3.2 Australian Water Balance Model (AWBM)

The Australian water balance model (AWBM) was developed in the early 1990s and has been used extensively throughout Australia. It is a lumped, conceptual rainfall-runoff catchment water balance model with interconnected storages and algorithms that mimic the underlying hydrological processes used to describe the movement of water into and out of storages. It allows calculation of runoff from rainfall at daily time increments and can be used for water yield and water management studies. The model uses three surface stores, representing the impacts of antecedent wetness and spatial variability of the abstractions, for modelling rainfall-runoff relationships. It is developed from the concept of saturation overland flow generation of runoff. The rainfall is added to each of the surface stores and evapotranspiration is subtracted (Boughton, 2004). If there is any excess from any store, it becomes runoff and is divided between surface runoff and baseflow. It has seven parameters some of which can be estimated from observed streamflow, rainfall and evaporation data (W. Boughton, 2004). AWBM also has an automated calibration methodology with a choice of six algorithms and seven objective functions. The software offers 6 calibration optimisers, a choice of 8 objective functions and 3 types of data transformation for comparison against observed data. The calibration optimisers included in the library are Uniform random sampling Pattern search, Multi start pattern search, Rosenbrock search, Rosenbrock multi-start search, Genetic algorithm, Shuffled Complex Evolution (SCE-UA) and AWBM custom optimiser. The objective functions provided include Nash-Sutcliffe criterion (Coefficient of efficiency), Sum of square errors, Root mean square difference about bias, Absolute value of bias, Sum of square roots, Root mean square error (RMSE), Sum of square of the difference of square root, Sum of absolute difference of the log. There are also three options available for calibration based on two objective functions which are Flow duration curve, Runoff difference in % and Base flow method 2 (Boughton, Chapman and Maxwell).The AWBM is part of the Rainfall Runoff Library, a toolkit developed by the Cooperative Research Centre for Catchment Hydrology (CRCCH), Australia. Sacramento, Simhyd, SMAR and TANK rainfall-runoff models are also included in the library. It was accessed freely from https://toolkit.ewater.org.au/.

3.2.1 Model structure

The model computes surface runoff and baseflow w components of streamflow at daily time steps. The model generates runoff by saturation excess from three surface stores. Each store is able to produce runoff independently of the others allowing for partial area runoff. The parameters of surface storage are the three capacities and their partial areas. Those are C1, C2 and C3 that extent to partial areas of the catchment A1, A2 and A3 respectively (A1 + A2 + A3 = 1.0). The average surface storage capacity CE is the single parameter that determines how much rainfall becomes runoff. This single parameter is disaggregated into a set of capacities and partial areas using a fixed pattern observed using a set of quality data from some catchments. The sum of the three products of capacity and partial area makes up the average surface storage capacity; C1*A1 + C2*A2 + C3*A3 (W. Boughton, 2004). The excess from the surface stores which is the runoff generated, is divided into surface runoff and baseflow recharge by the baseflow index (BFI). The discharge from baseflow storage at daily time step increments is determined by the baseflow recession constant (Kb) and calculated as (1 – Kb) times the amount in baseflow store (BS). The discharge from the surface runoff store (SS) is calculated as (1.0 – K_s) times the amount in the surface store. K_s is the daily surface runoff recession constant. The structure and parameters of AWBM are presented below.

Table 1: Description of the AWBM model parameters

Parameter	Description
A_1	Partial area of smallest store
A_2	Partial area of middle store
A_3	Partial area of largest store
BFI	Baseflow index
C_1	Surface storage capacity of smallest store
C_2	Surface storage capacity of middle store
C_3	Surface storage capacity of largest store
Kbase	Baseflow recession constant
Ksurf	Surface runoff recession constant

Description of the AWBM model parameters (W. Boughton, 2003)

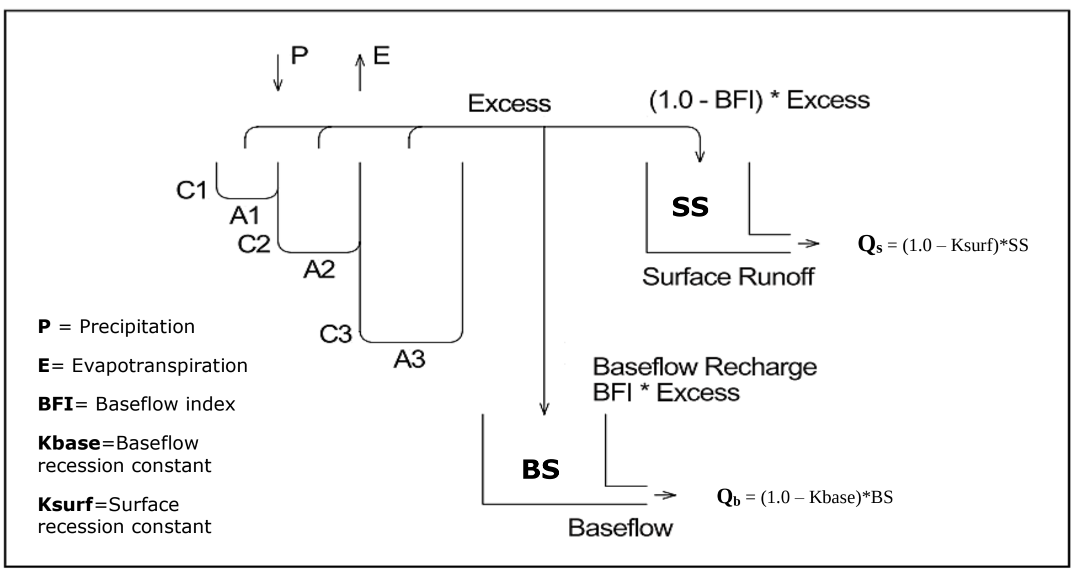


Figure 5: AWBM model structure adapted from (Boughton, 2004)

3.2.2 Calibration of AWBM

The process of selecting suitable values of model parameters such that the hydrological behaviour of the catchment can be simulated closely is termed as model calibration (Moore & Doherty, 2005). A significant feature of the AWBM has been the development of calibration procedures based on the structure of the model, rather than using trial and error testing of different sets of parameter values. This method of calibration summarised below from (Boughton, 2003) is operated by choosing the AWBM custom calibration features. It has two optimisation parameters including the maximum average storage capacity and the conversion criterion of the sum of the square roots between calculated and actual daily runoff values. This optimisation method has been chosen because it could allow for error quick detection, gives the same parameter values in the same condition and is based on the internal structure of the model. This was also to minimise the problem of equifinality (Beven, 1993). Manual adjustments were done to improve the models. Due to the context of data scarcity and the assumption that the catchments are not impaired in their hydrological behaviour and land-use changes are minor, different periods have been used for calibration according availability of data and concurrency with CHIRPS rainfall estimates. The parameters to be determined are the surface storage capacities and their partial areas, the surface recession constant and two baseflow parameters. The method of calibration has been improved from one version to another.

3.2.2.1 Surface storage capacities and partial areas

The main feature of the automatic calibration procedure was the development of a fixed pattern of surface storage capacities and partial areas that could be represented by a single parameter: the average surface storage capacity (Ave = C1*A1 + C2*A2 + C3*A3). First, default values for the baseflow parameters, BFI and Kbase, and the surface runoff recession constant Ksurf are assumed and then, a preliminary calibration of the surface stores is achieved by adjusting total calculated runoff to match the total actual runoff. By applying earlier methods of calibration to many catchments over several years on a number of high-quality data sets, it was found that the average value of surface storage capacity was more important to calibration than the individual set of capacities and partial areas.

An average pattern was found that could be used to disaggregate an average capacity (Ave) into three capacities and three partial areas as follows:

Partial area of smallest store	A1 = 0.134
Partial area of middle store	A2 = 0.433
Partial area of largest store	A3 = 0.433
Capacity of smallest store	C1 = 0.075*Ave
Capacity of middle store	C2 = 0.762*Ave
Capacity of largest store	C3 = 1.524*Ave

3.2.2.2 Baseflow index and recession parameters

After the surface store parameters are obtained, the baseflow parameters (BFI, Kbase) and the surface runoff recession constant (Ksurf) are calibrated in that order and then a second time in that order, using a measure of the difference between calculated and actual daily runoff hydrographs. The error measure is the sum of the square roots between calculated and actual daily runoff values, summed over the period of calibration data, with trial and error adjustments of BFI, Kbase and Ksurf to minimize the error function. In this way, the parameter that generates runoff (surface storage capacity) is calibrated against the amount of runoff, and the parameters that affect the temporal pattern of runoff (BFI, Kbase and Ksurf) are calibrated against the pattern of runoff.

3.3 Derivation of a Regional Model Parameter Set

A statistical model was established relating each parameter (dependent variables) to a set of catchment attributes (independent variables), on the assumption that the uniqueness of a catchment can be pictured in its specific combination of CAs. Model parameters for the ungauged catchments of the humid area of Kenya can then be estimated, for AWBM model, using the derived regression model and the corresponding set of CAs for the ungauged catchment. Once a model parameter set has been calculated for the ungauged catchment, not only daily streamflow can then be simulated but also the physical basis of the AWBM model can then be discussed. This process was applied to a part of the data to allow for the proxy-basin test (KlemeŠ, 1986). Over the seventeen catchments four was selected for testing and thus not using the establishment of the regional model and considered as ungauged catchments. These included KIBOS (1HA04), THIKA (4CB05), MOIBEN (1BA01) and ENDOROTO (1CB08). It involved the following sequential steps:

3.3.1 Development of MPs-CAs Relationships

The parameters of conceptual models are mostly designed to have a physical interpretation. For example, the parameters Ksurf, Kbase and BFI of AWBM are said to be derivable from the hydrograph (W. Boughton, 2004). Nevertheless little is known on the nature of the relationship between model parameters and the catchment attributes (Susana, 2014). This makes the selection of relevant catchment attributes for the description of the catchment hydrological behaviour a non-trivial task, despite the statistical techniques available to aid this process. Moreover, statistical relationships must also have physical meaning if they are to be reliably extrapolated to ungauged catchments (Beck et al., 2016).When the statistical relationships found cannot be explained through hydrological reasoning, it leads to erroneous predictions. An example can be found in (W. Boughton & Chiew, 2007) where a statistical regression equation meaning that an increase of PET would increase the streamflow was invalidated by the authors. This situation can occur and go unnoticed when the understanding of the misleading equation is not obvious. For this reason, relationships were established between CAs and PMs and between PMs among themselves and CAs among themselves. Moreover for an optimal statistical model, the independent variables explaining the dependent variable should not be correlated. The occurrence of model parameters interdependencies in the development of the regression equations undermines significantly the predictive capability of the regionally calibrated models (Kokkonen et al., 2003; Xue et al., 2017). This can be noticed and considered if this approach is followed.

3.3.2 Multiple linear regression

Regression analysis is a statistical tool for the investigation of relationships between variables. It is of interest to find a causal effect of one variable upon another. Multiple regression is a very flexible method and may be suitable when a quantitative dependent variable is in relationship to more independent or predictor variables. In hydrology, the use of multiple regression models to establish a link between hydrological parameter or response signature and a set of catchment descriptors is a long-established practice (Kjeldsen and Jones, 2009) as cited in (Susana, 2014). The independent variables assumed to provide information on the behaviour of the dependent variable are included in the regression model and regression parameters are estimated given observation data. The basic formula of a multiple regression model can be written as follows:

$$\boldsymbol{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_{p-1} X_{p-1} + \beta_p X_p + \varepsilon} \quad \text{(Eq. 1)}$$

Where Y is an observable random variable; X_1, X_2, X_{p-1} and X_p are p observable non-random variables assumed to be measured without error, $\beta_0, \beta_1, \beta_2, \beta_3, \beta_{p-1}, \beta_2$ are unknown model parameters also known as regression coefficients (or partial regression coefficients), and ε is an unobservable random variable, referred to as the error term, that represents the discrepancy between and the predicted values of the dependent variable. Statistical assumptions about having to be made for model formulation. It is usually assumed that ε has zero mean,$E(\varepsilon) = 0$ constant variance, σ^2, and that its terms are independent of each other and of the value of the dependent variables. Although these error assumptions are modest, additional assumptions such as normality in distribution$\varepsilon \sim N(0, \sigma^2)$ have to be added for the purposes of making confidence statements and hypothesis testing. Multiple regression is commonly used when one dependent variable and several independent variables are available and it is desired to find a linear model for predicting unobserved values for the dependent variable. A model has, therefore, to be developed that does not have to contain all of the independent variables. The development of the right model is normally complicated by the fact that in most cases the independent variables are not statistically independent of each other but are correlated. The first step in regression analysis, therefore, is to determine the correlation matrix of the independent variables.

3.3.3 Selection of catchment attributes

There are several ways to derive the statistical relationships relating response signatures to catchment descriptors. Many CAs are presumed to be able to explain predictors the MPs resulting in a long list of physical attributes. For this reason, the classical multiple regression method can be tedious to implement. An automated procedure is obviously preferred to an exhaustive variable selection. The forward entry method and the backward removal method are applied. In the forward entry method, the established significant single relationships are extended by forcing additional CAs in the relationships until the last added CA does not significantly contribute to the relationship. In the backward removal method, relationships incorporate all CAs after which these ones are stepwise reduced until a significant relationship is obtained. Next, the relationships for each model parameter were evaluated from a hydrological context since statistically significant relationships do not necessary have physical explanation. Finally, where possible, for each model parameter a relationship is selected with corresponding correlated CAs.

3.3.4 Validation of MPs -CAs Relationships

For the purpose of evaluating the usefulness of the developed estimation equations, the model parameter values (PMs) of all the calibration catchments were computed, including the four catchments not used in their establishment process. Thereafter, the calibrated parameter values and those obtained through estimation using the derived PM-CA relationships were statistically compared for error margins. NSE and r^2 are the performance mesasures used. The successful development of the relationships between PMs and CAs could make it possible to regionalise AWBM model by providing a regional parameter set where model parameter values captured in the uniqueness of the combinations of catchment characteristics can be calculated. The characteristics can then be used with the developed relationships to estimate model parameters which, together with daily time series of rainfall and evapotranspiration, can be used to simulate daily stream flows in any ungauged catchment of the humid areas of Kenya using the AWBM model. In addition, relating model parameters to catchment characteristics makes it possible to analyse the physical basis of the AWBM model. Stepwise regressions was carried out using the R_3.5.3 software.

3.3.5 Estimation of Daily Stream Flows

The estimation of the model parameters only is not really enough to give tangible conclusion about the performance of the regionalisation method. The estimated models parameters are therefore used to simulate the daily streamflow for the pseudo-ungauged catchments over the period of calibration and validation. The calibrated values are used as default values for unrealistic or non-estimable parameter. The pseudo catchments where selected through a random split of the data. These included KIBOS (1HA04), THIKA (4CB05), MOIBEN (1BA01) and ENDOROTO (1CB08). Even though the selection has been done randomly, the catchments selected were special. 1CB08, 1HA04 and 1BA01 are located fare from the majority and 4CB05 is the smallest catchment. However, since these catchments are in fact gauged, the estimated daily stream flows were then compared with the observed (recorded) daily stream flows in order to assess the accuracy of the estimations. The accuracy of these estimations was evaluated by comparing the values of the coefficients of determination, R^2 of estimated and observed streamflows as used for the prior calibration and validation.

3.2.6 Assessment of Model Performance

Comparison of predicted and observed hydrographs is a necessary step in assessing the performance of any model. An objective function is one of the common means of evaluating model performance. It is an equation used to compute the numerical measure of the difference between simulated model output and the observed (measured) catchment output.

3.2.6.1 Correlation Coefficient (r)

Correlation analysis is a statistical tool used to assess the degree of dependence between variables. Correlation coefficient (r) summarises in one number the direction and magnitude of the correlation. It is also a numerical means of assessing the performance of a model. The value of the coefficient, r, varies from zero to unity; with the highest value unity indicating the best performance, $|r| \leq 1$.

$$r = 1 - \frac{S_{sim}^2}{\sigma_{obs}^2} \tag{2}$$

Where:

r is the correlation coefficient between the observed and simulated streamflow

S_{sim}^2 is the standard error of the simulated streamflows

$$S_{sim}^2 = \sqrt{\frac{\sum_{i=1}^{n}\left(Q_{sim,i} - \bar{Q}_{sim,i}\right)^2}{n-1}} \tag{3}$$

σ_{obs}^2 is the standard deviation of the observed streamflow

3.2.6.2 Nash-Sutcliffe Coefficient of Efficiency (NSE)

This is the most commonly used objective function for assessing the goodness of fit after model calibration or simulation. It measures how well the simulated and observed flows correspond.

It is given by:

$$\mathrm{NSE} = \frac{\sum_{i=1}^{n}(\mathrm{Q_{obs,i}} - \mathrm{Q_{sim,i}})^2}{\sum_{i=1}^{n}(\mathrm{Q_{obs,i}} - \bar{\mathrm{Q}}_{\mathrm{obs,i}})^2} \tag{4}$$

Where:

$Q_{obs,i}$ is the observed streamflow on the day i, $Q_{sim,i}$ is the simulated streamflow on the day i, $\bar{Q}_{obs,i}$ is the mean of the observed streamflow on the day i.

NSE values of 1 indicate perfect fits. NS values between 0.9 and 1 indicate that the model performs extremely well. Values between 0.8 and 0.9 indicate that the model performs very well while values between 0.6 and 0.8 indicate that the model performs reasonably well. Negative NS values indicate that the observed mean discharge is a better predictor than the model simulation.

3.2.6.3 The Relative Volume Error RV_E

$$RV_E = \left(\frac{Q_{obs,i} - Q_{sim,i}}{Q_{obs,i}}\right) \tag{5}$$

Where:

$Q_{obs,i}$ is the observed streamflow on the day i,

$Q_{sim,i}$ is the simulated streamflow on the day i.

A relative volume error between -5% and 5% indicates that a model performs well while a relative volume error between +5% and +10% and between -5% and -10% indicate a model with reasonable performance. For a good model fit the value of R should have positive value and be as close to unity as possible.

4 Results and discussion

4.1 Selection of the catchments

After the preliminary selection of 30 catchments, it was realised based on the calibration that only 17 were suitable for the following steps. The remaining catchments were left for poor calibration results. Since the rainfall data used was CHIRPS estimates, the focus was given to the coefficient of determination r and visual observation. Some analysis was done prior to the calibration by visualising the plotting of hydrographs, calculating annual average rainfall, potential evapotranspiration and runoff, Evaporation ratio and runoff coefficient that was compared to the long term average values using the FAO's Local Climate Estimator (New_LocClim_1.10) dataset using the centroid of the corresponding catchment for location. The Nash-Sutcliffe model efficiency coefficient (NSE) has been calculated directly but was not strictly considered because of the rainfall uncertainties. Figure 1 shows the comparison between the calculated and estimates from New Loc Clim of catchments' runoff ratio and aridity index. This is to show that the type climate of each cathment. Some runoff coefficients and aridity index calculated from the data did not agree with the ones from the New Loc Clim dataset. This may be due to error in the measurement of the streamflow or from CHIRPS estimates. Missing data can also have impact on the averaged values depending on the period of flows when the data has not been recorded. Missing low flows will increase the average whereas missing high flows will reduce the average value. As New_LocClim is a regional dataset based on extrapolations and estimations, there should be some discrepancies as compared to the field estimates.

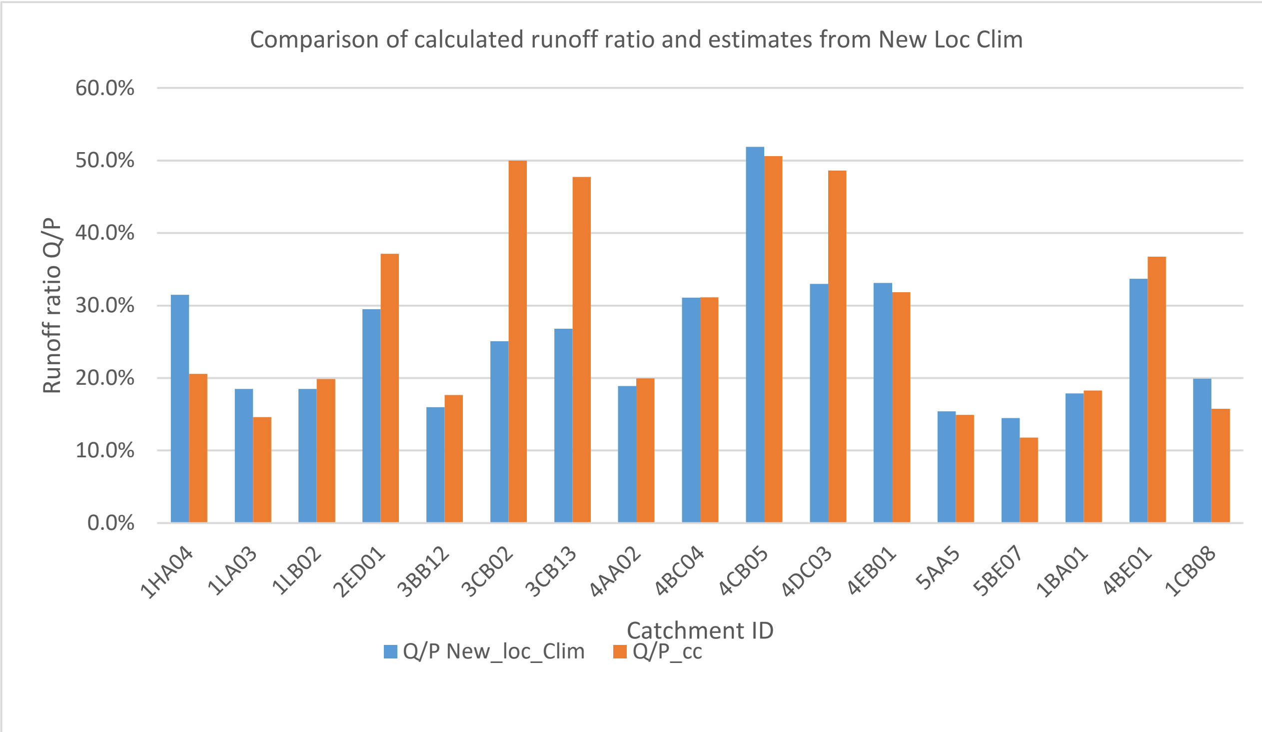


Figure6: Comparison of calculated runoff ration and estimates from New Loc Clim

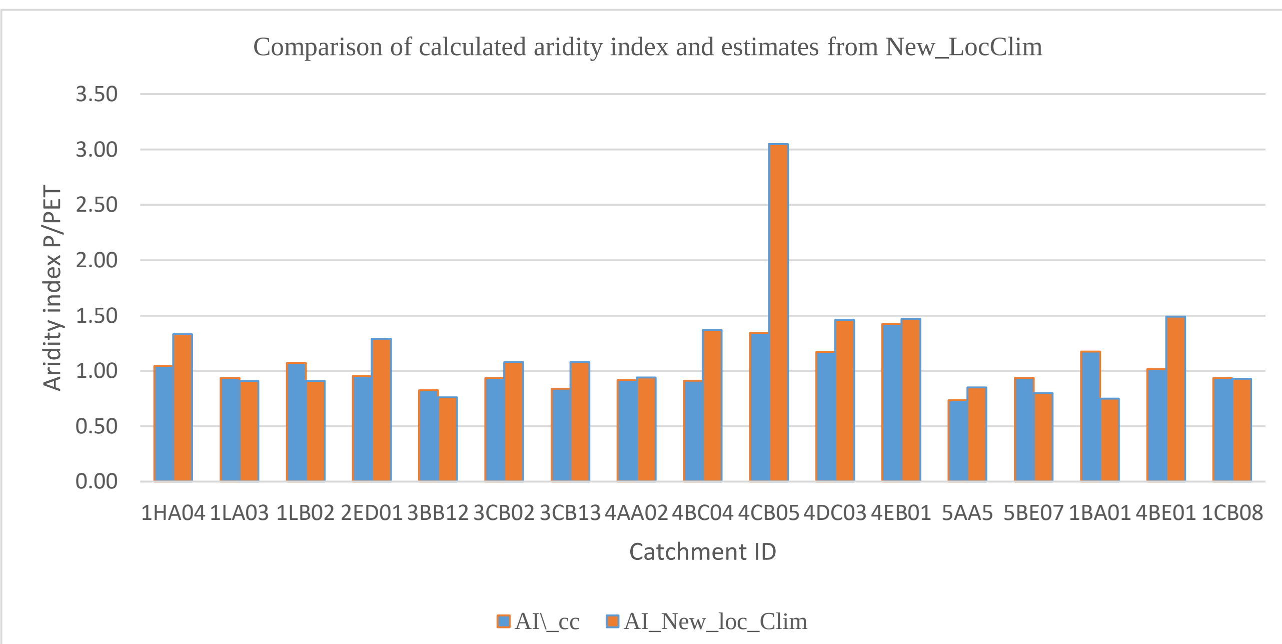


Figure 7: Comparison of calculated aridity index and estimates from New Loc Clim

4.2 Derivation of model parameters (MPs)

The models parameter which are the dynamic response descriptors of the catchments were obtained through calibration. The periods of calibration and validation has been selected according to the availability of data and concurrency with climatic data. The objective functions for calibration and validation and the periods have been compiled in table 2. The resulting MPs for each catchment after calibration are in Table 3. Figure 8 and Figure 9 show the observed and simulated streamflow over the calibration and validation periods respectively for Amala river (1LA03).

Table 2: Calibration and verification periods and performance measures

ID	Cal Start	Cal Wup	Cal End	Val Start	Val Wup	Val End	Cal R^2	Val R^2	Cal NSE	Val NSE
1HA04	23/9/1981	12/12/1982	28/08/1983	7/7/ 1986	27/09/1986	23/12/1987	**0.70**	**0.49**	**0.28**	**0.14**
1LA03	5/3/ 2001	25/05/2001	5/11/ 2008	6/21/ 2012	21/06/2012	8/24/ 2016	**0.71**	0.62	0.41	0.37
1LB02	12/11/1984	3/30/ 1985	7/13/ 1989	8/25/ 2009	11/14/2010	9/30/ 2017	**0.66**	0.56	-0.30	0.19
2ED01	7/27/ 1989	10/5/ 1990	6/20/ 1994	2/8/ 1993	12/16/1993	8/24/ 1997	**0.58**	0.77	0.09	0.39
3BB12	3/8/ 2007	6/16/ 2007	12/3/ 2011	9/29/ 2011	2/21/ 2013	5/8/ 2016	**0.56**	0.37	0.17	0.00
3CB02	3/25/ 1985	3/25/ 1985	9/15/ 1987	8/6/ 1989	6/8/ 1989	10/16/1993	**0.62**	0.55	0.18	0.02
3CB13	9/19/ 1984	1/23/ 1986	10/6/ 1988	11/11/1987	10/25/1988	7/17/ 1990	**0.55**	0.50	0.19	0.12
4AA02	2/27/ 1982	2/27/ 1982	11/16/1985	8/19/ 1988	8/19/ 1988	10/27/1992	**0.54**	0.52	-0.34	-1.15
4BC04	3/25/ 2001	11/13/2002	5/18/ 2005	8/17/ 2017	2/4/ 2011	9/25/ 2014	**0.59**	0.53	-2.43	-0.13
4CB05	10/18/1989	4/16/ 1990	8/28/ 1993	12/26/1999	8/6/ 2000	1/31/ 2005	**0.64**	0.51	-1.99	0.22
4DC03	7/1/ 1984	8/19/ 1984	7/17/ 1990	7/24/ 1996	7/18/ 1992	4/10/ 1996	**0.56**	0.72	-0.49	0.26
4EB01	19/1/ 1994	6/11/ 1994	8/19/ 1997	12/30/1999	7/13/ 2000	4/10/ 2003	**0.50**	0.51	0.11	0.16
5AA5	1/8/ 2005	10/27/2005	1/28/ 2010	2/20/ 2010	9/5/ 2010	12/25/2013	**0.83**	0.75	-1.07	-1.12
5BE07	2/2/2002	9/20/2002	4/3/2007	4/17/2009	9/6/2010	8/31/2018	**0.55**	0.55	-0.78	-1.59
1BA01	6/1/2010	1/6/2010	12/13/2011	5/13/2013	13/5/2013	6/1/2016	**0.80**	0.63	0.51	0.22
4BE01	7/1/1983	7/5/1983	12/31/1987	1/24/1988	1/27/1988	1/17/1997	**0.72**	0.72	0.46	0.48
1CB08	2/3/1989	4/14/1990	1/28/1999	2/11/1999	1/18/2000	8/31/2015	**0.65**	0.60	-0.20	-0.20

Cal : Calibration, Val: Validation, Wup: Warm up,

Table 3: optimal AWBM model parameters for selected catchments

ID	BFI	C1	C2	C3	Ce	Kbase	Ksurf
1HA04	0.45	**0.0**	16.8	33.5	21.77	0.983	0.88
1LA03	0.65	**6.2**	63.4	126.8	83.18	0.976	0.68
1LB02	0.65	**9.8**	181.2	246.9	186.68	0.980	0.84
2ED01	0.65	**7.3**	335.5	442.3	337.76	0.980	0.70
3BB12	0.36	**19.2**	195.8	382.4	252.93	0.985	0.68
3CB02	0.65	**3.3**	51.7	94.3	63.66	0.989	0.74
3CB13	0.65	**1.3**	9.1	27.4	15.97	0.981	0.75
4AA02	0.52	**9.0**	142.3	348.6	213.76	0.980	0.75
4BC04	0.65	**15.0**	153.6	307.1	201.49	0.985	0.65
4CB05	0.65	**2.8**	120.3	139.9	113.04	0.986	0.88
4DC03	0.65	**2.9**	103.0	142.0	106.47	0.988	0.78
4EB01	0.63	**1.6**	16.4	32.7	21.47	0.985	0.68
5AA5	0.50	**13.2**	134.8	269.6	176.87	0.975	0.77
5BE07	0.58	**26.9**	238.4	549.9	344.93	0.983	0.84
1BA01	0.65	**8.5**	247.0	548.7	345.67	0.981	0.73
4BE01	0.56	**4.1**	13.6	156.0	7.73	0.985	0.77
1CB08	0.56	**4.0**	205.8	429.9	275.79	0.9710	0.75

C1= Capacity of smallest store, C2 = Capacity of middle store, C3 = Capacity of largest store

Ce = Average surface store

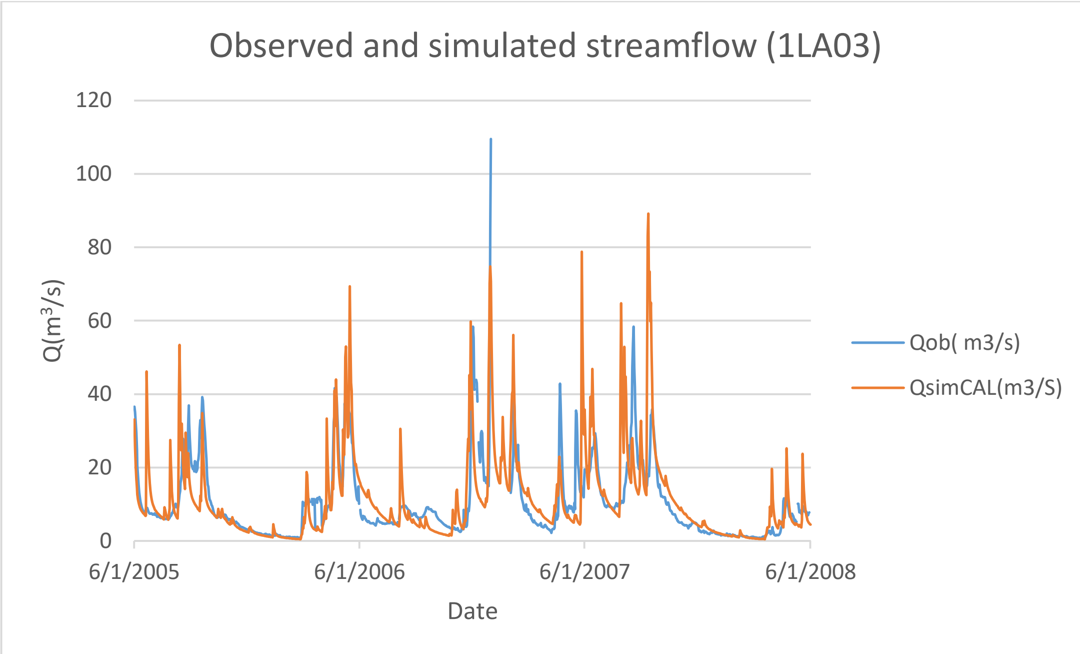


Figure 8: Observed and simulated flow over the calibration period for 1LA03

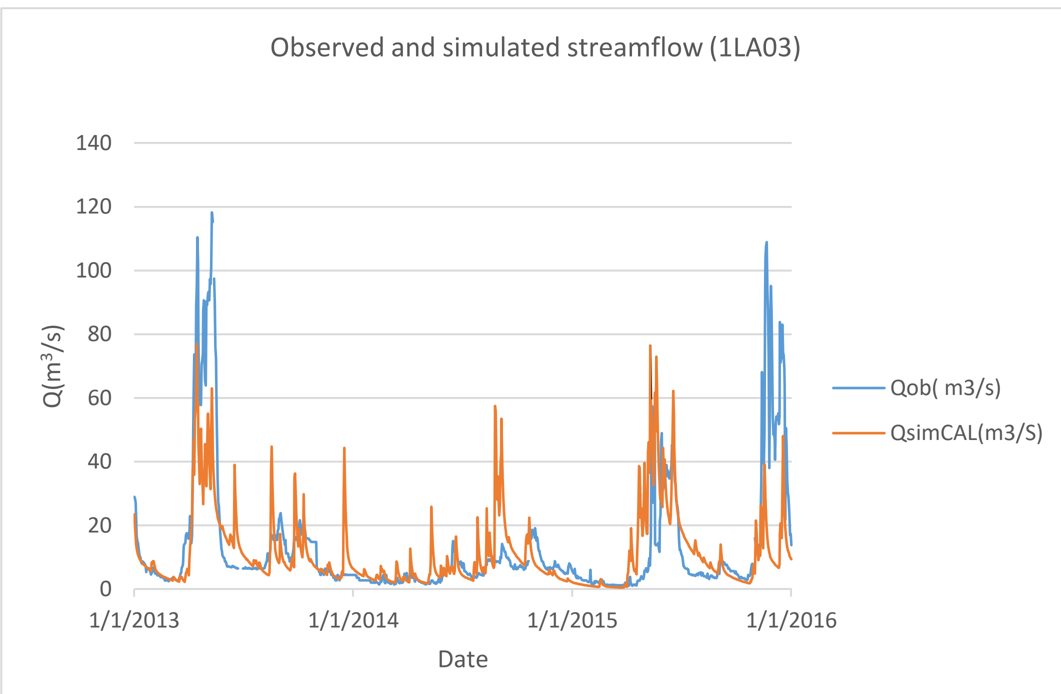


Figure 9: Observed and simulated flow over the verification period for 1LA03

4.3 Catchment attributes (CAs)

The hydrologically relevant geomorphometry, soil, land use/cover characteristics of the selected catchments easily accessible was used to characterize each catchment. Those characteristics include (Land use/cover) shrub cover, tree cover, built up areas and crop land, (Soil) hydraulic conductivity, Available water capacity, carbon content, percent sand, percent clay, (Topography) average slope, surface area, drainage density, minimum, maximum and average elevation.

4.3.1 Topographic characteristics

Topographic attributes taken into account for this study included average slope, surface area, drainage density, minimum, maximum and average elevation. The values for each attribute for each catchment are recorded in the table 4. In table it can be seen from the univariate statistics that the area, the drainage density and the maximum altitude present each a skew ranging from highly significant to moderately significant. For the other topographic based CAs the skew is not significant (table 7).

4.3.2 Land use/cover based catchment attributes

For the land use land cover characteristics, the percentage area of tree cover, shrubs cover, grassland and Built up area was considered. The univariate statistics showed that the built up area, grassland and shrub land were highly skewed, this can be explained by the fact that this types of land use indices are induced by human invasion of the forest. However the slight skew of the cropland shows a consistent conversion of the forest into agricultural land. It is normal to have an insignificant skew for the tree cover areas since majority of land cover is the forest. The values for land use/cover for each catchments are recorded in the table 5.

Table 4: Topography-based catchment attributes

ID	Area (Km^2)	AVERAGE_Elv(m)	Min_Elv(m)	Max_Elv (m)	D_D(m/Km^2)	SLOPE (%)
1HA04	123.95	1718.19	1209	2014	529.98	19.52
1LA03	694.95	2363.72	1898	2972	811.89	19.41
1LB02	698.11	2448.26	1847	3067	838.25	19.22
2ED01	135.17	2489.70	2103	2782	567.38	21.67
3BB12	237.46	1793.63	1493	2424	581.22	14.74
3CB02	93.22	2050.47	1606	2626	1071.41	21.74
3CB13	44.63	2080.30	1642	2626	1222.63	21.38
4AA02	139.80	2439.67	1755	4302	938.95	17.35
4BC04	421.54	1784.20	1144	3205	789.41	17.04
4CB05	38.45	2574.76	2021	3512	847.82	24.54
4DC03	215.36	2271.24	1299	4942	939.97	20.75
4EB01	122.67	2973.46	1308	4942	759.31	31.26
5AA5	147.04	2497.64	2331	2853	643.13	12.87
5BE07	174.43	2791.86	1931	5051	775.82	25.96
1BA01	254.93	2618.28	2031	3255	30.50	22.02
4BE01	419.08	1905.58	1211	3767	749.21	23.71
1CB08	195.54	2493.90	2204	2764	691.09	11.60

AVERAGE_Elv(m) = Average elevation Max_Elv (m) = Maximum elevation, Min_Elv(m) =Minimum elevation, D_D = Drainage density, SLOPE = Average slope

Table 5: Land use/cover based catchment attributes (Percentage areal coverage of dominant classes)

ID	Built Up Areas	Cropland	Grassland	Shrub Areas	Tree Areas
1HA04	0.00%	91.00%	1.00%	0.00%	7.17%
1LA03	0.08%	54.84%	0.84%	0.55%	43.66%
1LB02	0.02%	60.07%	1.90%	0.80%	37.20%
2ED01	39.12%	6.67%	0.00%	0.32%	53.46%
3BB12	11.04%	72.87%	6.31%	3.00%	6.00%
3CB02	0.76%	57.47%	8.20%	0.00%	33.33%
3CB13	1.94%	49.76%	8.10%	0.70%	39.48%
4AA02	0.24%	33.04%	5.97%	2.65%	57.92%
4BC04	1.25%	62.66%	6.79%	1.00%	28.30%
4CB05	0.06%	14.00%	3.53%	1.28%	81.00%
4DC03	0.14%	0.14%	71.39%	0.91%	20.17%
4EB01	0.00%	6.68%	21.56%	4.00%	67.00%
5AA5	1.46%	75.89%	7.49%	0.16%	14.77%
5BE07	0.34%	16.97%	8.62%	7.28%	66.39%
1BA01	0.01%	42.99%	8.68%	1.20%	46.77%
4BE01	0.95%	71.99%	9.12%	1.40%	16.46%
1CB08	0.05%	63.58%	6.63%	0.17%	29.49%

4.3.3 Soil characteristics based catchment attributes

The soil attributes considered comprised the areal weighted average hydraulic conductivity (k in mm/h), available water capacity (AWC in mm water/mm soil), total organic carbon (TOC in %soil weight) the Sand percentage and Clay percentage. The soil classes from the Harmonized World Soil Database (HWSD) has been used but for lack of representation over the catchments of the study, only the nitisols (NT) well represented across the catchment has been kept. The soils hydraulic conductivity and AWC has been computed from the attributes of the soil classes identified in the catchment using the SPAW software (Soil, Plant, Air, Water , a tool developed by U.S. Department of Agriculture). Only AWC and Clay percentage were slightly skewed. The other parameters a moderately to highly skewed (table 7). This reflects well the sparse distribution of the catchments over the study area and the high diversity of the soils. The soil characteristics based-CAs for each catchment are recorded in Table 6 below.

Table 6: Soil characteristics based catchment attributes

ID	K(mm/h)	AWC	TOC	%Sand	%Clay	NT
1HA04	6.85	10.36	3.03	45.30	32.89	0.00
1LA03	49.98	22.72	4.26	32.91	22.17	0.05
1LB02	45.07	23.13	3.94	33.44	21.61	0.00
2ED01	4.20	12.06	1.71	21.88	43.58	0.99
3BB12	1.18	9.55	1.41	19.43	67.68	0.82
3CB02	6.68	11.86	2.90	28.14	45.05	0.94
3CB13	3.07	12.32	3.52	26.38	54.23	0.76
4AA02	4.69	11.35	2.03	24.83	42.84	0.52
4BC04	3.58	10.78	2.15	25.43	54.98	0.93
4CB05	15.24	12.00	1.90	32.00	22.00	1.00
4DC03	7.59	15.36	3.33	24.54	33.13	0.84
4EB01	7.48	21.35	4.63	18.36	16.97	0.59
5AA5	0.99	9.66	1.33	16.61	62.23	0.84
5BE07	1.05	16.08	4.17	20.02	40.45	0.31
1BA01	28.77	13.79	4.38	47.20	27.70	0.22
4BE01	4.59	11.35	2.46	25.91	52.47	0.99
1CB08	3.28	12.14	1.72	21.43	42.71	0.71

K: Areal averaged soil hydraulic conductivity, **AWC**: Areal averaged soil available water content**, TOC**: Areal averaged soil total organic carbon, **%Sand**: Areal averaged soil sand percentage, **%Clay**: Areal averaged soil clay percentage, **NT**: Pencentage areal coverage of Nitisol

Table 7: Descriptive statistics of catchment attributes

CAs	N	Mean	Sd	Se	Min	Max	Skew
Area (Km^2)	17	244.49	200.92	48.73	38.45	698.11	1.22
AVERAGE_Elv(m)	17	2311.46	367.09	89.03	1718.19	2973.46	-0.14
Min_Elv(m)	17	1707.82	379.32	92.00	1144.00	2331.00	-0.06
Max_Elv(m)	17	3359.06	932.88	226.26	2014.00	5051.00	0.65
D_D(m/Km)	17	752.23	257.96	62.56	30.50	1222.63	-0.85
SLOPE (%)	17	20.28	4.83	1.17	11.60	31.26	0.18
Built Up Areas	17	0.03	0.10	0.02	0.00	0.39	3.06
Cropland	17	0.46	0.28	0.07	0.00	0.91	-0.28
Grassland	17	0.10	0.16	0.04	0.00	0.71	2.96
Shrubs Cover Areas	17	0.01	0.02	0.00	0.00	0.07	1.81
Tree Cover Areas	17	0.38	0.22	0.05	0.06	0.81	0.24
K(mm/h)	17	11.43	15.15	3.67	0.99	49.98	1.60
AWC	17	13.87	4.43	1.07	9.55	23.13	1.10
TOC	17	2.87	1.13	0.27	1.33	4.63	0.14
%Sand	17	27.28	8.68	2.10	16.61	47.20	1.00
%Clay	17	40.16	15.12	3.67	16.97	67.68	0.11
NT	17	0.62	0.37	0.09	0.00	1.00	-0.60

Sd = standard deviation, Se = standard error, N = number of catchments, max = maximum,

min = minimum

4.4 Derivation of a Regional Model Parameter Set

4.4.1 Development of MPs and CAs relationships

Pearson's correlation coefficient (r) between MPs and CAs, between the CAs themselves and between MPs themselves are calculated. The purpose of this first step is not to derive functional relationships, but instead to evaluate the correlations. The awareness of the correlation between catchment parameters is key to avoiding multicollinearty. That is when two or more predictors in a regression are highly related to one another in a way that they do not provide unique and/or independent explanation to the regression. It is source of errors in the estimation of the dependent variable and difficulty in the interpretation of the regression equation. When model parameters are highly correlated it potentially results in parameter-identifiability problems and poor performance in regionalization studies. The independence between the MPs is a good information about the suitability of AWBM for the study (Kokkonen et al., 2003; Xue et al., 2017). The correlation matrix highlighted the advancement of the agricultural land in the expense of the forest, materialised by the high negative Pearson correlation coefficient (-0.73) between both variable. The catchment at high elevation are covered by forest while those invaded for crop production lie at lower elevation (0.74 and -0.66 between average altitude and tree cover and average altitude and cropland respectively). It is also of interest to mention the correlation between the soil parameters among themselves and the areal coverage percentage of nitisols. The correlation between CAs and MPs showed that the BFI is high when the percentage of clay is low and reduces when forest is converted into agricultural land. This can be explained by the increase of infiltration rate in forest covered areas and low clay content soil. Also higher the AWC and TOC of a soil, the higher is the BFI. There seemed to appear some expected correlations (BFI with average elevation, slope and k) which could also agree the hydrological understanding. The baseflow recession constant correlated significantly in the positive direction with the slope and in the opposite direction the minimum elevation. These correlations appeared difficult to explain and can even be discussed. Elevation has a strong influence on the inter-relationship between climate soil and forest, but a correlation with only minimum elevation is not obvious. Also the slope can influence as an accelerator, steeper slopes should then result in smaller recession constants. The surface store reduces when the drainage density is increases and varies in the same direction as the minimum elevation. Again it is non-trivial to explain the role of the minimal elevation, but the quick accumulation and routing of water in high drainage density catchment can explain the relationship with the surface store.

This parameter act as a buffer to the error in the input data and one should be careful to draw definitive conclusion. If some of these relationship can explain physical processes, other seems to be merely statistical coincidences and, other are can be discussed to be hydrologically wrong or too complex to explain. The surface recession constant however did not show any significant correlation with any CAs. This is not uncommon in regionalisation studies. Seibert (1999) for example, chose three catchment characteristics (catchment area, forest and lake percentages) of 11 Swedish catchments to relate to HBV model parameters. Out of 13 model parameters relationships were found only for 6 , whereas the physical interpretation of some of these relationships only weakly relate to the physical basis of the hydrologic model. Reasons behind this situation can be diverse. The surface runoff is highly dependent on the shape factor and the slope and is very sensitive to land use change(L. S. Pereira & Keller, 1982). The shape factor was not included as CA and due to the availability and consistency of data concurrently for all the selected catchments, assumption was made that changes in land use/cover did not alter significantly, which is highly questionable. The interflow is an important process in high elevation, and the AWBM is constructed to interpret it as either a baseflow or attenuation of surface runoff (Boughton, 2017).

Table 8: Correlation matrix between Model Parameters and Catchment attributes

	BFI	CE	Kbase	Ksurf
Built Up Areas	0.00	0.41	-0.06	-0.30
Cropland	**-0.53**	-0.20	-0.28	0.01
Grassland	0.19	-0.18	0.39	-0.01
Shrubs Cover Areas	-0.16	0.29	0.23	0.05
Tree Cover Areas	**0.54**	0.19	0.04	0.11
NT	0.05	-0.07	0.31	-0.27
K(mm/h)	0.40	-0.03	-0.23	0.05
AWC	**0.48**	-0.12	-0.10	-0.03
TOC	**0.48**	-0.19	0.15	0.05
%Sand	0.16	-0.10	0.07	0.35
%Clay	**-0.53**	0.15	-0.04	-0.30
Area (Km^2)	0.18	0.01	-0.22	-0.17
AVERAGE Elv(m)	0.39	0.34	-0.29	0.09
Min_Elv(m)	0.10	**0.57**	**-0.68**	0.14
Max_Elv(m)	0.28	0.05	0.30	0.05
D_D(m/Km)	0.25	**-0.53**	0.22	0.07
SLOPE (%)	0.46	-0.30	**0.56**	0.13

Bold: significant at 0.05 P-level values

Table 9: Correlation matrix between MPs and CAs

	Built Up Areas	Crop land	Grassland	Shrubs Cover Areas	Tree Cover Areas	NT	K(mm/h)	AWC	TOC	%Sand	%Clay	Area (Km²)	AVERAGE_ Elv (m)	D_D (m/Km)	SLOPE (%)
Built Up Areas %	1														
Cropland %	-0.26	1													
Grassland%	-0.18	-0.47	1												
Shrubs Cover Areas	-0.11	-0.40	0.06	1											
Tree Cover Areas %	0.05	**-0.73 ****	-0.14	0.44	1										
NT	0.32	-0.20	0.21	-0.13	-0.03	1									
K(mm/h)	-0.19	0.04	-0.16	-0.21	0.17	**-0.65 ****	1								
AWC	-0.19	-0.31	0.12	0.21	0.37	**-0.57***	**0.74 ****	1							
TOC	-0.36	-0.26	0.19	0.31	0.32	**-0.64 ****	**0.53***	**0.76 ****	1						
%Sand	-0.24	0.25	-0.19	-0.35	-0.03	**-0.58 ***	**0.54***	0.09	0.38	1					
%Clay	0.22	0.44	-0.12	-0.05	**-0.56**	**0.53***	**-0.64****	**-0.73 ****	**-0.66****	-0.47	1				
Area (Km²)	-0.15	0.29	-0.12	-0.12	-0.19	-0.46	**0.75 ****	**0.59***	0.30	0.20	-0.22	1			
AVERAGE_Elv(m)	0.00	**-0.66 ****	0.07	0.42	**0.74****	-0.16	0.20	**0.50***	0.36	-0.20	**-0.54 ***	-0.12	1		
D_D (m/Km)	-0.20	-0.14	0.19	-0.00	0.11	0.29	-0.14	0.11	-0.01	-0.40	0.09	-0.07	-0.13	1	
SLOPE (%)	-0.01	**-0.60 ***	0.16	0.47	**0.60***	-0.04	0.06	0.42	**0.63 ****	0.09	**-0.54 ***	-0.15	0.39	0.09	1
Min_Elv (m)	0.22	-0.11	-0.35	-0.08	0.35	-0.07	0.21	0.03	-0.18	-0.09	-0.06	-0.08	**0.58***	-0.22	-0.30
Max_Elv (m)	-0.24	**-0.71 ****	**0.58***	**0.68****	**0.50***	0.04	-0.11	0.37	0.39	-0.34	-0.34	-0.06	**0.57***	0.17	**0.56***

***Significant at 0.05 level ** Significant at 0.01 level**

4.4.2 Multiples linear models

The forward entry method and the backward removal method are applied. The models was established for three out of the four AWBM parameters used. The linear models were established for three AWBM out of four. There was no significant correlation between individual CAs and combinations with the surface recession constant (Ksurf). The optimal models for base flow parameters and surface store are the following:

Table 10: Linear models

Linear Models	$^{a}R^{2}$	$^{a}R^{2}_{adj}$
BFI= $2.093*10^{-02}$ * %SAND + $2.391*10^{-04}$ * Average Elv + 0.2313 * NT	0.71	0.62
Kbase = 0.9879 - $8.221*10^{-6}$ * AVERAGE Elv + $6.009*10^{-04}$ * SLOPE + $9.574*10^{-03}$ * Grassland	0.70	0.61
CE= 359.720 + 4175.159* Shrubs + 656.763* Built - 13.958* SLOPE	0.80	0.74

The highest multiple linear correlation coefficient $^{a}R^{2}$, was obtained for the average surface store, followed by the baseflow index and the baseflow recession constant and; the values are 0.71, 0.7 and 0.69 respectively (table 9). The baseflow recession constant has the highest difference between the multiple linear correlation coefficient $^{a}R^{2}$ and the adjusted multiple linear correlation coefficient $^{a}R^{2}_{adj}$ (0.1), followed by the base flow index constant and the average surface store (0.09 and 0.05 respectively). This means that the problem of overfitting is minor. The logarithm of the average surface store CE was used to reduce the skew and allow for possible non-linear relationships. But the result was not better. The equation suggest that the steeper is the slope, the least is the store. This can be explained by the favouring factor slope has for the runoff in the expense of the infiltration and storage into the soil. The built up area percentage is thought to increase the impervious areas and reduce the soil storage and infiltration capacity (Klungniam, 2016). This equation implying that an increase of the average surface storage correlate positively with the built up area increases cannot be explained using widely accepted hydrological knowledge. The term of shrub in the equation, concur with the property of this vegetation type in increasing infiltration rate. The baseflow index model suggests that it increases when the sand proportion increases. This can be justified by the high infiltration rates of soils when the sand percentage increases. The nitisols correlated significantly with soil parameters (K, AWC, TOC, %SAND and % CLAY) showing a good definition of its characteristics by them. If its inclusion in the baseflow index model might be seen as a violation of statistical theories, the variance inflation factor remained low, in addition, the coefficient of determination and the significance has increased. The inconvenience of using percentage of catchment area under Nitisols as a descriptive is that the accuracy of calculation on catchments where they are poorly or not represented will be undermined. There was a coincidence that catchments that met the criteria to be selected for further steps of the study have Nitisols as the main soil type. This shows the possibility that other features of soils (e.g.: Infiltration rate, their origin) or a combination of some of the attributes could better explain the BFI. Other soil types were tested but the low representation disapprove their use in the linear regression even though they showed some correlation. Defining the soils characteristic on the basis of hydrological class could improve the results and the confidence in the applicability in an extended area. The regional model for BFI claims an increase of the baseflow index with the average altitude. This can be explained by the fact that higher altitude areas have these deep and well drained soils like Nitisols and Andosols and also tend to be covered by forest and not agriculture, which may influence BFI. Singh (1968) investigates the factor affecting the baseflow; some of his findings were that the baseflow is affected by the amount of precipitation and the evapotranspiration which depends on soil properties and vegetation type and density. His results are concordant Gibbs et al.,(2008) who found high correlations between baseflow parameters of AWBM and annual pecipitation, PET, average elevation and slope. But the use of general regression neural network in their study does not alow to undrestand how they relate. Same reasoning can be used for the baseflow recession constant which also significantly included the average elevation with high significance (0.001 p-value level) into the model, but the other part of the model of Kbase does not make sense hydrologically. In general the slop has a quickening effect on flows. For this reason higher slopes should have a decreasing effect on the baseflow recession constant as high amount of water are released in shorter time from the groundwater reservoir.

4.4.3 Validation of MPs -CAs Relationships

The MPs were estimated using the linear models established. The parameter values were estimated not only for the catchments used in the statistical model development (Training data) but also for the ones left for testing (Validation data). The model predict relatively well the parameter values for catchment used for their establishment (training catchments) but predict poorly for testing or validation catchments. This can be explained by the particularity of those catchments. Three (1BA01, 1CB08, 1HA04,) of them are located far from most of the training catchments and the other (4CB05) has the smallest size ($38Km^2$). Despite the difficulty to explain the baseflow recession constant model, it gives acceptable values unlike the baseflow index which give for three catchments values out of the range of values obtained through calibration and the surface storage. The estimated BFI for 1BA01 was even nonsensical since BFI should be less than one. The prediction performance was measured by calculating the correlation coefficient R^2 and the NSE for both training and validation for each model (Table 11). Overall the Kbase model performed the best with r^2 values for training (R^2_T) and validation (R^2_V) of 0.71 and 0.7 respectively NSE values for training (NSE_T) and for validation (NSE_V) of 0.30 and 0.32 respectively. Contrary, CE and BFI did not perform well. For BFI, R^2_T and R^2_V values of 0.71 and 0.42 respectively and NSE_T and NSE_V values were 0.28 and 10.95 respectively. The CE did not show better results; R^2_T and R^2_V values were 0.81 and 0.26 respectively and NSE_T and NSE_V values were 0.19 and 1.29. This is depicted well on the graph (figure 10-15)

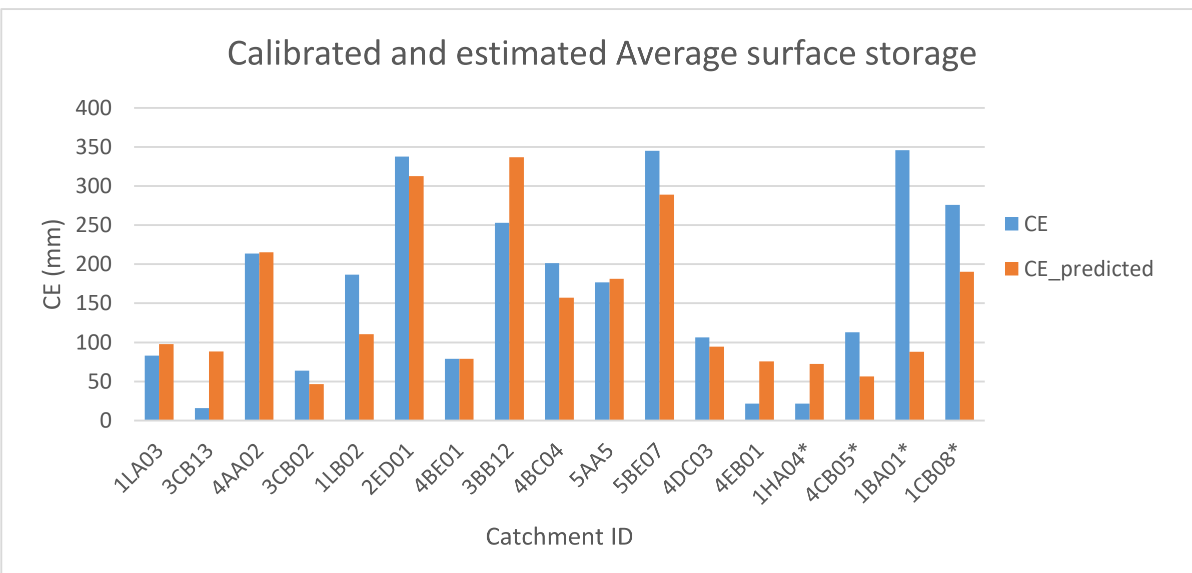


Figure 10: Calibrated and estimated values of surface storage (CE)

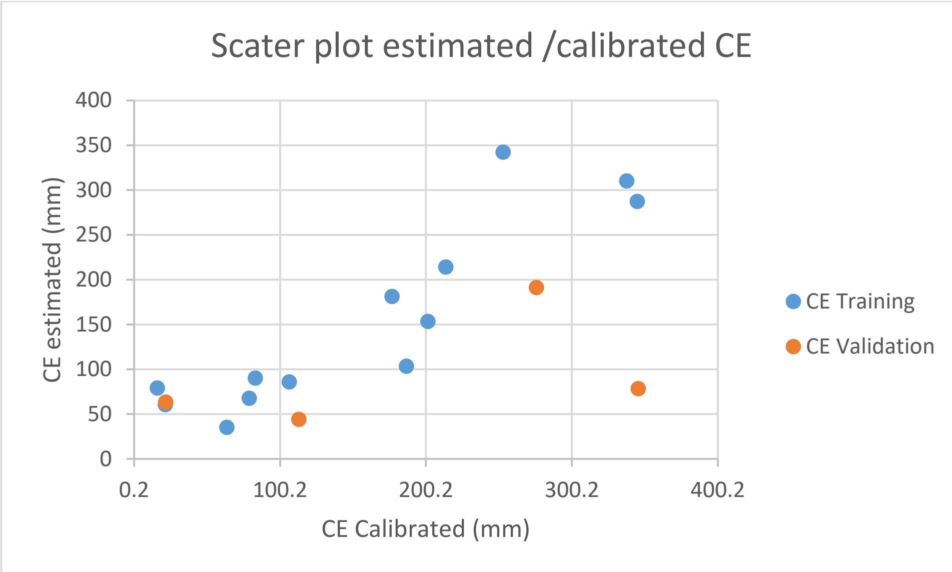


Figure 11: correlation between estimated and calibrated value of the surface storage for training and validation

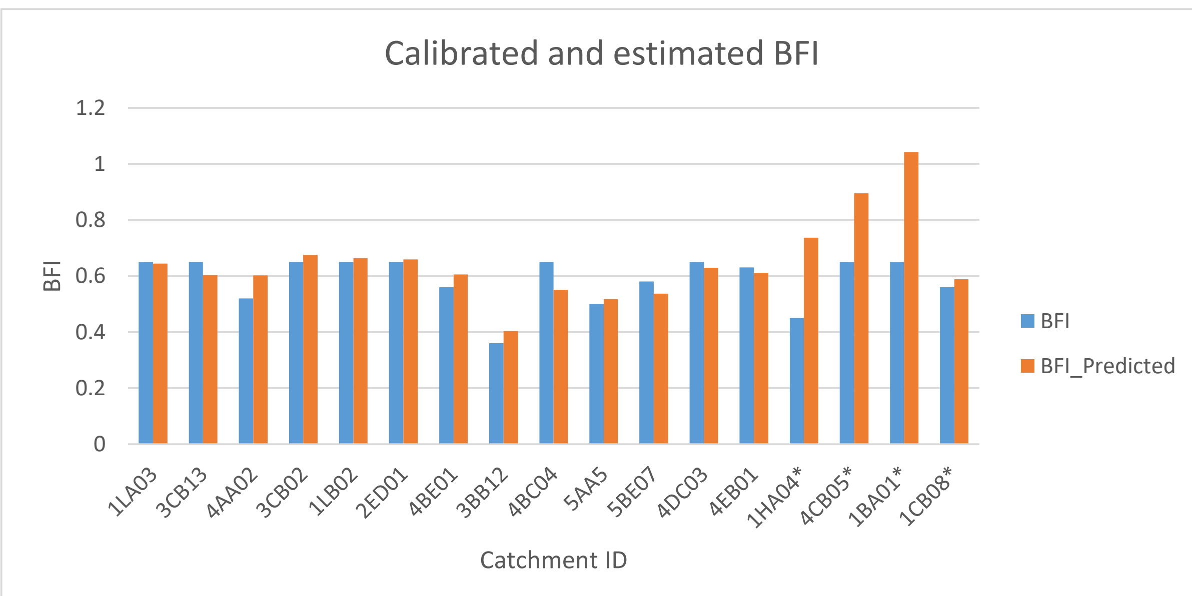


Figure 12: Calibrated and estimated values of baseflow index (BFI)

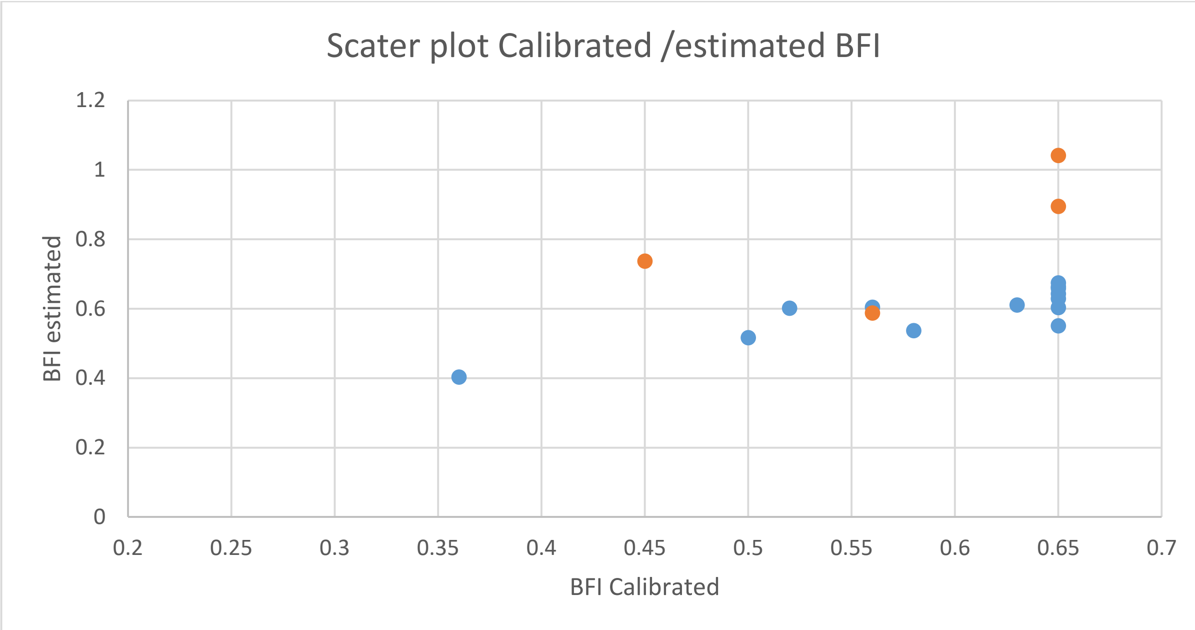


Figure 13: correlation between estimated and calibrated value of BFI for training and validation

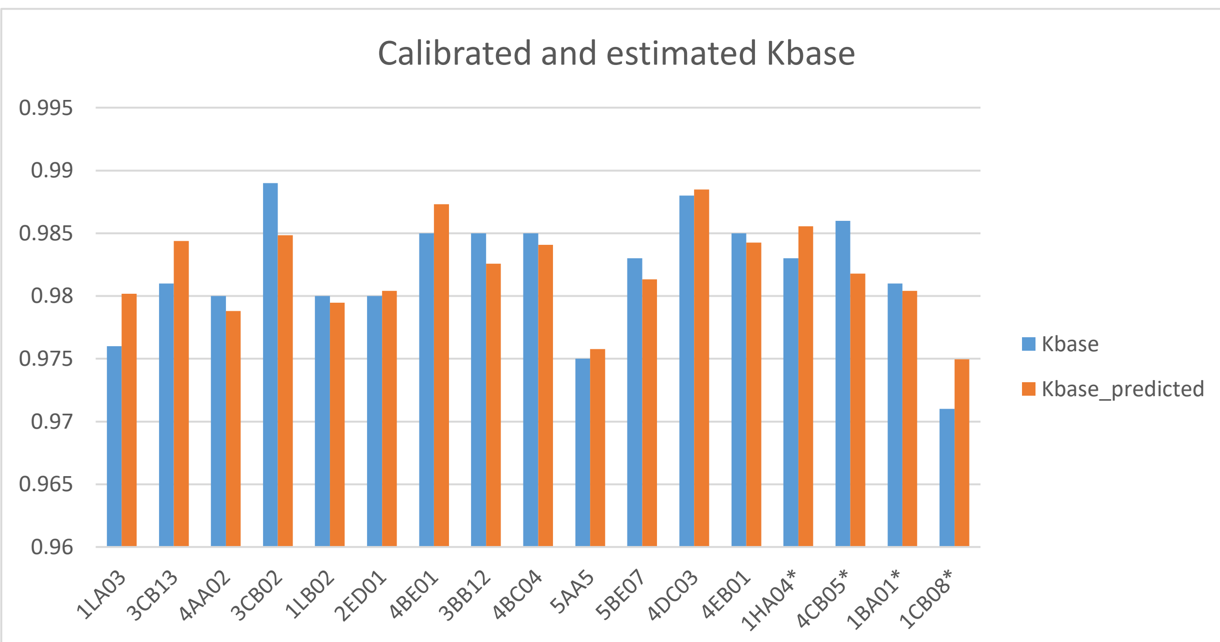


Figure 14: Calibrated and estimated values of baseflow recession constant (BFI).

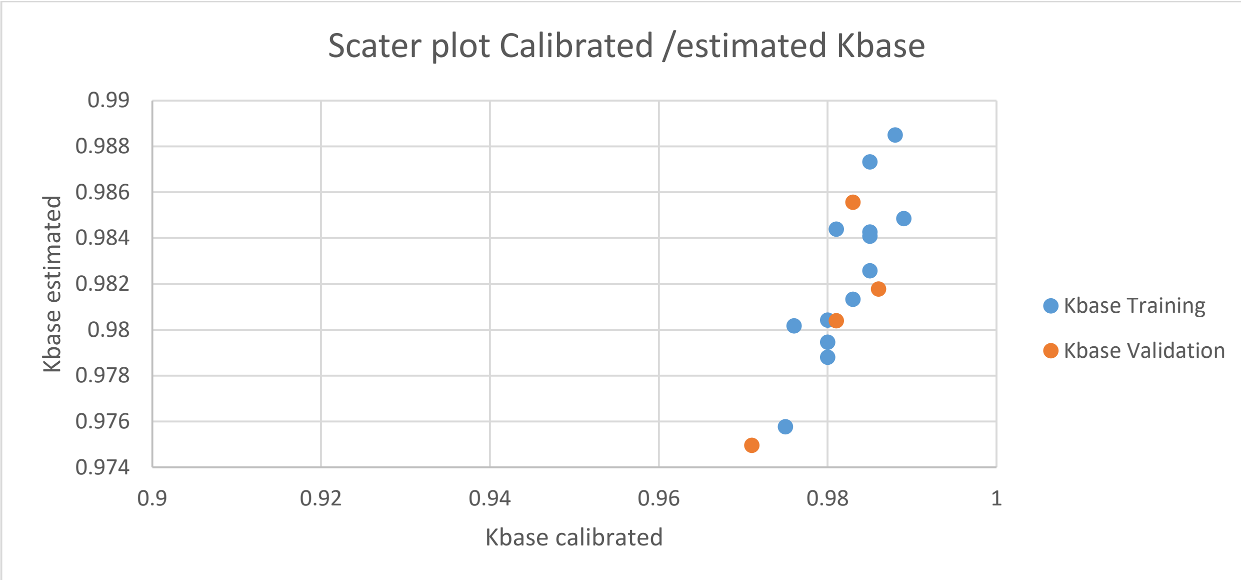


Figure 15: correlation between estimated and calibrated value of Kbase for training and validation

Table 11: Performance measures value of the linear models

	NSE_T	NSE_V	R^2_T	R^2_V
CE	0.19	1.29	0.81	0.26
BFI	0.28	10.95	0.71	0.42
KBASE	0.29	0.24	0.7	0.7

4.5 Estimation of Daily Stream Flows

The estimated parameters were used to estimate daily streamflow for the pseudo-ungauged catchments. Since the surface recession constant could not be estimated, the calibrated has been used for simulation. The average surface store has been disaggregated to get the partial store using the pattern in (Boughton, 2004). This did not give the same proportion of the average store as the calibrated value since the value obtained through the calibration method developed on the basis of the model structure and the pattern found by Boughton (2004). Attempt to improve the pattern did not give better results. The surface storage and the base flow parameters estimated using the regional model and the default value of surface recession constant obtained through by averaging the calibrated value (table 12) were used for simulations over the calibration and validation periods.

The extreme values of the calibrated parameters were used as default values for the estimated parameters that were found to be out of the range. The maximum value where used for values exceeding it. This was applied particularly to the BFI.

Table 12: Estimated model parameter values

ID	C1	C2	C3	BFI	K_{BASE}	K_{SURF}
1HA04	5.44	55.31	110.61	0.74*	0.983	0.88
4CB05	4.23	43.00	85.99	0.89*	0.986	0.88
1BA01	6.59	66.96	133.92	1.04*	0.981	0.73
1CB08	14.28	145.08	290.16	0.59	0.971	0.75
Default	7.95	131.1	251.65	0.59	0.982	0.76

*Values out of the range of calibrated values

Table 13: performance measures for estimated and calibrated model parameter values

ID	C1	C2	C3	BFI	K_{base}	K_{surf}	R^2 cal	R^2 val	NSE cal	NSE val
1HA04*	5.44	55.31	110.61	**0.65****	0.983	0.76**	0.70	0.41	0.33	0.08
1HA04	0.00	16.8	33.5	0.45	0.983	0.88	0.70	0.49	0.28	0.14
4CB05*	4.23	43.00	85.99	**0.65****	0.986	0.76**	0.63	0.54	0.30	0.20
4CB05	2.8	120.3	139.9	0.65	0.986	0.88	0.64	0.51	-1.99	0.24
1BA01*	6.59	66.96	133.92	**0.65****	0.981	0.76**	0.70	0.63	-0.01	-0.85
1BA01	8.5	247	548.7	0.56	0.981	0.73	0.80	0.63	0.51	0.21
1CB08*	14.28	145.08	290.16	0.59	0.971	0.76**	0.64	0.62	-0.43	-0.09
1CB08	4	205.8	429.9	0.56	0.971	0.75	0.65	0.60	-0.2	-0.20

*** IDs for Estimated parameter values, ** Default values.**

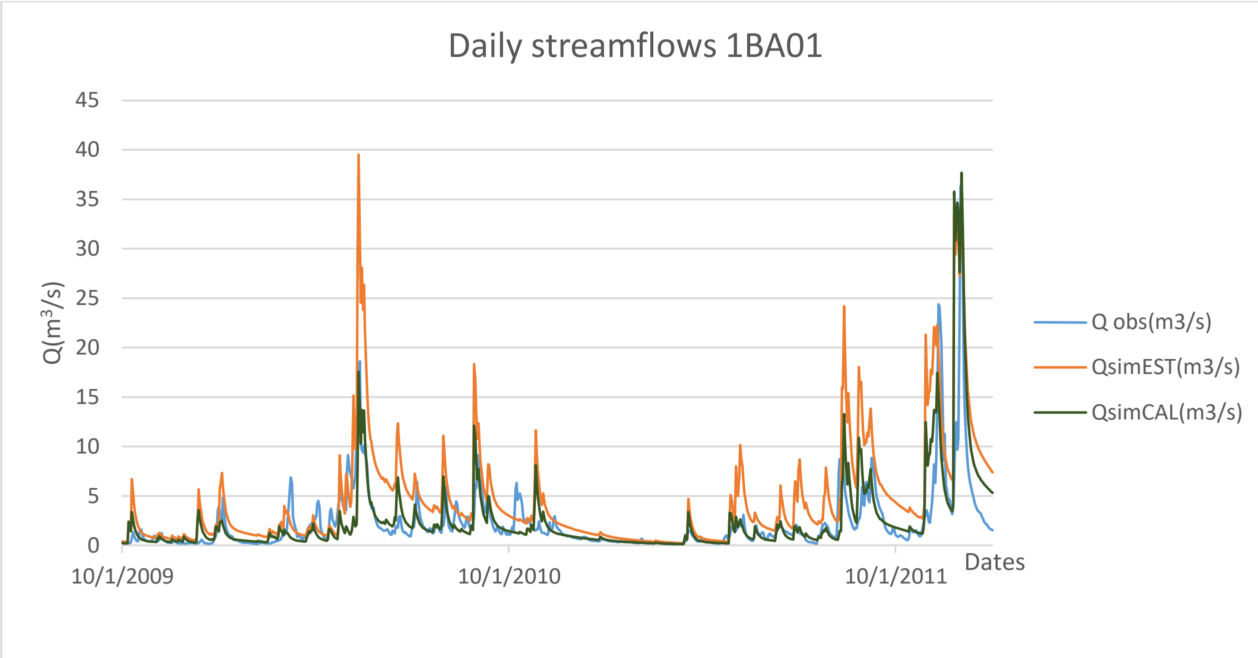


Figure 16: Observed and simulated streamflow using estimated and calibrated parameters for 1AB01 over the calibration period

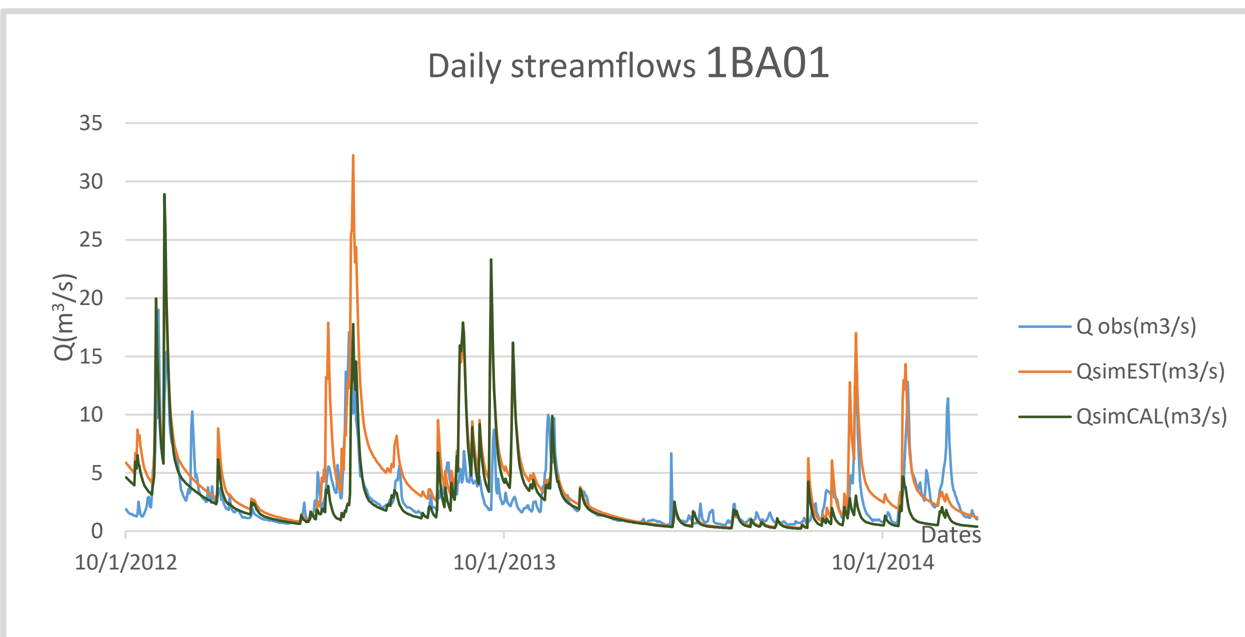


Figure 17: Observed and simulated streamflow using estimated and calibrated parameters for 1AB01 over the validation period

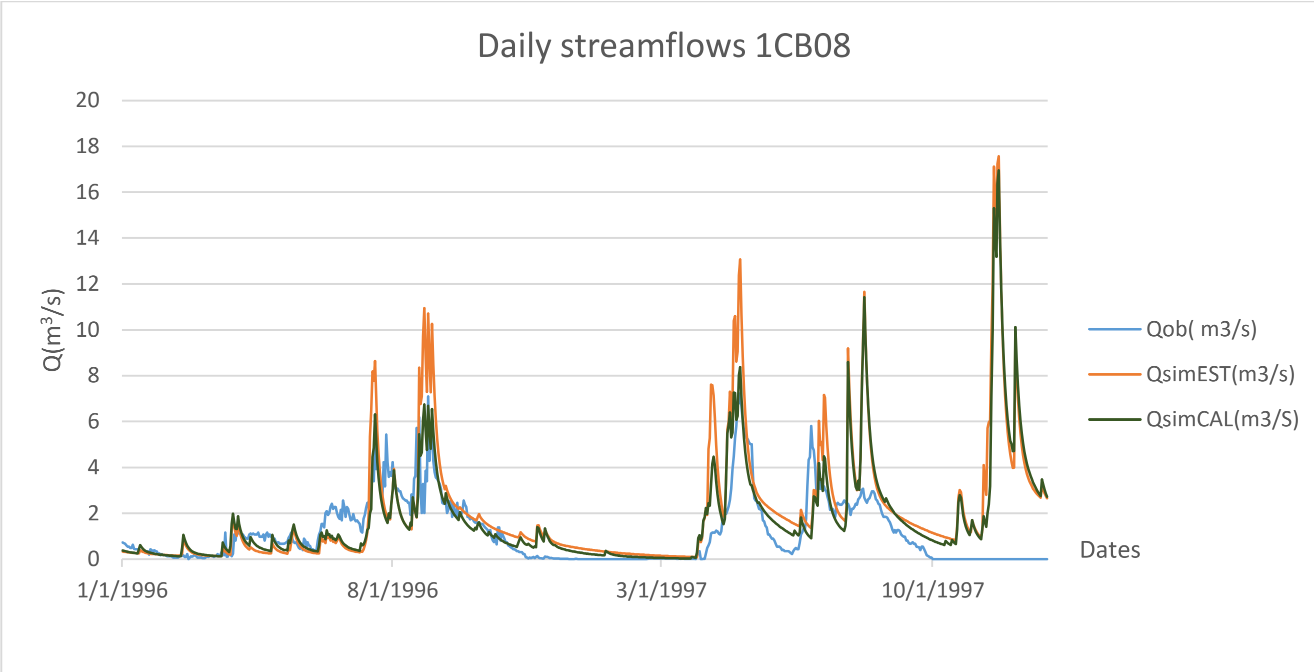


Figure 18: Observed and simulated streamflow using estimated and calibrated parameters for 1CB08 over the calibration period

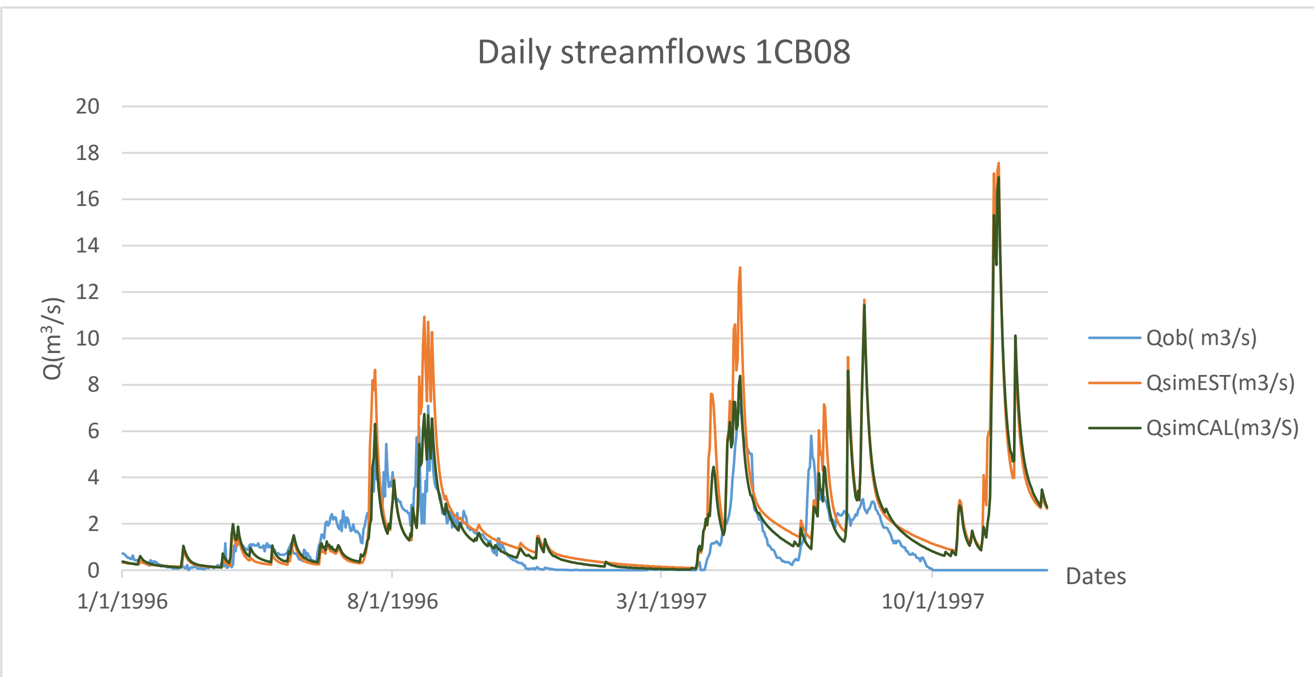


Figure 19: Observed and simulated streamflow using estimated and calibrated parameters over the validation period

Comparing both parameter sets, estimated and calibrated for each catchments, showed not greater difference. The average values for R^2 is 0.67 for estimated parameters and 0.7 for calibrated. This relatively good performance for the estimated values is due to the use of the calibrated values of the surface recession constant and the default value of the baseflow index for some catchments. Those parameters are very important for depicting daily flow pattern (Boughton & Chiew, 2007), this explain such close performances. The only parameter successfully estimated was the baseflow recession constant Kbase, no default value was applied. The value 0.71 estimated for 1CB08 was used despite being below the minimal calibrated value because of the little extrapolation from the minimum. There is worth to mention that for that catchment the BFI estimated was also acceptable. The determination coefficient, R^2, for estimated and calibrated parameters for that catchment are very close, 0.64 and 0.65 for calibration period and 0.62 and 0.6 for verification period respectively. This is positive, considering the isolated location of that catchment from others. The Nash-Sutcliffe coefficient of efficiency indicate very poor results. This reflected well the fact that the data was not bias-corrected. The bias correction of CHIRPS rainfall estimates, potential evapotranspiration estimates and streamflow data was not in the scope of the study but has proven to be crucial. Considering the model structure, the surface store behaves like a buffer towards errors in the input data. It is found that errors of ±20% in the estimation of areal rainfall potentially cause errors of +98% to -58% in the calibrated value of the average surface storage capacity of the AWBM (Boughton, 2010, p. 74). The surface store is highly sensitive to the input data uncertainties. Overestimated rainfall would increase the surface store in order to match the observed streamflow and the same way reduce the store when underestimated. Streamflow data errors and evaporation data errors at a less important magnitude could have the same effects on the surface store capacity but in the opposite direction. The constructor proposed scaling down or up the rainfall, evaporation or runoff data by a factor but stressed that this could be sensible to apply when the purpose of modelling is for practical application or extending streamflow record but useless and even worse if the parameters values of calibration are to be transferred for use on ungauged catchments with different rainfall data (Boughton, 1996). Haque et al., (2015) conducted a quantitative assesment of uncertainties of AWBM model, in both gauged and ungauged catchments. The main results of this study was that modeling output of AWBM model could vary from -1.3 to 70% due to different rainfall input data. In the same line, it was found by Jones et al., (2006) that AWBM model showed a mean sensitivity of 2.5% change in mean annual flow (the highest in comparison to SIMHYD and Zhangh01; 2.4 and 2.1% respectively) for every 1% change in mean annual rainfall and a mean sentivity of -0.8% change in mean annual flow for every 1% change in mean annual evapotranspiration. 22 catchments from Australia, covering a range of climates, from cool temperate to tropical and humid to arid were used in that study (Jones et al., 2006). Considering the use of CHIRPS estimates and Penman-Monteith potential evaporation it makes it understandable the poor results during the calibration process, the drastic reduction of the number of catchments and the poor confidence in the use of the regionalised model. Dinku et al., (2018) conducted a study on the validation of CHIRPS rainfall estimates over eastern Africa. They tested the performance in terms of detection of occurrence of rainfall and accuracy in terms of rainfall quantity. The CHIRPS skill in detecting rainfall occurrence at dailly steps has not been tested over kenya for lack of rainfall data but was poor in Tanzania. This result can be pressumed worst Kenya since, since the perferance measures measured in both contries showed worst result over Kenya. It was highlited a low skill of determination over montainous and costal areas. The area of this study is essentially the montainous part ot Kenya. Another relavent finding from (Dinku et al., 2018) is the overestimation of rainfall amounts with a bias of 1.13 for pixel-to-pixel statistic and 1.10 for point-to-pixel statistics over the country with an emphasis on the western part where high rainfall coverage are particarly overestimated. Most of the catchments selected in that regions, arround the Mt Elgon, was been left after preliminary analysis. The inconsistencies in term of rainy days and rainfall amount in comparison with the rain gauges is the main challenge in the use of satellites data for hydrologicall modeling. The potential evapotranspiration data have been scaled down purposely, so to compensate for the overestimation, but the bias appears to be inconsitent. Some irregularities in the dataset obtained from the national authorities in charge of Water Resources Authority (WRA) has also brought some challenges and may have undermined the results. That is the inaccuracy of the river gauging stations location coordinatesm used as river outlets. When the station lies near the conection points with tributaries, making decision on where exactely on the river it is installed is crucial as selecting it upstream or downstream of the connection point can increase or reduce the catchment area. This affects also surface store value during calibration and the estimation of catchments attributes. The worst senario is when the gauging station on a river is given coordinates placing it on another river. One could be found using a complete dataset of rainfall and evaporation from a location to be calibrated with the streamflow of a river from another location.

Some studies resulted in regional models that were not satisfactory and some results could necessarily. Deckers et al., (2010) numbered some studies that were not successful. This included the works by Young (2006) who used the Probability Distributed Model (PDM) toolkit (Moore 1985, 1999) and Wagener and Wheater (2006) using the Rainfall Runoff Modelling Toolbox (RRMT; Wagener et al. 2002) in the UK showed that regionalisation was not successful in all cases (Deckers et al., 2010). This makes the investigators eligible to give useful recommendations.

5 Conclusion and recommendation

5.1 Summary

In this study, 17 catchments selected in the humid areas of Kenya, essentially located in the mountainous areas of Kenya, was calibrated in other to derive a regional model for calibration of ungauged catchments in the area. CHIRPS rainfall estimates and wind speed, potential evapotranspiration estimated from minimum and maximum temperatures, relative humidity and solar radiation from NASA POWER in the INSTAT software were used as input data. The catchments attributes were defined based on the topography, land use/cover and soil characteristics using readily available information. Multiple regressions were used to develop functional relationships between defined catchments descriptive attributes and the model parameters obtained from calibration.

The calibration results were poor in general; over around forty catchment only seventeen were selected for further analysis only on the basis of the correlation coefficient of determination $R>0.5$. This criterion was established based on the data-scarcity context of the study. More rigorous selection criteria, like in (Deckers et al., 2010) where the authors set the threshold of Nash–Sutcliffe coefficient, $NSE>0.75$ and the relative volume error, $|RVE|<5\%$, would have resulted in no catchments being eligible for the study. This makes the context of data quality and availability a crucial in making trade-offs between the worthiness and unworthiness of a study. The regression equation was established for only three out the four parameters of AWBM targeted. The average surface storage capacity, the BFI, Kbase and Ksurf. The partial surface storage was aggregated to ease the work.

The model for the surface storage was established. The performance measures showed relatively good estimation accuracy on training data, with R^2_T and NSE_T values of 0.81 and 0.19 respectively. However, errors in the estimations were considerable, for validation catchments. Especially for 1BA01, the estimated value was 78% smaller than the calibrated value. The NSE_V and R^2_V for the validation catchment were 1.29 and 0.26 respectively, which is very poor in terms of prediction accuracy. The fact that the surface storage is greatly influenced by the errors in the input dataset could be part of the reasons. Same observation can be made on the regional model for the BFI estimations which showed also very poor accuracy with most values for validation catchment out of the range of the calibrated values. Only one estimate (1CB08) over the four estimations was within the range of calibrated values. The worst estimation was found for 1AB01 with the meaningless value of 1.04. This results are well depicted with an NSE and an R^2 for the validation catchment of 10.95 and 0.42 respectively for the BFI regional. The last parameter Ksurf gave overall acceptable results even though the terms in the regression model are not easily explainable and can be discussed hydrologically implausible. The model performance was as good for training data as for validation data. Overall the Kbase model performed the best with R^2 values for training (R^2_T) and validation (R^2_V) of 0.71 and 0.7 respectively NSE values for training (NSE_T) and for validation (NSE_V) of 0.30 and 0.32 respectively. Nevertheless, the regional model for the surface recession constant could not be established using this method. The reason could be the high dependence of this parameter on the land use/cover not accurately captured in the study since the periods for calibration where different from one catchment to the other. In addition, the period of development of the land use map/cover used for this study does not fall within the period of calibration and verification of some catchments. The model structure could also be the reason. The interflow is combined with the surface runoff or baseflow in AWBM structure (W. Boughton, 2004). With the interflow being the major flow process on forested, mountainous watersheds (Chanasyk & Verschuren, 1983), the main landscape of the study area but at different degrees from one catchment to another, it is possible the parameter Ksurf has different meaning from one catchment to other based on the level of each of those processes (interflow and surface runoff).

Since some the regional model of Ksurf was not established and some estimated parameter values were not applicable, default values were assumed using the averaged parameter values. The results surprisingly were comparable with calibrated parameters in terms of performance measures. The average R^2 for estimated and calibrated parameters for the catchments are very close, 0.64 and 0.65 for calibration period and 0.62 and 0.6 for verification period respectively.

More investigations for the estimation of streamflow measurement uncertainties could allow the application of the scaling factors to CHIRPS rainfall estimates to improve the estimation of this parameter. The bias correction of the rainfall estimates over the area, if possible could also improve the method.

The coordinates of the gauging stations were used as outlet to delineate the catchments areas. The resulting surface area and geographic location where used for rainfall extraction and derivation of catchment attributes. Important deviation from the exact locations of the outlets was noticed as a reason for poor calibration results and establishments of functional relationship.

There discrepancies resulted mainly from the slight misrepresentation of low flows and pick flows governed by Kbase and Ksurf respectively and BFI affecting both of them. Those are the most sensitive parameters. The surface storage affects highly flows at the onset of rainfall season. When the soil moisture is close to the saturation in the middle of the season, the effect is much less important. This is the less sensitive of the AWBM parameters.

5.2 Conclusion

We generally learn most when a model or theory is shown to be in conflict with reliable data so that some modification of the understanding on which the model is based must be sought (Beven, 2012). This is not the not the case for the data of this study. Nevertheless, this method in the strict case of lack of rainfall data could be thus recommended for use in ungauged catchments. However, it should be seen as a positive attempt to deal with the double challenge of poor streamflow and lack of rainfall data in data-scarce context in developing countries in general, and particularly in complex landscape like the case of Kenya.

5.3 Recommendations

Upon the uncertainties encountered during this study, we recommend that:

- Investigations about land use change should be considered as a specific objectives in other to understand and consider the effect on model parameter values. That would provide more realistic even though complex, approach to get insight on the relationships between catchment physical characteristics and its hydrological response signatures.
- Satellite rainfall estimates are very important source of rainfall information but should subjected to thorough analysis and cross-checking with observed data for bias correction to improve the quality.
- The geo-referencing of hydrological information even if it is not the hardest part in producing hydrological data is as crucial, since one of the challenges faced was the selection of the location of the outlets.

References

Abimbola, O. P., Wenninger, J., Venneker, R., & Mittelstet, A. R. (2017). Journal of Hydrology : Regional Studies The assessment of water resources in ungauged catchments in Rwanda. *Journal of Hydrology: Regional Studies*, *13*(August 2017), 274–289. https://doi.org/10.1016/j.ejrh.2017.09.001

Araujo, F. C., Mello, E. L. De, Gollin, G. M., Quadros, L. E. De, & Gomes, B. M. (2018a). *STREAMFLOW REGIONALIZATION IN PIQUIRI RIVER BASIN*. *4430*, 22–31.

Bai, L., Shi, C., Li, L., Yang, Y., & Wu, J. (2018). Accuracy of CHIRPS satellite-rainfall products over mainland China. *Remote Sensing*, *10*(3). https://doi.org/10.3390/rs10030362

Beck, H. E., van Dijk, A. I. J. M., de Roo, A., Miralles, D. G., McVicar, T. R., Schellekens, J., & Bruijnzeel, L. A. (2016). Global-scale regionalization of hydrologic model parameters. *Water Resources Research*, *52*(5), 3599–3622. https://doi.org/10.1002/2015WR018247

Beven, K. (1993). *Prophecy , reality and uncertainty in distributed hydrological modelling*. *16*.

Beven, K. (2012). Rainfall-Runoff Modelling. In *Rainfall-Runoff Modelling* (2nd ed.). https://doi.org/10.1002/9781119951001

Blöschl, G., Sivapalan, M., Wagner, T., Viglione, A., & Savenije, H. (2013). *Runoff Prediction in Ungauged Basins Synthesis across Processes, Places and Scales*. Cambridge University Press.

Bonell, M., McDonnell, J. J., Scatena, F. N., Seibert, J., Uhlenbrook, S., & van Lanen, H. A. J. (2006). HELPing FRIENDs in PUBs: Charting a course for synergies within international water research programmes in gauged and ungauged basins. *Hydrological Processes*, *20*(8), 1867–1874. https://doi.org/10.1002/hyp.6196

Boughton, W. (1996). *DETECTING DATA ERRORS IN RAINFALL-RUNFALL DATA SETS, Report 96/2*. Melbourne.

Boughton, W. (2004). The Australian water balance model. *Environmental Modelling and Software*, *19*(10), 943–956. https://doi.org/10.1016/j.envsoft.2003.10.007

Boughton, W. (2010). *RAINFALL-RUNOFF MODELLING WITH THE AWBM*. Retrieved from https://books.google.dz/books?id=_drIZwEACAAJ

Boughton, W. (2017). Adaptation of the AWBM for estimating runoff from ungauged catchments. *Australasian Journal of Water Resources*, *8*(2), 123–132. https://doi.org/10.1080/13241583.2005.11465249

Boughton, W. C., & Askew, A. J. (1968). HYDROLOGIC CHARACTERISTICS of CATCHMENTS LAG TIME for NATURAL CATCHMENTS/LAG TIME FOR NATURAL CATCHMENTS. *New Zealand Engineering Institute (NZAEI)*. Retrieved from https://core.ac.uk/download/pdf/35467657.pdf

Boughton, W. C. C. (2003). *CATCHMENT HYDROLOGY CALIBRATIONS OF THE AWBM FOR USE ON*. (December).

Boughton, W., & Chiew, F. (2007). *Estimating runoff in ungauged catchments from rainfall , PET and the AWBM model*. *22*, 476–487. https://doi.org/10.1016/j.envsoft.2006.01.009

Chanasyk, D. S., & Verschuren, J. P. (1983). An interflow model: I. model development. *Canadian Water Resources Journal*, *8*(1), 106–119. https://doi.org/10.4296/cwrj0801106

Cho, J., Bosch, D., Lowrance, R., Strickland, T., & Vellidis, G. (2009). Effect of spatial distribution of rainfall on temporal and spatial uncertainty of SWAT output. *Transactions of the ASABE*, *52*(5), 1545–1555.

Clark, M. P., Kavetski, D., & Fenicia, F. (2011). *Pursuing the method of multiple working hypotheses for hydrological modeling*. *47*(August), 1–16. https://doi.org/10.1029/2010WR009827

Cordery, I., & Cloke, P. S. (1992). Economics of streamflow data collection. *Water International*, *17*(1), 28–32. https://doi.org/10.1080/02508069208686125

Deckers, D. L. E. H., Booij, M. J., Rientjes, T. H. M., & Krol, M. S. (2010). Catchment Variability and Parameter Estimation in Multi-Objective Regionalisation of a Rainfall-Runoff Model. *Water Resources Management*, *24*(14), 3961–3985. https://doi.org/10.1007/s11269-010-9642-8

Dembélé, M., & Zwart, S. J. (2016). Evaluation and comparison of satellite-based rainfall products in Burkina Faso, West Africa. *International Journal of Remote Sensing*, *37*(17), 3995–4014.

https://doi.org/10.1080/01431161.2016.1207258

Devi, G. K., Ganasri, B. P., & Dwarakish, G. S. (2015). *A Review on Hydrological Models*. *4*(Icwrcoe), 1001–1007. https://doi.org/10.1016/j.aqpro.2015.02.126

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., & Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, *144*(January), 292–312. https://doi.org/10.1002/qj.3244

Ekeu-wei, I. T. (2018). Evaluation of Hydrological Data Collection Challenges and Flood Estimation Uncertainties in Nigeria. *Environment and Natural Resources Research*, *8*(2), 44. https://doi.org/10.5539/enrr.v8n2p44

Funk, C., Barbara, S., Peterson, P., Barbara, S., Pedreros, D. H., States, U., … Barbara, S. (2015). *The climate hazards infrared precipitation with stations — a new environmental record for monitoring extremes*. (December). https://doi.org/10.1038/sdata.2015.66

Gibbs, M. S., Dandy, G. C., & Maier, H. R. (2008). *Calibration of Rainfall Runoff Models in Ungauged Catchments: Regionalization Relationships for a Rainfall Runoff Model*. 1–10. https://doi.org/10.1061/40976(316)377

Hailegeorgis, T. T., Abdella, Y. S., Alfredsen, K., & Kolberg, S. (2015). *Evaluation of Regionalization Methods for Hourly Continuous Streamflow Simulation Using Distributed Models in Boreal Catchments*. 1–34.

Haque, M. M., Rahman, A., Hagare, D., & Kibria, G. (2015). Parameter uncertainty of the AWBM model when applied to an ungauged catchment. *Hydrological Processes*, *29*(6), 1493–1504. https://doi.org/10.1002/hyp.10283

Houghton-Carr, H., & Matt, F. R. Y. (2006). The decline of hydrological data collection for development of integrated water resource management tools in Southern Africa. *Climate Variability and Change: Hydrological Impacts*, *308*(November), 51–55. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-33845532798&partnerID=40&md5=ff6a8b265ed3f3a1a463c46547b65be1

Ibrahim, B., Wisser, D., Barry, B., Fowe, T., & Aduna, A. (2015). *Journal of Hydrology : Regional Studies Hydrological predictions for small ungauged watersheds in the Sudanian zone of the Volta basin in West Africa*. *4*, 386–397.

Jones, R. N., Chiew, F. H. S., Boughton, W. C., & Zhang, L. (2006). Estimating the sensitivity of mean annual runoff to climate change using selected hydrological models. *Advances in Water Resources*, *29*(10), 1419–1429. https://doi.org/10.1016/j.advwatres.2005.11.001

KARANI, P. W. (2005). *National Nile Basin Water Quality Monitoring Baseline Report for Kenya*. NAIROBI.

Karina, F. Z., & Mwaniki, A. W. (2011). *Impact of the Economic Stimulus Programme and Long-term Prospects for Food Security in an Era of Climate Change*.

Kidd, C. (2001). Satellite rainfall climatology: A review. *International Journal of Climatology*, *21*(9), 1041–1066. https://doi.org/10.1002/joc.635

Kirchner, J. W. (2006). *Getting the right answers for the right reasons : Linking measurements , analyses , and models to advance the science of hydrology*. *42*(4), 1–5. https://doi.org/10.1029/2005WR004362

KlemeŠ, V. (1986). Operational testing of hydrological simulation models. *Hydrological Sciences Journal*, *31*(1), 13–24. https://doi.org/10.1080/02626668609491024

Klungniam, C. (2016). *the Effects of Urbanization on Urban Hydrology Characteristics*. 41–47.

Kokkonen, T. S., Jakeman, A. J., Young, P. C., & Koivusalo, H. J. (2003). *Predicting daily flows in ungauged catchments: model regionalization from catchment descriptors at the Coweeta Hydrologic Laboratory, North Carolina*. *17*(Mm), 1–18. https://doi.org/10.1002/hyp.l329

Liew, M. W. Van, & Mittelstet, A. R. (2018). *Comparison of three regionalization techniques for predicting streamflow in ungaged watersheds in Nebraska , USA using SWAT model*. *11*(3), 110–119. https://doi.org/10.25165/j.ijabe.20181103.3528

Luo, X., Wu, W., He, D., Li, Y., & Ji, X. (2019). Hydrological Simulation Using TRMM and CHIRPS Precipitation Estimates in the Lower Lancang-Mekong River Basin. *Chinese Geographical Science*, *29*(1), 13–25. https://doi.org/10.1007/s11769-019-1014-6

Makungo, R., Odiyo, J. O., Ndiritu, J. G., & Mwaka, B. (2010). Rainfall – runoff modelling approach for ungauged catchments : A case study of Nzhelele River sub-quaternary catchment. *Physics and Chemistry of the Earth*, *35*(13–14), 596–607. https://doi.org/10.1016/j.pce.2010.08.001

Merz, R., & Blöschl, G. (2004). *Regionalisation of catchment model parameters*. *287*, 95–123. https://doi.org/10.1016/j.jhydrol.2003.09.028

Moore, C., & Doherty, J. (2005). Role of the calibration process in reducing model predictive error. *Water Resources Research*, *41*(5), 1–14. https://doi.org/10.1029/2004WR003501

Moradkhani, H., & Sorooshian, S. (2008). General Review of Rainfall-Runoff Modeling: Model Calibration, Data Assimilation, and Uncertainty Analysis. *Hydrological Modelling and the Water Cycle*, 1–24. https://doi.org/10.1007/978-3-540-77843-1_1

Mwangi, J. K. (2008). *Estimation of Stream Flows in Ungauged Catchments of the Upper Tana Basin, Kenya*. Kenyatta University.

Näschen, K., Diekkrüger, B., Leemhuis, C., Steinbach, S., Seregina, L. S., Thonfeld, F., & van der Linden, R. (2018). Hydrological modeling in data-scarce catchments: The Kilombero floodplain in Tanzania. *Water (Switzerland)*, *10*(5), 1–27. https://doi.org/10.3390/w10050599

Patil, S., & Stieglitz, M. (2011). Hydrologic similarity among catchments under variable flow conditions. *Hydrology and Earth System Sciences*, *15*(3), 989–997. https://doi.org/10.5194/hess-15-989-2011

Pechlivanidis, I. G., Jackson, B. M., Mcintyre, N. R., & Wheater, H. S. (2011). Catchment scale hydrological modelling: A review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. *Global Nest Journal*, *13*(3), 193–214.

Pereira, L. S., & Keller, H. M. (1982). Factors affecting recession parameters and flow components in eleven small Pre-Alp basins. *Hydrological Aspects of Alpine and High-Mountain Areas. Proc. Exeter Symposium, July 1982*, (138), 233–242.

Pereira, Luis S., Allen, R. G., Smith, M., & Raes, D. (2015). Crop evapotranspiration estimation with FAO56: Past and future. *Agricultural Water Management*, *147*, 4–20. https://doi.org/10.1016/j.agwat.2014.07.031

Satgé, F., Ruelland, D., Bonnet, M. P., Molina, J., & Pillco, R. (2019). Consistency of satellite-based precipitation products in space and over time compared with gauge observations and snow- hydrological modelling in the Lake Titicaca region. *Hydrology and Earth System Sciences*, *23*(1), 595–619. https://doi.org/10.5194/hess-23-595-2019

Seibert, J. (1999). Regionalisation of parameters for a conceptual rainfall-runoff model. *Agricultural and Forest Meteorology*, *98–99*, 279–293. https://doi.org/10.1016/S0168-1923(99)00105-7

Singh, K. P. (1968). Some Factors Affecting Baseflow. *Water Resources Research*, *4*(5), 985–999. https://doi.org/10.1029/WR004i005p00985

Susana, M. C. L. de A. (2014). *The Value of Regionalised Information for Hydrological Modelling*. Imperial College London.

WARMA. (2017). *LAKE VICTORIA SOUTH CATCHMENT AREA SUB CATCHMENT MANAGEMENT PLAN (SCMP) ITARE-CHEMOSIT WATER RESOURCE USERS ASSOCIATION (WRUA) ITARE-CHEMOSIT WATER RESOURCE USERS ASSOCIATION (WRUA) SUB CATCHMENT MANAGEMENT PLAN (SCMP)*.

Wheater, H. S. (2002). Progress in and prospects for fluvial flood modelling. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *360*(1796), 1409–1431. https://doi.org/10.1098/rsta.2002.1007

Worqlul, A. W., Maathuis, B., Adem, A. A., Demissie, S. S., Langan, S., & Steenhuis, T. S. (2014). Comparison of rainfall estimations by TRMM 3B42, MPEG and CFSR with ground-observed data for the Lake Tana basin in Ethiopia. *Hydrology and Earth System Sciences*, *18*(12), 4871–4881. https://doi.org/10.5194/hess-18-4871-2014

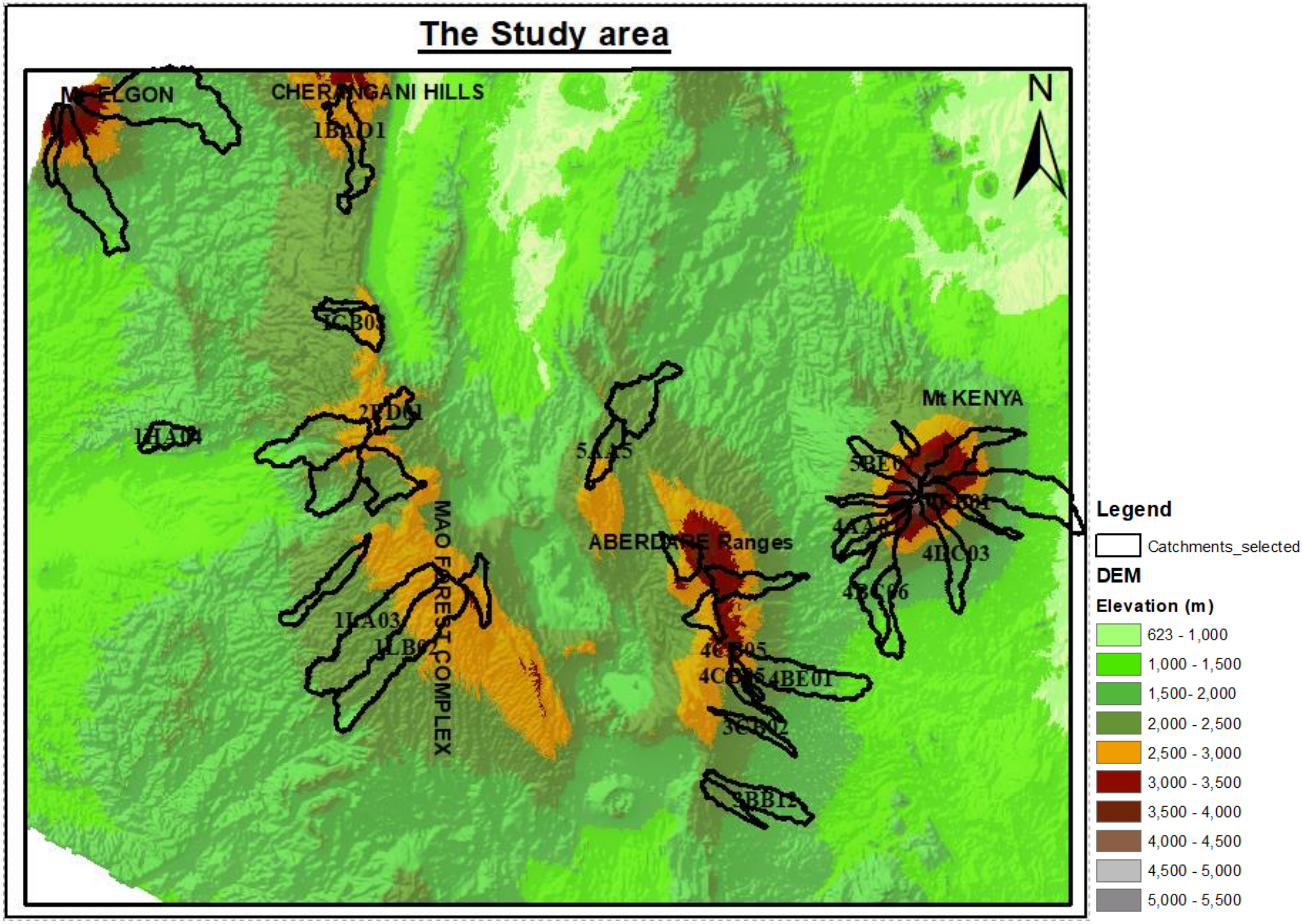
Xu, C. Y., & Singh, V. P. (1998). A Review on Monthly Water Balance Models for Water Resources Investigations. *Water Resources Management*, *12*(1), 31–50.

Xue, Y., Rizzi, J., & Xu, C. (2017). *Runoff prediction in ungauged catchments in Norway : comparison of regionalization approaches*. (December). https://doi.org/10.2166/nh.2017.071

APPENDIX

Appendix1: **River gauging stations**

ID	NAME	LAT	LONG
1AB01	MALAKISI	0.843	34.524
1BA01	MOIBEN	0.804	35.443
1BE06	KOITOBOS	0.965	35.09
1CB08	ENDOROTO	0.446	35.367
1CB09	ELLEGIRINI	0.457	35.383
1DB01	KUYWA	0.624	34.7
1GB11	AINOPSIWA	-0.025	35.176
1GC05	MASAITA	-0.194	35.535
1GG01	NAMUTING	-0.203	35.347
1HA04	KIBOS	-0.008	34.804
1HD02	AWACH	-0.45	34.883
1JA02	KIPTIGET	-0.551	35.257
1LA03	NYANGORES	-0.786	35.347
1LB02	AMALA	-0.897	35.438
2ED01	TIGERI	0.103	35.691
2FC05	NJORO	-0.372	35.925
2GB04	WANJOHI	-0.279	36.483
2GC05	NANDARASI	-0.551	36.559
3BA10	RUARAKA	-1.227	36.823
3BB12	KAMITI	-1.197	36.971
3BC13	KOMOTHAI	-1.066	36.872
3CB02	NDARUGU	-0.996	36.917
4AA01	SAGANA	-0.367	37.067
4AA02	THEGO	-0.35	37.05
4AC04	NEW CHANIA	-0.421	36.958
4BE01	MARAGUA	-0.75	37.153
4CA04	KIMAKIA	-0.879	36.875
4CB05	THIKA	-0.808	36.817
4DC03	RUPINGAZI	-0.533	37.438
4EB01	NITHI	-0.288	37.646
4F05	MARIARA NEW	0.042	37.658
5AA05	EQUATOR	0.02	36.363
5AC15	EWASO NAROK	0.257	36.537
5BE05	TELESWANI	0.083	37.23
5BE07	LIKI	0.021	37.087
5BC02	NAROMORU	0.165	37.025

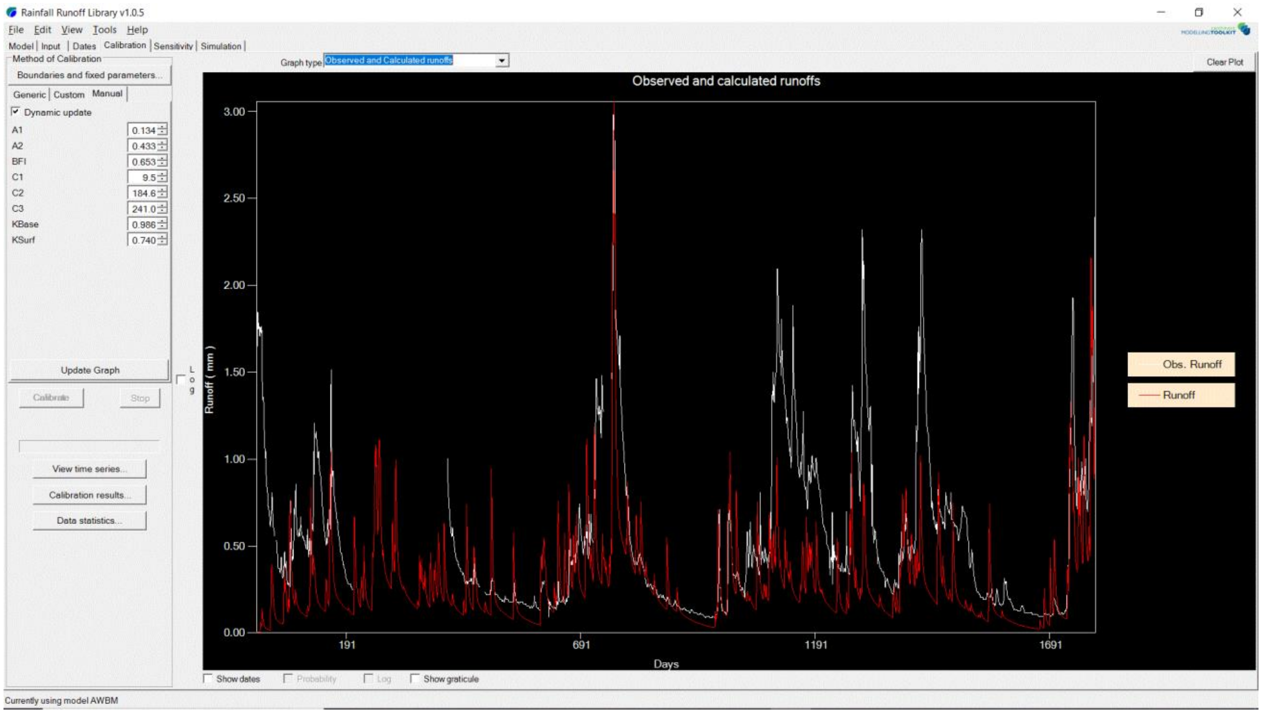


Appendix 2: Preliminary Selected Catchment

Appendix 3: Simulated and observed hydrographs of AWBM from RRL interface

2ED01_TIGERI

Calibration



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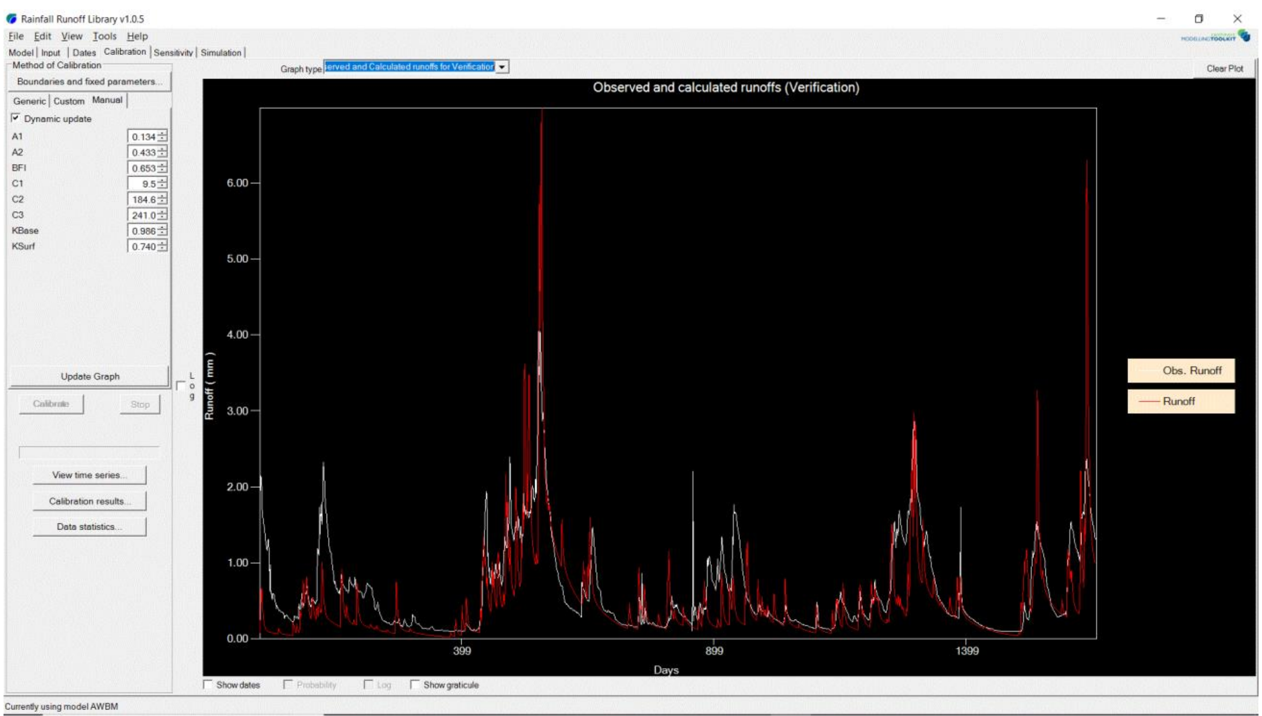

1LA03 NYAGORES

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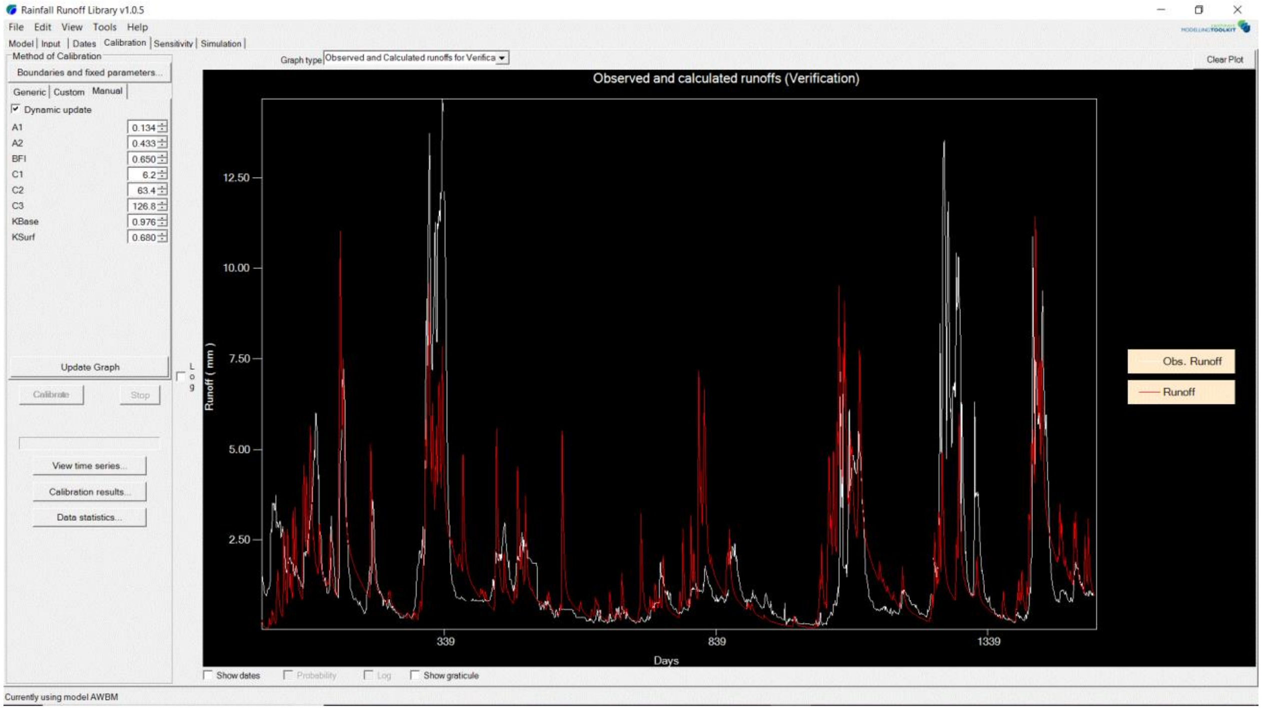

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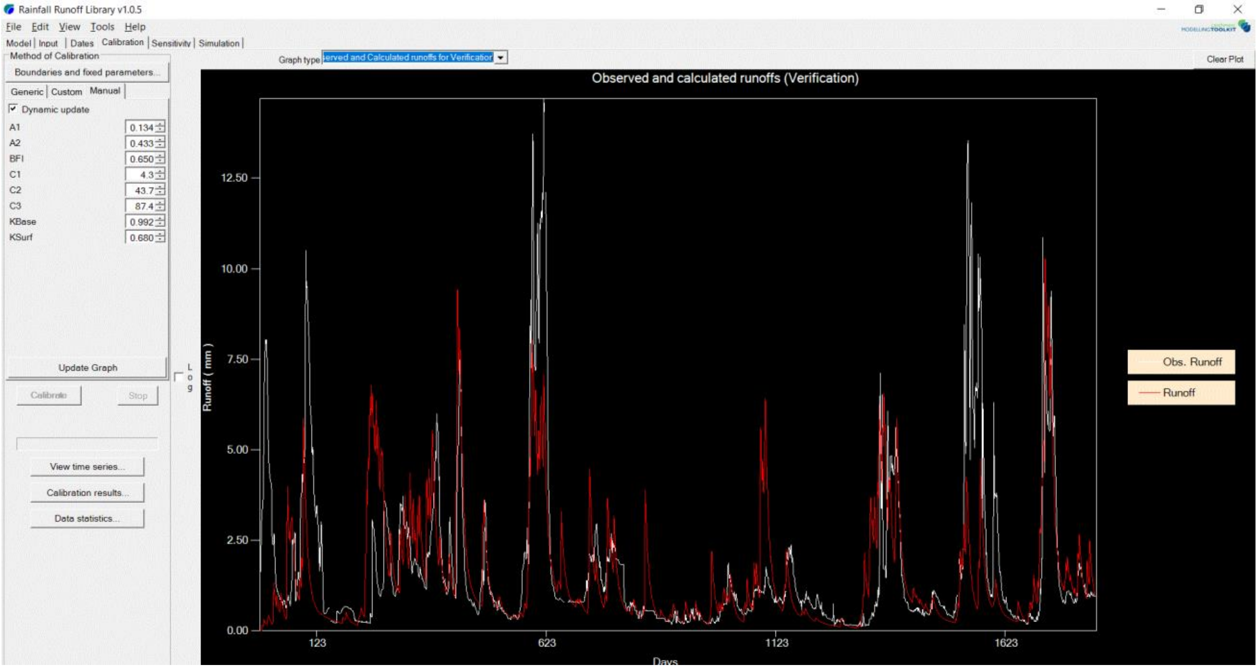

1LB02 AMALA

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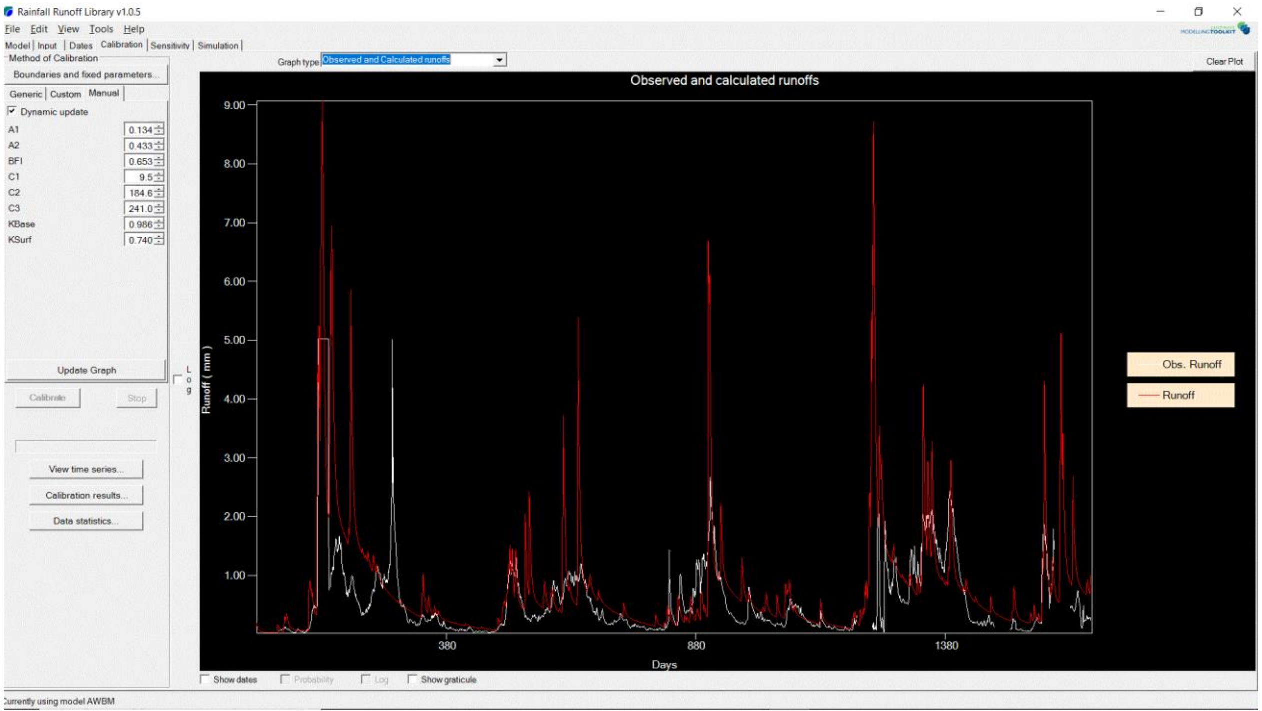

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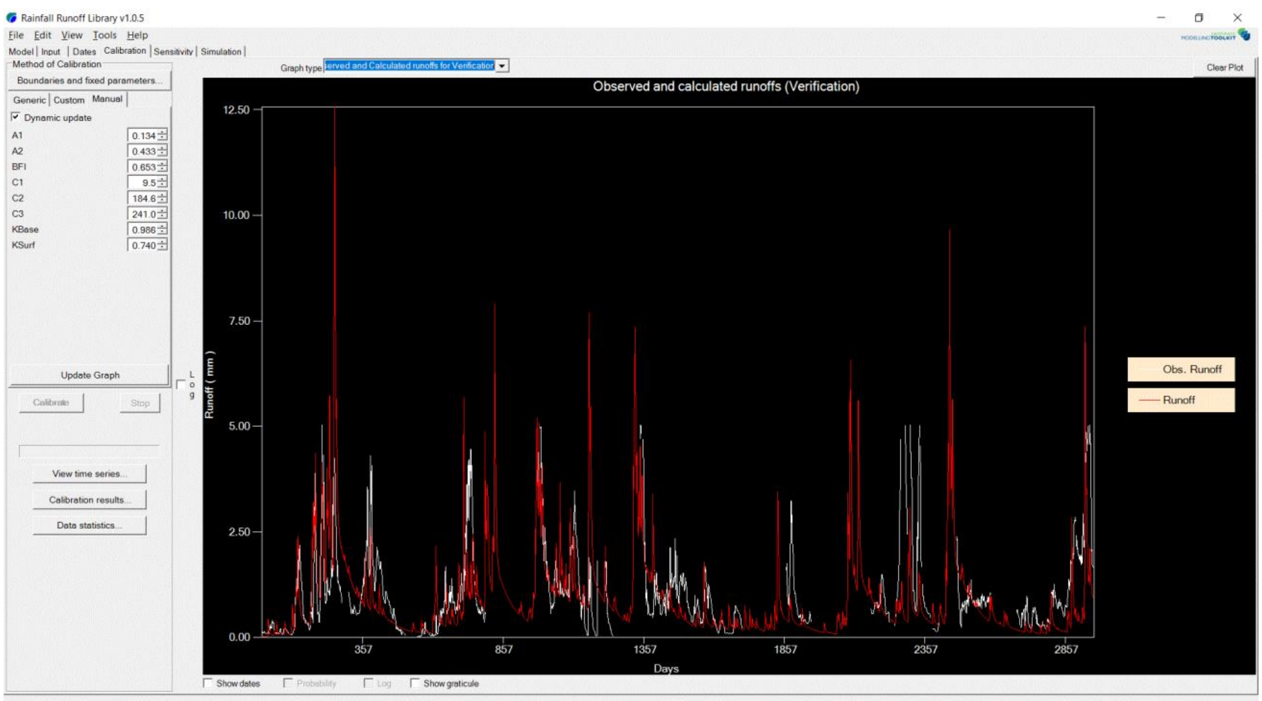

5AA15 EQUATOR

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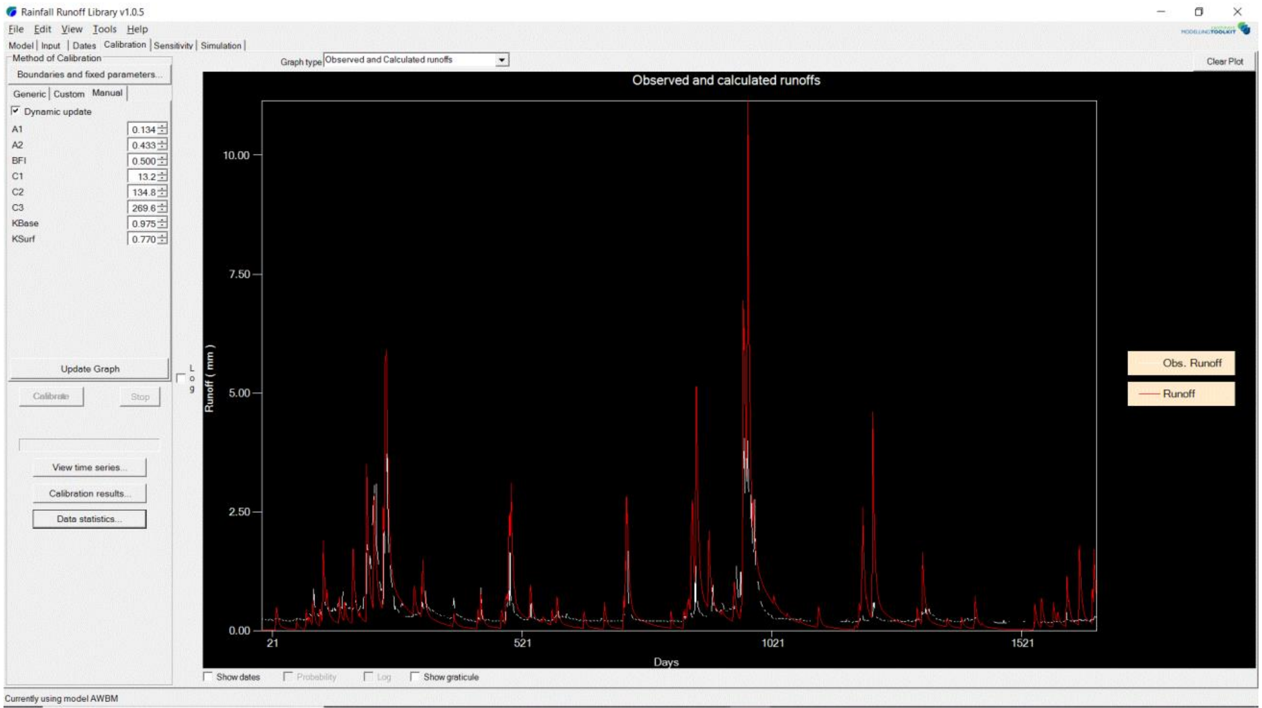

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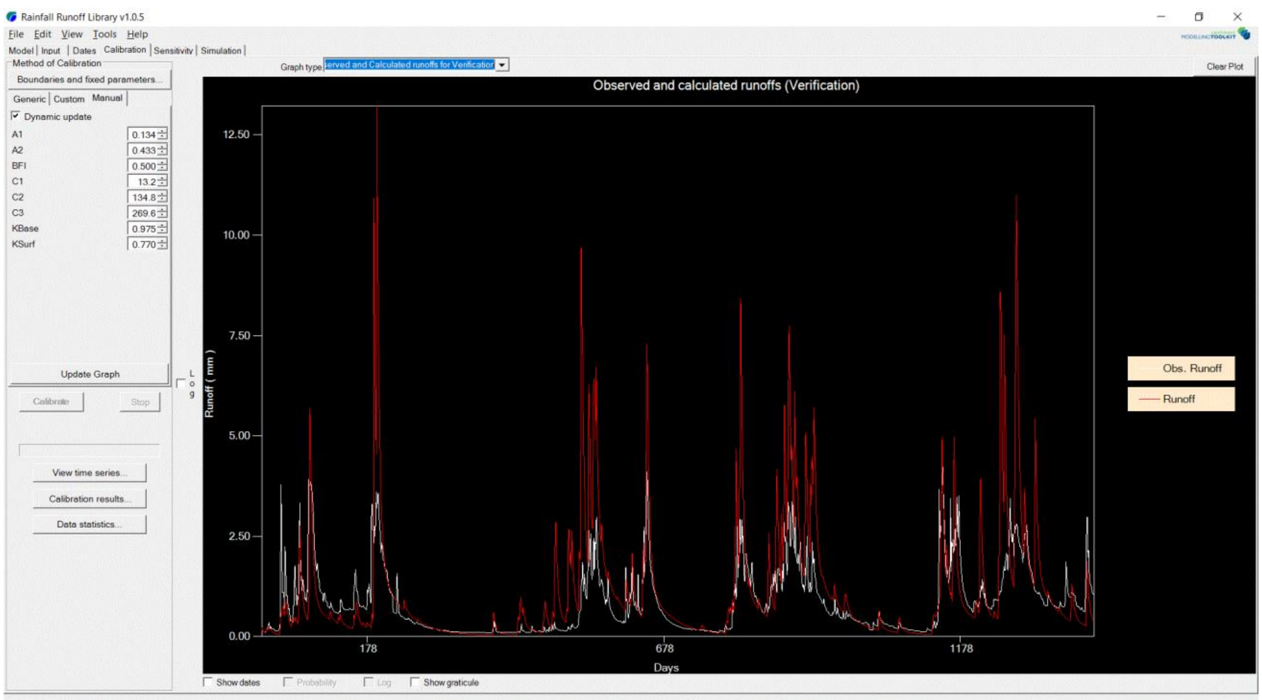

4AA02 THEGO

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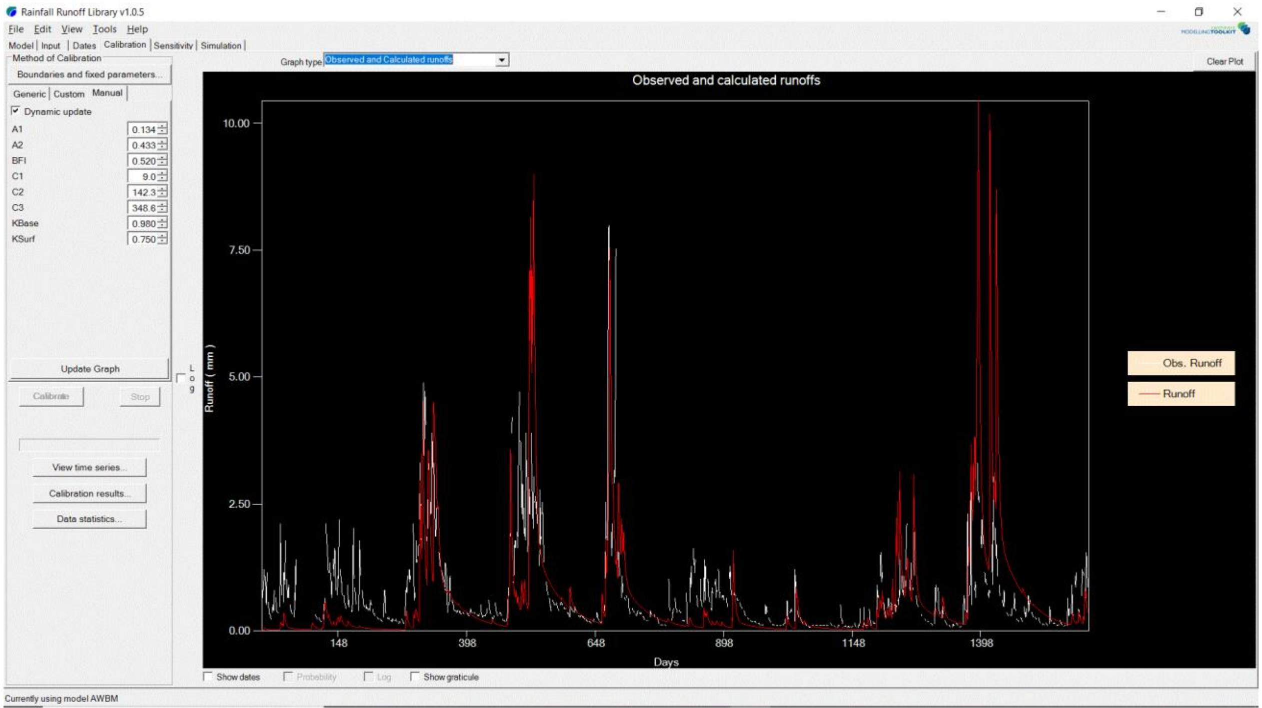
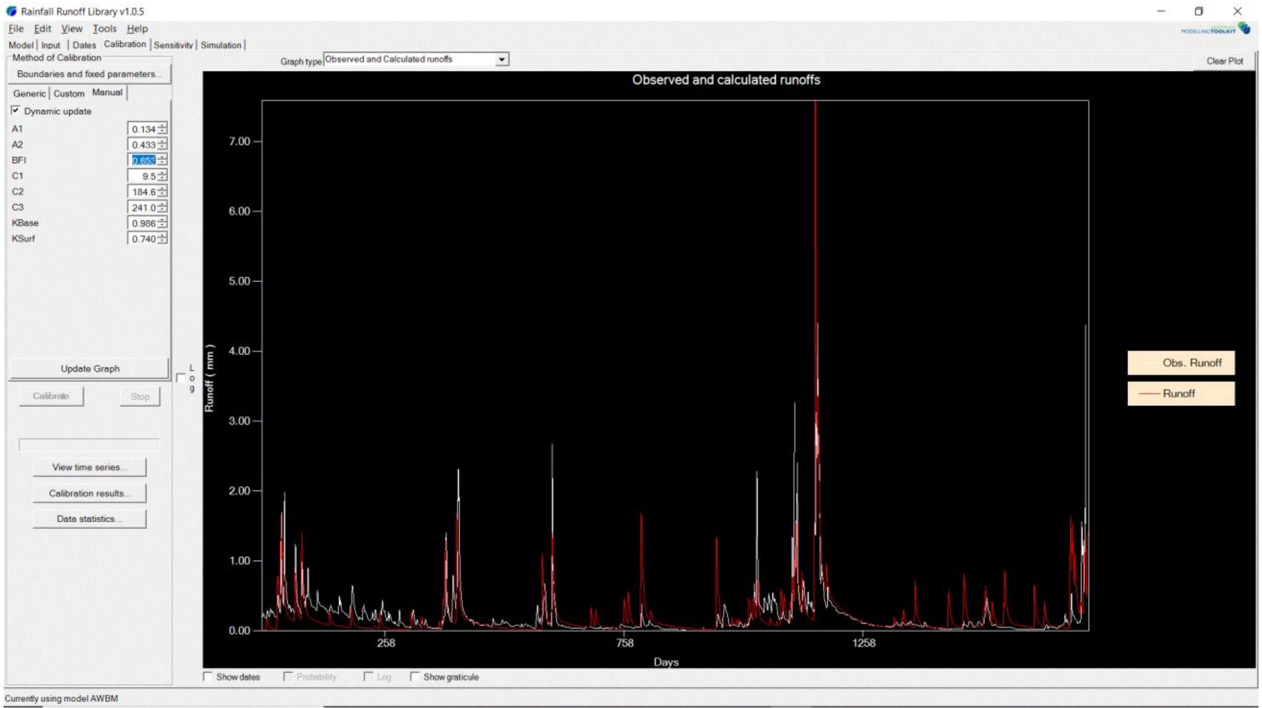


3BB12 KAMITI

Calbration



3BC13 KOMOTHAI

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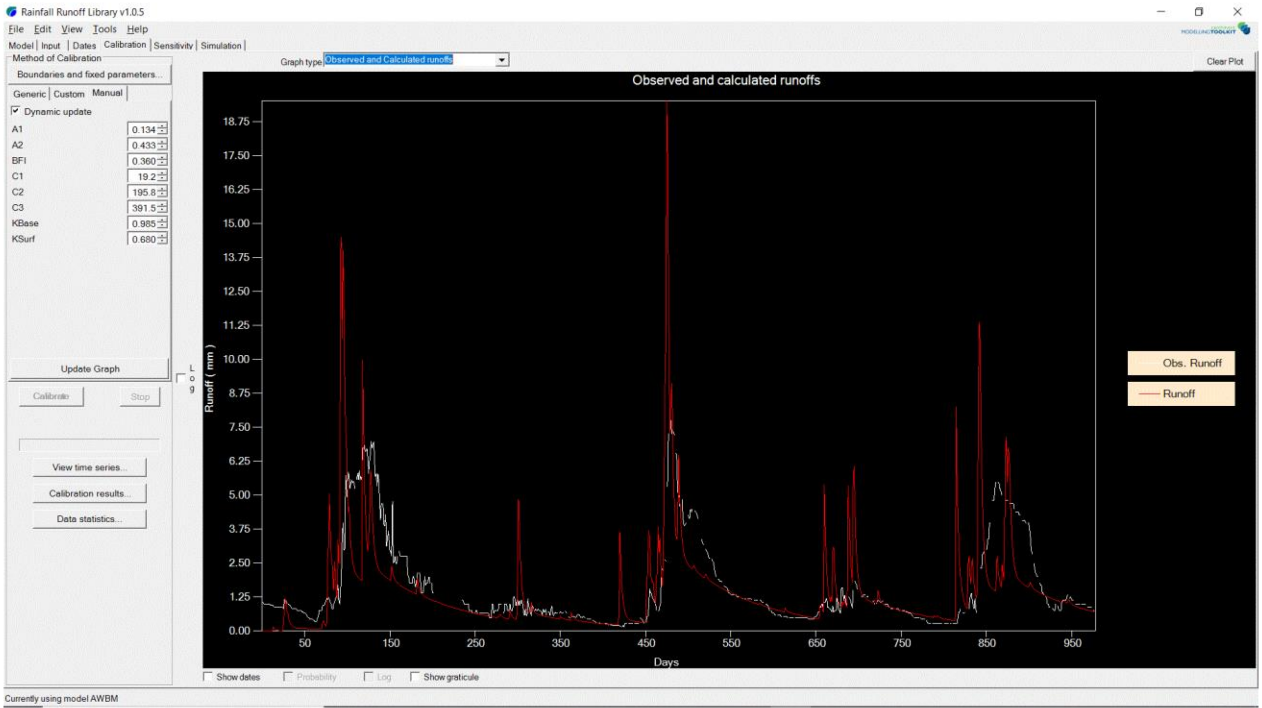

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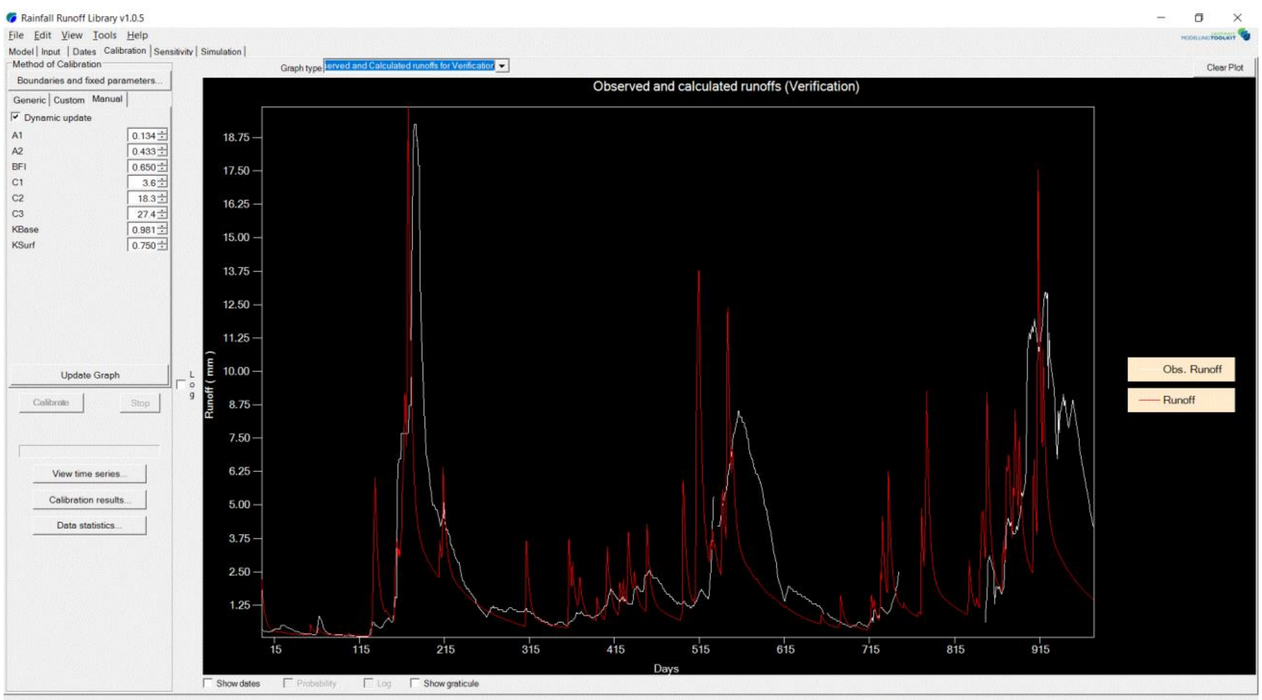

1BA01 MOIBEN

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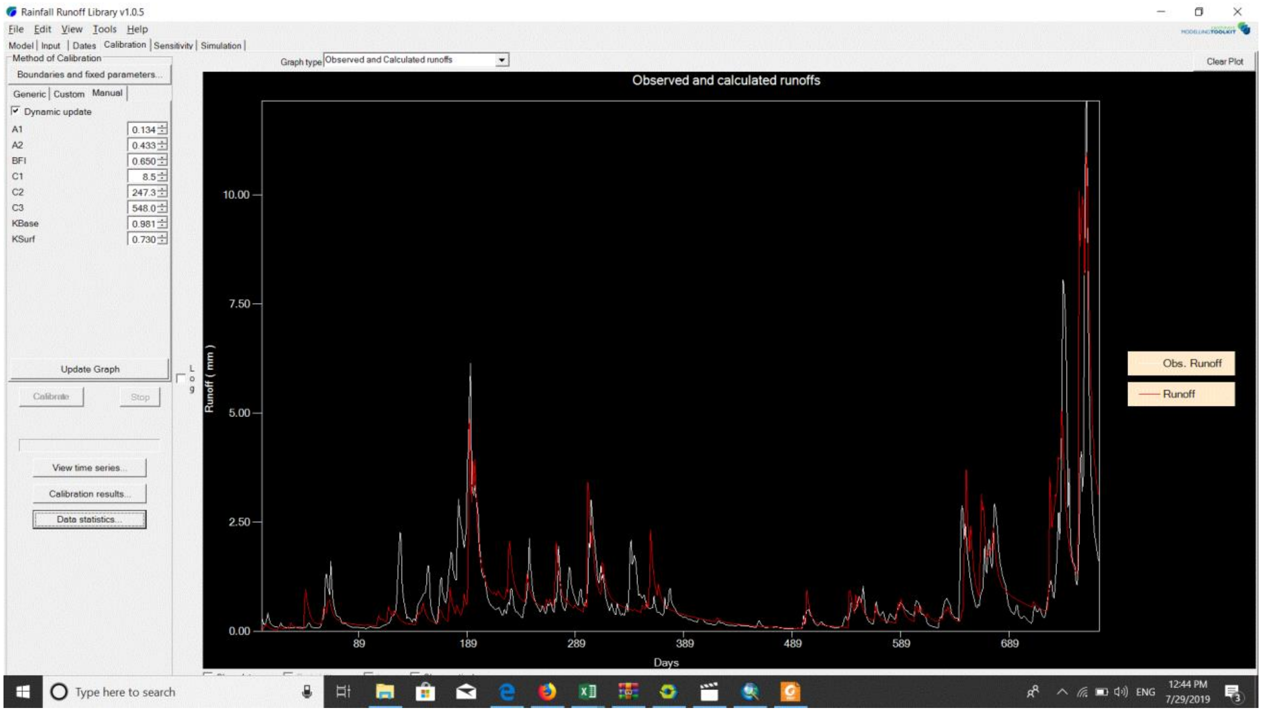

Verification