ASSESSMENT AND REGIONALIZATION OF HYDROLOGICAL MODEL PARAMETERS IN NEIGHBORING PHO CHHU AND MO CHHU BASINS IN BHUTAN - A STUDY BASED ON ABCD MODEL

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DECLARATION

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ASSESSMENT AND REGIONALIZATION OF HYDROLOGICAL MODEL PARAMETERS IN NEIGHBORING PHO CHHU AND MO CHHU BASINS IN BHUTAN -A STUDY BASED ON "ABCD" MODEL

ABSTRACT

In the cold regions because of harsh climates, there exists no or an inadequate number of monitoring stations. It is indeed a challenge to generate the hydrographs of ungauged basins with scanty information from limited gauged basins. As a result, it has important implications for existing water resources systems as well as for future water resources planning and management since high elevation mountains are all important sources of water to the billions in the lowlands in these climatic regions.

The Mo Chhu and Po Chhu catchments in Bhutan are used in this study to assess the regionalization of hydrological model parameters from one catchment to the other neighbouring catchment having similar characteristics using ABCD hydrological model incorporating snowmelt parameter. The Mo Chhu catchment was considered as the gauged catchment and its hydrological parameters were simulated through model calibration and validation, and then transferred to the neighbouring Pho Chhu catchment. For the corresponding watersheds, precipitation, streamflow and temperature daily data were collected for the 11 years from 2006~2017 from the National Centre for Hydrology and Meteorology in Bhutan and checked by visual comparison, single and double mass curve analysis and annual water balance to ensure data reliability, consistency and to identify suitable data periods for model calibration and validation. For the model performance evaluation, Root Mean Square Error (RMSE), Pearson correlation coefficient (r) and Coefficient of determination (R^2) were used as the objective functions. The Pearson correlation values for calibration and validation of Mo Chhu basin are 0.84 and 0.88, respectively. When the same model parameters were transferred to Pho Chhu basin, Pearson value for validation was found to be 0.82, indicating good inter-basin parameter transferability and effective model regionalization.

Comparing and analyzing the results of ABCD model with and without snow parameter "*m*", it can be concluded that the model with snow parameter performs better due to proper simulation of the major contribution to basin flow from snowmelt. Approximately, over 52% of the basin flows can be attributed to snowmelt during summer and spring and the incorporation of snow processes in the monthly ABCD model has thus significantly improved model performance in snow-covered areas in Bhutan.

Keywords: Snowmelt runoff; Gauged and ungauged catchment, Snow dominant area

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1. INTRODUCTION

1.1 General

Estimation of streamflow is crucial in managing scarce water resources in the basins.. Most of the catchment in the Himalayan region are inaccessible due the harsh weather and terrain. This makes the monitoring of hydrometeorology data inconvenient and strenuous for managing the catchment. For the management of the catchment, availability of the streamflow data for mathematical modelling and analysis plays greater significant importance. Due to shortage of data, hydrological models which are capable to simulate runoff from rainfall input only, are found inefficient for prediction of daily streamflow in mountainous high elevation basins because of significant snowmelt contribution to the runoff in these basins (Martinez & Gupta, 2010).

Many rainfall-runoff models are available due to continuous research on the topic. In the basins where snow covers a major portion, the snow too contributes towards the streamflow generation. A variety of hydrological models considering snowmelt runoff component are also available (Guo et al., 2015). For the mountainous basin with major snow cover, hydrological models considering both runoffs, i.e rainfall and snowfall simulation, is essential. Such hydrological models have been used and applied in similar basins around the different parts of the world (Yilmaz et al., 2012; Gyawali & Watkins, 2012; Rezaeianzadeh et al., 2013; Joo et al., 2014; Pokharel, Neupane, Tiwari, & Köhl, 2014). The objective of this study is to assess the transferability of model parameters, by evaluating the use of parameter estimates derived from one basin to the other ungauged neighbouring basin.

Water resource management globally demands expert's prediction on the behaviour and characteristics of the water in its hydrologic cycle. The aim is to be able to measure the availability and distribution of water for consumptive use and to make any imperative measures to budget its use in safe and rational way. Moreover, , the study is focused on securing available water, thus it will not be exhausted due to overutilization. Further, it aims at predicting the adverse outcomes of water if a certain phase of the hydrologic cycle gets extreme or becomes persistently stressed causing undesirable situations like floods and necessitates taking mitigatory measures for the developed consequences.

As a water resources manager, there is a need to develop tools that enable the predictions for better understanding and management of the resources as climate change is perpetual. Further attention must be drawn to the fact that for decision-makers who are trying to distribute resources to ease local water scarcity in the midst of data-scarce conditions, the complex models which bring about outputs on continental scales are of little usage. Decision-makers need vital tools that can reliably forecast hydrologic changes that tally with the foreseen climate changes. In this condition, if decision-makers have a watershed model which can generate streamflow for given input parameters then such models would provide them with the ability to assess climate change impacts on stream water.

The key to successfully predict runoff and its fluctuation in both gauged and ungauged basins is the availability of a reliable hydrologic model and an appropriate parameter regionalization approach.

The current (present-day) generation of rainfall-runoff models is classified into different categories based on different criteria. The present-day rainfall-runoff models are classed into a variety of categories based on different criteria. One such categorization is based on the way the different components of the catchment processes are treated within the model. There are a group of models in which the modelling procedure is based on establishing a mathematical relationship between the input and the output variables using data analysis and fitting. Such models fall into a class of empirical models. The modelling approach in this class of models mainly relies on the estimation of the catchment runoff from a range of predictor variables using multiple regression (Hirsch, 1982; Kletti and Stefan, 1997), or implementation of a soft computing approach such as artificial neural networks or fuzzy rules (Smith and Eli, 1995; Bárdossy, 1996; Minns and Hall, 1996; Haberlandt, et. al, 2001; Hundecha, et al. 2001). Another group of models try to model the components of the hydrologic cycle using simplified mathematical relationships, which are physically sound but are not based on the precise description of the physical processes involved based on known physical laws. These models are referred to as conceptual models and there are dozens of such class of models that are widely used, such as the HBV model (Bergstrom, 1995), the HACRES model (Jakeman et. al., 1990), and the VIC model (Wood, et. al., 1992). There is also another group of models, in which the different components of the catchment process are described by equations derived from known physical laws. These constitute what is known as physically-based models. Examples of this class of models are SHE (Abbott et al., 1986a,b) and IHDM (Beven et al., 1987).

1.2 Background

Ice and snow on land surfaces and sea collectively called the cryosphere are one of the most important components of the earth’s climate system. About 70% of the world’s freshwater resources are stored in ice and snow (UNEP, 2007). Snow has a large influence on the water balance and the energy balance. Seasonal snowmelt is one of the main contributors to the runoff in many mountainous regions and it is the main source of water for irrigation and water supply for billions of people living in these regions. In the mountainous regions, snowmelt is the main source of water. The snowmelt acts as one of the main contributors to runoff. People living in the downstream of those mountains depends on this source for irrigation and water supply. The energy balance is affected since the snow has a very high albedo and low thermal conductivity (Hall & Riggs, 2007). Because of its physical properties, snow cover plays a very important role in influencing global and regional energy cycle as well as the water and carbon cycle (after FAO, 2009). Over the last four decades, snow cover has globally decreased substantially (UNEP, 2007) and is attributed to global warming (IPCC, 2007). The decrease in spatial snow cover extent and increased snow cover melt is expected to continue for the decades ahead by projected increases in global temperature. Changes in snow cover potentially could have very serious impacts on ecology, water resources, agriculture, and economic activities including hydropower generation, industry, transportation and other social impacts. Therefore, monitoring of snow cover has been identified to be of prime importance for the better understanding of global and regional climates, and assessment of water resources (FAO, 2009). At the international level, snow cover has been declared as an essential climate variable for Global climate observing system (GCOS) of the World Meteorological Organization (GCOS,2010).

The Hindu Kush Himalayan (HKH) region extending from Afghanistan in the east to Myanmar in the west, covers an area of approximately 4.19 million square kilometres (ICIMOD, 2011) and contains the largest concentration of ice and snow cover outside the Polar region. The area forms one of the largest storehouses of freshwater sources and in the higher altitude (above 3000 m) a substantial amount of the annual precipitation falls as snow (Gurung et al., 2011). The HKH region is the source of some of the largest Asian river systems like Indus, Ganges, Brahmaputra and Mekong among others (Kulkarni et al., 2011). These major rivers originate from the mountainous regions which have their catchments in snow-covered areas and snowmelt is one of the major components of streamflow. The large population living in these river valleys depends on the rivers for their livelihood and the ever-increasing demand for freshwater has initiated the need to predict the amount of meltwater contributing to the streamflow for better management of water resources in the HKH region.

Bhutan has always been following a conservation centred development policy which has resulted in maintaining and preserving the country's natural resources. Currently, Bhutan has a forest cover of approximately 70.46% (NSB, 2013). As a result of the good forest cover and average annual precipitation of about 2,200 mm, the country is endowed with abundant water resources. Almost all the valleys in Bhutan have swiftly flowing river(s) which are fed by snow/glacial melt and rainfall during the summer monsoon or both. Bhutan has one of the highest total renewable water resources per capita in the South East Asian region estimated at 109,294 cubic meters per capita per year (2009) (UN-Water: KWIP, 2014). Almost 80 % of the total population depends on agriculture and livestock farming for their livelihood, and the farmers depend on the rivers, springs and rainfall for irrigation purposes. The steep mountains, deep valleys and swiftly flowing rivers are the source of the country's hydropower generation, which is one of the major contributors to the country's economy.

Even if endowed with rich and plentiful water resources, Bhutan still faces localized and seasonal water shortages for both drinking and agricultural purposes. Only 78% of the population has excess to clean drinking water and 12.5% of arable land is irrigated (NEC,2003.). Precipitation is unevenly distributed spatially; river sediment loads have drastically increased over the years and there is a wide variation in river flows during dry and monsoon seasons. To aggravate problems further pressure on water resources is increasing due to water demands from various growing sectors like industries, increasing population apart from agricultural purposes.

Like in the other parts of the Himalayas, Bhutan’s rivers are fed by glacier and snowmelt. Agriculture is the main source of livelihood for about 80% of the people. Hydropower is one of the largest contributors to the kingdom’s economy generating over 45% of the national revenue (NSB, 2013). In Bhutan snow and glacier melt contributes substantially to streamflow more so during the dry season, and there are indications that climate change has serious impacts on seasonal and annual runoff (IPCC, 2007). Studies show that in recent times glaciers have been melting which will eventually have long term effect on the amount of snow and glacier melt causing a reduction in the streamflow during the dry season which can have serious impacts on the hydropower sector of the economy (Rupper et al., 2012a). Dietz, et al. (2012) describe that it is crucial to have an accurate snow cover and snow water equivalent map for assessing the contributions of snow and glacier melt to streamflow for better management of hydropower and better understanding, planning and development of the water resources in the country.

In the last few decades, many hydrological models have been in use for various applications. Singh, (1995) has documented the most popular computer models of watershed hydrology. Singh and Frevert (2002a, 2002b) published a 2-volume book with a comprehensive account of 38 models for large and small watershed hydrology. The World Meteorological Organization was among the first ones to carry out inter-comparisons of hydrological models (WMO, 1982) and snowmelt models (WMO, 1986). Hydrological models facilitate in understanding the influence of the variability of snow cover on various other aspects of climate. In areas where the primary source of runoff in the streamflow is from snowmelt, snowmelt runoff modelling has become an inevitable tool for water resource management. Snow cover area and snow water equivalent which is the liquid water which would be released upon complete melting of the snowpack are the important inputs for modelling snowmelt (Mhawej et al., 2014).

1.3 Problem statement

One repeated difficulty that scientists confront in developing countries is the deprivation from informative data corresponding to the studies. For the study of an ungauged catchment, hydrological model parameters estimation is important. But in the Himalayas, there is a severe lack of monitoring stations making it hard to retrieve the necessary data required for the catchment studies. It is important to cover this setback keeping into consideration how important it is to manage water and develop its resources sustainably in future.

1.4 Main Objective and Specific Objectives

1.4.1 Main Objective

The main motive of this study is to develop a methodology which validates regional estimation of the parameters of a conceptual continuous water balance model derived from the catchment characteristics which incorporate the land cover, soil type and topographic features of the catchment.

It was aimed at improving the weaknesses inherent in the traditional two-step regionalization approach in estimating the relationship between the model parameters and the physical catchment characteristics. The catchment characteristics used for regionalization were all determined from readily measurable physiographic and land cover attributes of the catchments. Measured physiographic and land cover attributes of the catchments were used to determine the catchment characteristics for the regionalization. The main reason for conducting the study is for investigation and regionalization of ABCD hydrological model parameters from the gauged Mo chhu catchment to the neighbouring Pho chhu catchment in the northern Bhutan.

1.4.2 Specific objectives

1. State of art literature review to comprehend the present status of research in the area and related to the topic.
2. ABCD model development for Mo chhu catchment
3. Model calibration, validation using available data for Mo chhu

4. Transfer of model parameters to neighbouring Pho chhu catchment
5. Validation and verification/ Optimization
6. Sensitivity analysis identifying crucial paratemetrs
7. Conclusions / Recommendations

1.5 Thesis Outline

This thesis is divided into five chapters. Chapter 1 gives the introduction to the study area, the problem statement and the research objectives and specific objectives. Chapter 2 provides an extensive literature review on hydrological models and the ABCD model followed by the regionalization of parameters with a brief review on objective functions. Chapter 3 introduces the study area and the datasets used for this research work. Chapter 4 discusses the regionalization of parameter adoptions. Chapter 5 gives the analysis and results and discussions and finally, the conclusions and recommendations are made.

2. LITERATURE REVIEW

2.1 Modelling Concept

A model is a simplified depiction of the actuality. A hydrological model is the mathematical representation of the response of a catchment system to hydrologic events during the time period under consideration. Generally, hydrological models are classified based on the process description, based on spatial representation and based on the aspect of randomness (Moreda, 1999).

Based on the assumptions and concepts formulating the structure of transformation (Operator) the resulting models may have different forms. According to Clarke, 1973 mathematical models may be classified into four main groups as Stochastic, Deterministic, Conceptual and Empirical.

Though there are many different types of hydrologic models, most of these models can be divided into three main categories:

(1) Empirical models (i.e. black-box models),

(2) Physically-based models, and

(3) Models based on the water balance concept.

Empirical models, such as those based on the application of linear and nonlinear systems theory (Xu & Singh, 1998), make use of statistical and mathematical relationships to relate inputs to outputs. A major limitation of these models, however, is that they do not facilitate physical understanding of the hydrologic processes. Physically-based equations, such as the Green-Ampt equation (Green & Ampt, 1911), are believed to govern water and energy processes in a vertical column of soil (Schaake et al., 1996). Models based on these equations are effective at representing the water budget at the point scale. Ideally, these models would form the basis of most hydrologic models. However, physically-based equations are most often used in models where accurate representation of surface runoff processes is not of great importance (Schaake et al., 1996). The reason is that at large spatial scales, application of the equations is difficult, due to the spatial heterogeneity of surface and subsurface characteristics.

Likewise, physically-based equations have been developed for applications at very short time scales, making it difficult to apply them for surface water budget estimations in applications at time scales greater than a day. Thus, either data at a very fine resolution is required to account for the spatial and temporal heterogeneity of surface runoff processes (which is currently infeasible) or, more commonly, a significant degree of spatial and temporal homogeneity must be assumed, which considerably limits the performance of physically-based models. Water balance models offer a simpler, and often, a more effective alternative method.

All water balance models are based on the water balance concept, a concept analogous to mass balance. Thornwaite (1944) defined it as the balance of precipitation and snowmelt (i.e. the inflow of water) with evapotranspiration, groundwater recharge, and streamflow (i.e. the outflow of water) (Dunne & Leopold, 1978). A net change in the balance of water is usually accounted for and is most commonly expressed as a change in soil moisture.

Water balance models are generally based on mass continuity and the hydrologic cycle of water in the natural environment. Monthly water balance models evaluate the importance of various hydrological parameters under diverse hydrological conditions. As water balance models are becoming widespread, there is a significant effort devoted to the development of these models towards estimating the hydrological components of the basin. Different models and algorithms consider various parameters which range from relatively complex conceptual models for dry areas to very simple models for areas with temperate climates. Therefore, it is essential that these models be closely and precisely analyzed, and ultimately, reviewed. Generally, rainfall data have long been recorded, but discharge data are often scarce. Therefore, the need to estimate the discharge of rivers resulted from rainfalls has motivated a great number of researches in this area of study. In this paper, parameter naming in different models has been homogenized, presenting a clearer image of similarities and differences among different models. The overall framework of the models is similar and inspired by the Thornth Waite model. The input parameters are precipitation and temperature, and the output is the monthly runoff of the basin. All models include soil water storage capacity, evapotranspiration, and runoff. However, some of the models consist of water storage capacity layers, separation of rain and snow, groundwater storage, and base discharge. These differences in the number of parameters distinguish the models from each other.

2.2 Modelling ungauged catchments and prediction of the effect of changes

The difficulty (complication) in estimating model parameters a-priory through measurement and the ultimate(consequent) necessity(essential) of model calibration against observed catchment responses has a serious(crucial) practical consequence. The difficulty in estimating model parameters through measurement and consequent essential of model calibration against observed catchment responses has a crucial practical consequence. The non-uniqueness of the model parameters evaluated through model alignment makes it hard to connect any of the parameters with the promptly quantifiable physical catchment attributes. Therefore, the parameters may partly lose their physical significance; even though they have physical meanings in the model structure they are used in. This, consequently, limits the transferability of the model parameters to other catchments based on the physical properties of the catchments. The model should then be adjusted independently for every catchment for which expectation of the catchment reaction is looked for. Since model alignment needs at least one watched reaction information, use of the model to ungauged catchments will be troublesome.

Prediction of the impact of changes in the catchment properties, like land use, on the response of a catchment also requires quantification of the model parameters corresponding to the changed catchment properties. Unless there is a relationship between the model parameters and the catchment properties, such quantification cannot be done in a physically meaningful way, thus limiting the applicability of the model for prediction of the effect of changes.

In an attempt to address the issues aforementioned, various studies had been carried out in the past years in an effort to establish ideas of regionalization of the model parameters determined from promptly measurable physiographic, land cover and climatological attributes of catchments. A great quantity of the works in the previous days was specialized in evolving a means of portraying event-based catchment behaviour with rainfall and topographic features considering a multiple regression approach (Heerdegen and Reich, 1974; Waylen and Woo, 1984; Nathan and McMahon, 1992). Nevertheless current doings turned out to be concentrating on the advancement of a regionalization measure to assess the parameters of a better type of continuous water balance models of time systems varying from monthly to hourly from readily measurable catchment properties. Abdulla and Lettenmaier (1997) put in an application a method of regionalization of the parameters of the VIC-2L land surface hydrologic model (Liang et al., 1994) for the development of everyday streamflow for catchments in the Arkansas- Red River basin relying on distributed land surface and climatological characteristics developed from station meteorological data. Thus, to address the issues referenced over, a few investigations have been made and Sefton and Howarth (1998) likewise utilized a comparable parameter regionalization plot for the IHACRES model (Jakeman et al., 1990; Littlewood et al., 1997) to assess daily streamflows for catchments in England and Wales utilizing physical catchment descriptors including geology, soil type, atmosphere, and land spread. Some increasingly comparative works are recorded in Xu and Singh (1998) for estimation of the monthly streamflows, followed by Post and Jakeman (1999), and Seibert (1999).

The entirety of the parameter regionalization approaches referenced in the previous passage follow a general two-advance technique of parameter regionalization. The initial step is to discover ideal arrangements of parameters for various measured catchments by aligning the model against watched reactions for every one of the catchments freely. The subsequent advance is attempting to set up a connection between the ideal model parameters and the catchment qualities. In numerous past investigations, this has taken a straight or non-direct relapse structure. In any case, such a methodology has met with constrained achievement. As referenced in the past segment, model adjustment brings about just a single acknowledgement among numerous other conceivable parameter sets that lead to a comparable model execution. The connections built up between such arrangement of model parameters and the catchment attributes are along these lines liable to be powerless or "irregular".

Fernandez, et al. (2000) executed an alternate methodology that would deal with the issue referred to above. Rather than following the two-advance system actualized in past investigations, they treated them simultaneously. They aligned the ABCD monthly water balance model (Thomas, 1981) for 30 measured catchments in the Southeastern part of the United States with the multiple goals of imitating the observed catchment reaction and, moreover, to get great connections between model parameters and catchment attributes. Their methodology brought about an almost ideal local connection between model parameters and catchment properties, yet didn't prompt improvement in the capacity of the regionalized model to demonstrate stream at approval catchments situated inside a similar report territory. Lamentably, a considerable lot of the catchment descriptors they utilized for regionalization require examination of stream information and, in this manner, its application to ungauged catchments is beyond the realm of imagination.

2.3 Application Potential of Water Balance Model

Water balance models are extensively used to identify water availability, watershed characteristics, and water resources management and to evaluate the hydrologic consequences of climate change. The main practical reasons for using water balance models are, for the water resources planning and prediction of effects of climate change, monthly streamflow discharges may be adequate and the abundance of monthly hydro climatological data. For humid regions, it is sufficient to use a model which has been formulated with three to five parameters to represent most of the hydrological information in the catchment. But for arid and semi-arid regions, relatively complex models with ten to fifteen parameters may be used (Xu & Singh, 1998). According to Thomas, Marin, and Brown (1983), approximately four to six parameters are needed to define the parameters adequately for a catchment and the parameters need not have the conventional meanings of hydrologic variables. In comparing monthly water balance models with daily water balance models, monthly water balance models are advantages if the main interest of the application is monthly, seasonal, or annual streamflow volume. Subsequently, monthly water balance models have low computational cost, because it requires only monthly data (Wang et al., 2011). In addition to the above facts, model complexity must be increased when increasing the dryness index and decreasing the time scale (Atkinson, Woods, & Sivapalan, 2002).

According to Xu & Singh (1998), monthly water balance models are generally used for reconstruction of the hydrology of watersheds, climatic change impacts assessments, and evaluation of the seasonal and geographical patterns of water supply and irrigation demand.

There are two practical reasons, among others, for utilizing monthly models. To begin with, for the reasons for arranging water resources and foreseeing the impacts of climatic change, the monthly variation of discharges might be sufficient. Next monthly hydro climatological data are most adequately obtainable. Monthly precipitation, temperature and/or evaporation appears to be satisfactory and at times solely precipitation data seems to serve the purpose.

Apparently, three to five parameters might be adequate to replicate the vast majority of the data in a hydrological record on a monthly scale in damp locations. It might be beneficial to utilize models with a moderately intricate structure in dry and semiarid areas, for example, in African catchments. Since most monthly water balance models require fewer parameters to clarify hydrological wonders, the data contained per parameter is then expanded, which allows a progressively exact assurance of parameters and the increasingly dependable relationship between parameter values and catchment qualities. Thusly, relevance to ungauged catchments is another significant preferred position of such models.

2.4 Lumped Water Balance Model

According to Thomas (1981), one of the main important principles in developing lumped models is the usage of the limited number of parameters which represent the regime characteristics which can change with the land use and installation facilities of water management. In these models, all the spatial variability is being neglected. The catchment is seen as a whole. Variables and parameters represent averages.

The three models represent a lumped conceptual modelling system (NAM), a distributed physically-based system (MIKE SHE), and an intermediate approach (WATBAL). It is concluded that all models performed equally well when at least one year's data were available for calibration, while the distributed models performed marginally better for cases where no calibration was allowed.

Although there appears to be a certain degree of consensus at the theoretical level regarding the potential of the distributed physically-based types of models, there are widely divergent points of view as to whether they offer a significant improvement in actual performance when compared to the well-proven lumped conceptual model type. Beven (1989, p. 161) argues from theoretical consideration of scale problems that "the current generation of distributed physically-based models are lumped conceptual models," and, further, that all current physically-based models" are not well suited to applications to real catchments. Raysone et al. (1992] support this view and claim that physically based models have been oversold by their developers. Other authors, for example, Smith et al. (1994], argue that this criticism is "overly pessimistic."

2.5 Parameter Sensitivity Analysis

Some model parameters might be overly sensitive and may have more impact on the simulated outcome, though other parameters may have a lesser impact. It is fundamental to decide the affectability of all the parameters utilized in the model and fix the most sensitive parameters. The accuracy of the model simulation results largely depends upon the precise estimation of the most sensitive parameter of the model. The sensitivity analysis is carried out by changing one parameter at a time while keeping all the remaining parameters the same and the effect on the result is observed.

The purpose of the sensitivity analysis is to investigate how the variation in the model parameters can affect the outputs (streamflow in this study). The main idea of this step is to identify the factors that contribute most strongly to the variability and characteristics of the input-output responses. The difference between the simulated outputs and observed output was measured by the Mean Squared Error (MSE) function given by Equation 1 as:

$$MSE = (O_{tobserved} - O_{tmodeled})^2 \qquad \text{Equation 1.}$$

Which measures the fit of the modelled streamflow ($O_{tmodeled}$) to the observed streamflow ($O_{tobserved}$) in order to evaluate the performance of the model. The value of MSE is expected to be close to zero for a good simulation of the total volume of the observed streamflow series.

Three different techniques can be applied in order to evaluate the parameter significance and sensitivity (e.g. Xu, 1996).

2.5.1 Evaluation of the parameter values during the optimization.

Automatic optimization procedures are mathematical search algorithms that seek to minimize differences between selected features of modelled and observed streamflows by systematic trial alterations in the values of the model parameters. These trial alterations are called 'literation's'. The objective function, i.e. the quantitative measure of the fit of modelled runoff to the observed runoff, is calculated after each parameter search iteration. Successful iterations are those which cause a reduction in the value of the objective function. During the search, only the parameter set associated with the current least objective function value is retained, which, at the end of a search, is regarded as the optimal parameter set. The end of a search is usually decided by: (1) a convergence test of the rate of reduction of the objective function value; (2) a predetermined number of iterations; and (3) a computer runtime limitation. The stabilization of the parameter values can be studied with the graphs of the parameter values versus the number of iterations. If the search is ended under conditions (2) or (3) it does not guarantee that the parameters are stabilized.

2.5.2 Checking if the global minimum is obtained

Note that stabilized parameter values do not necessarily mean that a global optimum has been found. In order to check whether the minimization is performed properly, graphs of the sum of squares (SSQ) versus parameter values at the neighbourhood of the optimal value can be plotted.

2.5.3 Detailed analysis of the variance–covariance matrix

The correlation matrix of the parameters must be checked. If the correlation coefficient between two parameters is very near to –1 or 1, and this means that perhaps a model can be found with a smaller number of parameters and with the same explanatory power, or that perhaps the parameters have to be built into the model in a different way, so that their explanatory effects are more dissociated, and optimization is easier. To answer the question of whether all parameters are necessary, one can test the hypothesis that parameters are significantly different from zero. This can be done by checking whether the zero value belongs to the 95% confidence interval.

2.6 Regionalization of Parameters

Hydrological regionalization is an important tool for the analysis of the spatial pattern of variations in hydrological phenomena. In this study, the transferability of model parameters is investigated from one glaciated alpine catchment to a physically similar nearby catchment in the Eastern Himalayas using the process-based J2000 hydrological model. This model calculates the water balance in daily time steps and the underlying hydrological processes based on distributed modelling entities (hydrological response units or HRUs). The processes are controlled by calibration parameters, whereas the spatial properties are retained at HRU level in the form of distributed parameters for soil, land use, topography, and geology. Thus, the J2000 hydrological model can retain the spatial variability of static landscape features. The model was applied in the donor catchment, and the validated model parameters were then transferred to the neighbouring catchment. Sensitivity and uncertainty analyses were carried out to investigate the variation in sensitivity of the parameters in both catchments. Testing the transferability of parameters basically means using the proxy - basin test (Klemeš, 1986) to determine the portability of the calibrated model and its parameter set for regional application in other gauged and ungauged river basins for applications related to sustainable water resources development. The performance of the model in the two catchments is compared and the results are discussed. Furthermore, we compare not only the simulated.

2.7 Parameter Regionalization Options

Four groups of regionalization methods were explored. In the first group, each parameter as the arithmetic mean of all calibrated values (termed "global mean") or, alternatively, as the arithmetic mean of a region within a radius of 50 km from the catchment of interest (termed "local mean"). This group of methods assumes that all catchments within the selected radius are similar and differences in the parameter values arise only from random factors.

The second group of regionalization methods is based on the spatial proximity (or spatial distance) between the catchment of interest and the gauged catchments. The spatial distance between the two catchments was measured by the distance of the respective catchment centroids. The methods of this group were the nearest neighbour method where the complete set of model parameters was taken from one donor catchment; the inverse distance weighting where parameters from a number of donor catchments were combined; and the ordinary kriging method. The ordinary kriging method was based on an exponential variogram with a nugget of 10% of the observed variance, a sill equal to the variance, and a range of 60 km. This is consistent with the empirical variograms of most of the calibrated model parameters. To complement the ordinary kriging method, the examination of ordinary kriging where the immediate upstream and downstream neighbours to assess the effect of nested catchments are left out. This method is termed as kriging without nested neighbours.

In the third group, the estimation of each model parameter is independent of regressions to catchment attributes. Global multiple linear regression was tested, where local multiple linear regression within a 50 km search radius; and local georegression interpolated the residuals of the local multiple regression by ordinary kriging using an exponential semivariogram with 50 km range. In all cases estimating the regression coefficients by the ordinary least squares method. The number of catchments included in the local multiple regression and the georegression differed regionally. To diagnose and avoid multicollinearity, we examined the variance inflation factor (Hirsch et al., 1992). If the inflation factor was greater than 10, then this set of three attributes was rejected and the scheme proceeded to the second-best correlation. The rationale of this choice is that a large correlation coefficient may be a good indicator of the predictive power of the attributes provided there is no collinearity.

The fourth group of methods is also based on catchment attributes but uses a different regionalization model structure. The main idea of this group is to find a donor catchment that is most similar in terms of its catchment attributes and to transpose the complete parameter set to the catchment of interest. Leaving the combination of model parameters unchanged may address some of the problems encountered with the regression approach (Merz and Bl¨oschl, 2004). The donor catchment was selected as the gauged catchment with the smallest similarity index (Equation 2):

$$\emptyset = \sum_{i=1}^{k} \frac{\left|X_i^G - X_i^U\right|}{\Delta X_i} \qquad \text{Equation 2.}$$

which is defined as the sum of absolute differences of the k selected physiographic attributes of the gauged (XG) catchment and the (ungauged) catchment of interest (XU), normalized by its range (1X). The following combinations of catchment attributes were examined: combinations based on topography (average catchment elevation, slope, topographic index); geomorphology (average stream network density, FARL index and areal proportion of porous aquifers); land use classes; soils classes; geology classes; rainfall (long-term mean annual precipitation, maximum daily summer and winter precipitation, 1 hourly rainfall intensity); and an a priori defined combination of selected attributes (mean catchment elevation, stream network density, FARL index and areal proportion of porous aquifers, land use, soils and geologic units). We also tested a diagnostic case termed “perfect”. For the perfect similarity case we transposed the complete parameter set from the donor catchment that was most similar to the catchment of interest in terms of the model parameter values. The similarity was defined by the sum of the absolute differences between the parameter values, normalized by its range similar to Equation. This is a diagnostic case which probes the potential of the catchment model performance that can be achieved with an ideal donor catchment selection. In this study, it helps assess the criteria for selecting the catchment attributes used for finding the donor catchment. In a practical application, this is not a viable method as the model parameters are of course unknown at the ungauged site of interest. Note that all similarity index-based regionalization methods as well as the geo-regression have not been used in Merz and Bl¨oschl (2004) while the other regionalization methods have also been examined in Merz and Bl¨oschl (2004).

2.8 The ABCD Water Balance Model

2.8.1 Introduction

The ABCD or “abcd” model is a physics-based, lumped, and nonlinear watershed model which accepts monthly precipitation and potential evapotranspiration as inputs, producing streamflow as an output. Internally, the model also represents soil moisture storage, groundwater storage, direct runoff, groundwater outflow to the stream channel and actual evapotranspiration. It was originally introduced by Thomas (1981) and Thomas et al. (1983) as a suitable model structure for performing regional water resource assessment using an annual time scale. The ABCD model was later compared with numerous monthly water balance models (Fernandez et al., 2000).

2.8.2 The ABCD model structure

The model is composed of two storage compartments: Soil moisture and Groundwater. The soil moisture gains water from precipitation and loses water to evapotranspiration (ET), surface runoff and groundwater recharge. The groundwater compartment gains water from recharge and loses water as discharge. The total streamflow is the sum of surface runoff from the soil moisture and groundwater discharge. Internally, the model also represents soil moisture storage, groundwater storage, direct runoff, groundwater outflow to the stream channel and actual evapotranspiration. The model runs on a daily time step and takes input timeseries of precipitation, minimum and maximum air temperature, and observed streamflow.

The ABCD model has four parameters *a*, *b*, *c*, and *d*, as shown in Figure 2-1 with each one having a particular physical interpretation. The ABCD model has four parameters a, b, c, and d, each having a specific physical interpretation. The parameter a (0 <= a <= 1) reflects the propensity of runoff to occur before the soil is fully saturated (Thomas et al., 1983). The parameter b is an upper limit on the sum of actual evapotranspiration and soil moisture storage in a given month. Presumably, this parameter depends on the ability of the catchment to hold water within the upper soil horizon.

The parameter c is equal to the fraction of streamflow which arises from groundwater discharge in a given month. Over the long-term c is then defined simply as the baseflow index (BFI), an index used commonly in studies which develop relationships between drainage basin characteristics and groundwater discharge to a stream channel. The reciprocal of the parameter d is equal to the average groundwater residence time.

The model defines two state variables: W_t, termed “available water” and Y_t, termed “evapotranspiration opportunity”. Available water is defined by Equation 3 as:

$$W_t = P_t + XU_{t-1} \qquad \text{Equation 3.}$$

where P_t is precipitation during period t and XU_{t-1} is upper soil zone soil moisture storage at the previous time step. Evapotranspiration opportunity "Y_t" is water which will eventually leave the basin in the form of evapotranspiration and is defined by Equation 4 as:

$$Y_t = E_t + XU_t \qquad \text{Equation 4.}$$

where E_t represents actual evapotranspiration during period t and XU_t represents upper soil zone soil moisture storage at the current time step. Evapotranspiration opportunity Y_t is postulated as a nonlinear function of "available water" W_t using Equation 5:

$$Y_t(W_t) = \frac{W_t + b}{2a} - \sqrt{\left(\frac{W_t + b}{2a}\right)^2 - \frac{W + b}{a}} \qquad \text{Equation 5.}$$

Evapotranspiration opportunity Y_t is further partitioned into actual evapotranspiration E_t and residual soil moisture storage XU_t by relating the rate of soil moisture loss to potential evapotranspiration, leading to the nonlinear relationship represented by Equation 6:

$$E_t = Y_t . \left(1 - \exp\left({}^{-PE_t}/_{b}\right)\right) \qquad \text{Equation 6.}$$

Water available for runoff ($W_t - Y_t$) is further partitioned into upper zone contribution to runoff QU_t and recharge to groundwater R_t by the parameter c, as per Equation 7:

$$QU_t = (1 - \mathrm{C}).(W_t - Y_t) \text{ and}$$
$$R_t = \mathrm{C}.(W_t - Y_t) \qquad \text{Equation 7.}$$

Recharge R_t is added to the lower soil zone state variable XL_{t-1} and base flow to the stream is computed according to the linear recession relationship $QL_t = d \cdot (XL_t)$. Using continuity, we updated $XL_t = (XL_{t-1} + R_t) \cdot (1 + d) - 1$. Finally, total streamflow is computed by Equation 8 as:

$$Q_t = QU_t + QL_t \qquad \text{Equation 8.}$$

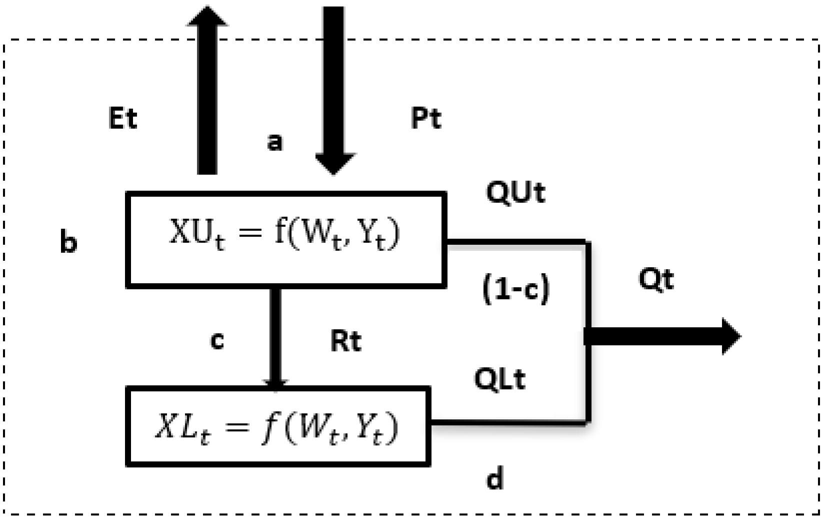

Figure 2-1: Schematic structure of the ABCD model

2.8.3 The ABCD model with snow component

Most of the hydrologic cycles in northern latitude river basins are dominated by snow accumulation and snowmelt processes. In this regard, an extension of ABCD model coupled with a snow model (Figure 2-2) is utilized which takes the snow component into account by using a temperature index method. In the ABCD-Snow model, total precipitation is partitioned into effective precipitation *Pet* and *Snowfall* based on a comparison between the monthly mean temperature T_t and a base near-freezing temperature T_b. When precipitation falls as snow, the effective precipitation is zero and a simple snow accounting model computes the snow accumulation as the sum of the previously accumulated snow water equivalent and the snowfall at time *t*. In a warm month (i.e. $T_t > T_b$), effective precipitation is defined as the sum of snowmelt M_t and rainfall. Furthermore, snow accumulation is computed by subtracting snowmelt from the accumulated snow storage.

$$\text{If } T_t \leq T_b \rightarrow \begin{cases} A_t = A_{t-1} + P_t \\ P_t^e = 0 \end{cases} \qquad \text{Equation 9.}$$

$$\text{If } T_t > T_b \rightarrow \begin{aligned} M_t &= min\,\{A_{t-1}, e(T_t - T_b)\} \\ A_t &= A_{t-1} - M_t \end{aligned} \qquad \text{Equation 10.}$$

$$P_t^e = P_t + M_t$$

where the parameter e is a new model parameter termed as the Snowmelt factor. Here, it is assumed that the modelled snowmelt which can occur in a given month cannot exceed the snow storage. The initial snow accumulation A_0 in the ABCD-Snow model was assumed to be zero since the model simulation starts in October and generally basins experience the lowest snow storage at the end of September.

In addition, initial groundwater recharge G_0 and initial soil moisture storage S_0 were assumed to be equal to monthly climatology of streamflow and precipitation, respectively. The ABCD-Snow model was tested in the selected basin using minimum, maximum temperatures, or average monthly temperature T_t as model input.

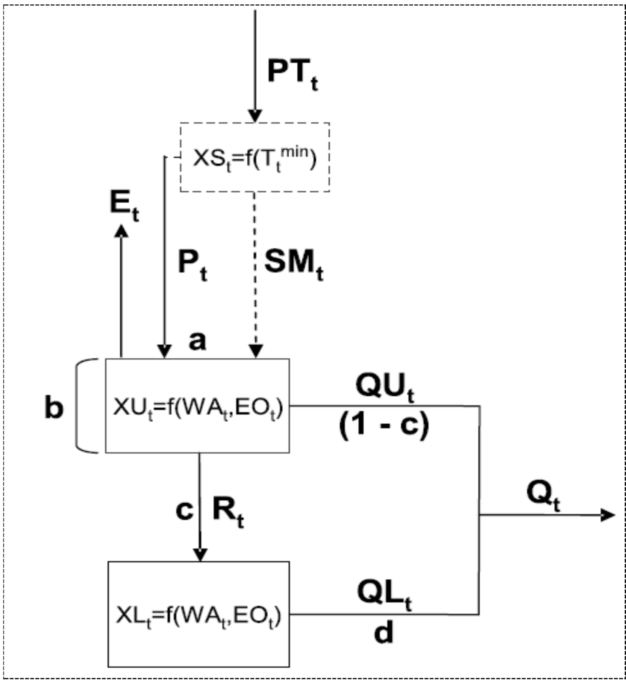

Figure 2-2: Schematic structure of the ABCD model, with snow component added (Source: Martinez, G. F., & Gupta, H. V. (2010))

This water balance model formulation does not model snow sublimation or other, more complex, spatiotemporal dynamics of the snow accumulation/ablation process. Further, we assume that the effects of sub monthly distribution of timing and intensity of precipitation events, potential evapotranspiration and temperature variations, and other factors are negligible. McCabe and Wolock (1999] and Hay and McCabe (2002) have used similar approaches.

2.8.4 Implications of snow-hydrological process dynamics

Snow cover and depletion in many places characterizes the winter and spring runoff dynamics. This leads to fundamental regional differences in flow regime influenced by snow reserves, based on the regularity of outflows, their temporal distribution and volume effects. Regional characteristics of the discharge events are also influenced by local factors and typical meteorological conditions. In particular, the influence of rain is mentioned in sub-alpine, mid-mountain and lowland climatic conditions during the ablation process (Herrmann and Rau, 1984; Baumgartner and Liebscher, 1996; Singh et al., 1998). High-intensity rain events can thereby lead to a short-term release of significant volumes of melt (Singh et al., 1998). Accordingly, rainfall on similar level surfaces with thin snow cover is one of the main factors for the flood generation (Baumgartner and Liebscher 1996).

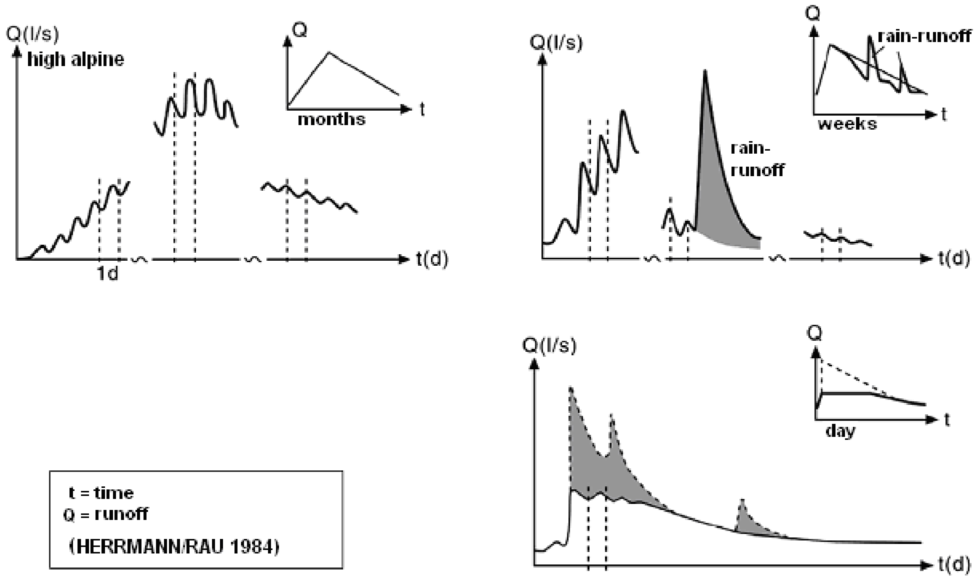

Figure 2-3: Schematic representation of typical hydrograph curves of melt runoff in selected Central European region (Herrmann and Rau 1984). (Source: Herpertz, 2006:P. 30)

Figure 2-3 shows that in the high-alps during one period of months (usually between late spring and summer) melt runoff can occur. The predominantly radiation-induced reduction of the seasonal thick snow covers determines the runoff regime. During the ablation, the runoff is characterized as a function of the radiation due to more or less pronounced diurnal variations. With reduced snow depth and snow cover at the end of ablation, the regular runoff development is modified increasingly. In the outside alpine regions of central Europe, thin snowpack combined with an unstable weather condition in principle is the case of a lower regularity of snow-induced runoff than alpine areas. In sub-alpine basins, extending ablation can be seen at the start of weekly, daily variations of the hydro-graphs is still significant, which are dissolved but increases also by weather conditions. The snow-affected outflows of the mountain regions are characterized by changing climatic conditions. At any time during winter or spring, there may be sporadic snow cover up and depletion that controls the runoff. Characteristic of the lower regions are also secondary rain induced melting peak runoff, prevent the development of regular outflow. During ablation of a snow cover, the effective runoff extends only for a period of days (Herrmann and Rau, 1984; Baumgartner and Liebscher 1996).

2.8.5 Application of ABCD model

According to Thomas (1981), the ABCD model was initially applied as a monthly water balance model. Later the model was applied under different time scales as seasonal, monthly and annual, and the results were examined for "reasonableness" and consistency. According to the results, it was shown that the model performs better under annual time scale (Thomas et al., 1983). But the ABCD model had been applied successfully in the monthly time scale for 3 basins in the United States according to Al-Lafta et al. (2013) and 764 basins according to Martinez and Gupta (2010).

In the application of the model, it is not necessary to separate the direct and indirect runoff of the observed flow even though the model has two compartments for storage of water in aquifers and the subsoil. The availability of data related to soil moisture and groundwater will make easy to determine the parameters of the model but even without those data, the model can be fitted (Thomas, 1981).

According to Lafta et al. (2013), it was found that the ABCD model does not perform well in regions dominated by snow without appropriate modifications in the model structure and further, it was observed that the model shows an intermediate level of performance in mild climates (warm and humid). Martinez and Gupta (2010) have addressed the effect of snow successfully by doing appropriate modifications to the ABCD model structure.

2.9 Potential Evapotranspiration (PE) for the Model

The potential evapotranspiration can be expressed in terms of pan evaporation and pan co-efficient as,

$PE = Cp\ (E_{pan})$

This *C*p can be expressed as,

$Cp = Kp \times Kc$

The parameter *Kp* is the pan coefficient which can be taken as 0.8 on average, for the common Class *A* pan. *Kc* is the crop coefficient which is dependent on the type of vegetation and growth stage (Brutsaert, 2013). The *Kc* values are given in the crop evapotranspiration guidelines for computing crop water requirements-FAO Irrigation and Drainage Paper 56, by Allen, Pereira, Raes, and Smith (1998) was used for the calculation of a weighted *K*c value considering various land uses in both watersheds.

2.10 Warm up Period and Initial Values for Model

Since ABCD model has a soil moisture compartment and a groundwater compartment in the model structure, initial values are needed for the initial soil moisture content and groundwater storage.

Initialization bias occurs when a model is started in an unrealistic state which needs modifications for the initial value and generally this occurs in non-terminating simulations, but it can also take place in terminating simulations (Hoad, Robinson, & Davies, 2008). According to Robinson (2004), there are five main methods for dealing with initialization bias as follows;

1. Run-in model for a warm-up period until it reaches a realistic condition (steady-state for nonterminating simulations). Delete data collected from the warm-up period.

2. Set initial conditions in the model so that the simulation starts in a realistic condition.

3. Set partial initial conditions then warm-up the model and delete warm-up data.

4. Run the model for a very long time making the bias effect negligible.

5. Estimate the steady-state parameters from a short transient simulation run (Sheth-Voss, Willemain, & Haddock, 2005).

In hydrological modelling, calculation of warm up period is important. Robinson (2004) has categorized the available methods in calculating warm up period into five main categories as below;

1. Graphical methods – Truncation methods that involve visual inspection of the time-series output and human judgement.

2. Heuristic approaches – Truncation methods that provide (simple) rules for determining when to truncate the data series, with few underlying assumptions.

3. Statistical methods – Truncation methods that are based upon statistical principles.

4. Initialization bias tests – Tests for whether there is any initialization bias in the data. They are, therefore, not strictly methods for obtaining the truncation point but they can be adapted to do so in an iterative manner or can be used in combination with the above truncation methods to ascertain whether they are working sufficiently.

5. Hybrid methods – A combination of initialization bias tests with truncation methods to determine the warm-up period.

According to Xiong and Guo (1999), the initial value for soil moisture (S0) has some effect on the model performance and it will be more important in cases where the data period is less. For the two-parameter model, 150-200 mm value had been taken as S (0) and it had been re-estimated by using the mean value of the soil water content values in the positions of having the same rank of the cycle. Xiong and Guo (1999) had considered the cycle period as one year and estimated the *S* (0) as;

$$S(0) \approx \Sigma S(j \times 12)/m$$

where *m* is the number of years of the calibration data series, i.e. m = *N*c/12, *N*c is the number of months in the calibration period. If the cycle period is one year, the values of *S* (12), *S* (24), *S* (36), etc., cannot be very much different.

At the first development of ABCD monthly water balance model, Thomas (1981) had assumed trial values as initial values for the soil moisture and groundwater with a tentative a,b,c and d parameter set and routed the system over 8 cycles until the initial soil moisture and groundwater storages attained a quasi-steady state.

By studying the above literature, it is apparent that different modellers had used different methods to handle the warmup period and initial moisture content in the modelling exercise. For this study, considering the first method of Robinson (2004), the model will be routed for a number of cycles until the soil moisture and groundwater storages are achieved the quasi-steady state by using arbitrary values as initial values.

2.11 Parameter Optimizations

Though numerical indicators provide a facility to identify the best fit, it is necessary for the modeller to look at the water balance, time series of estimates with respect to the observed rainfall and duration curves to select the best parameter set for a catchment (Wijesekera, 2000).

When a model has been developed or selected for use in predicting hydrologic outputs for a particular practical problem, it is then necessary to assess its applicability and potential accuracy for the problem at hand, and to determine the values of the model parameters or constants for the catchment under consideration. In general, several levels of evaluation are necessary before a model should be applied to estimate the output from a catchment (Pilgrim, 1975). These are: (i) rational examination of the model structure, (ii) estimation of parameter values, (iii) testing the fitted model to verify its accuracy, and (iv) estimation of its range of applicability. Conceptually, these evaluations are done in sequence. Estimation of the parameter values and model tests are emphasized in this paper, although it is important to recognize that all four evaluations are of equal importance, and neglect of anyone can lead to serious errors. Many types of techniques are employed for the estimation of parameters of different hydrological models (e.g. Pilgrim, 1975). Of these, automatic optimization using search techniques has been the most common method in the calibration of water balance models. This is partly because most water balance models have a simpler structure and a smaller number of parameters, which surmount some of the practical difficulties encountered with optimization methods. Moreover, automatic optimization techniques yield a reproducible and unique parameter set, which is one of the conditions when the relationship between parameter values and physical characteristics is to be established.

2.12 Objective Functions

The objective function (OF) is a function associated with an optimization problem which determines how good a solution is. It is the actual function which needs to be minimized for an optimal choice or a solution to be selected from the many alternatives offered.

Several levels of evaluation are necessary before a model can be applied to estimate the output from a catchment and these are: (i) rational examination of the model structure, (ii) estimation of parameter values, (iii) testing the fitted model to verify its accuracy, and (iv) estimation of its range of applicability (Pilgrim & Cordery, 1975).

The most common indicators used in the literature to evaluate outflow hydrograph are Nash and Sutcliffe (1970), MRAE, RMSE, RE, criterion R^2 and correlation coefficient (Guo, 1995; C. Xu, 1997; Xu & Singh, 1998; Xiong & Guo, 1999; Wijesekera, 2000; Mouelhi et al., 2006; Chen et al., 2007; Wang et al., 2011; Karpouzos et al., 2011). Estimating the model performance by comparing the simulation results with observed data is accomplished by defining different statistical indicator objective functions (OF) to calculate the model efficiency, i.e. how model simulation fits observed data (Mata-Lima, 2011). The objective function (OF) is a function associated with an optimization problem which determines how good a solution is. It is the actual function which needs to be minimized for an optimal choice or a solution to be selected from the many alternatives offered.

The performance of both the models used in this study have been evaluated using three well known statistical evaluation indices; Root Mean Square Error (RMSE), Pearson correlation coefficient (r) and Coefficient of determination (R^2).

2.12.1 Root Mean Square Error (RMSE)

RMSE serves to aggregate them into a single measure of predictive power.

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i}-X_{model,i})^2}{n}} \qquad \text{Equation 11.}$$

2.12.2 Pearson correlation coefficient (*r*)

Indicates the strength and direction of the linear relationship between two variables.

$$r=\frac{\sum_{i=1}^{n}(x_i-\bar{x})\cdot(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\cdot\sum_{i=1}^{n}(y_i-\bar{y})^2}} \qquad \text{Equation 12.}$$

2.12.3 Co-efficient of Determination (R^2)

The coefficient of determination in observed data explains the fraction of the total variance. The coefficient of determination value ranges from 0 to 1.

$$R^2=\left\{\frac{\sum_{i=1}^{N}(Oi-O)(Pi-P)}{[\sum_{i=1}^{N}(Oi-O)^2]^{0.5}[\sum_{i=1}^{N}(Pi-P)^2]^{0.5}}\right\} \qquad \text{Equation 13.}$$

where

Oi = observed discharge

Pi = simulated discharge

O = mean of observed discharge

P = mean of simulated discharge

The coefficient of Determination having a value of one indicates better agreement, while the value of zero reflect that there is no co-relation (predicted and observed values are equal) (Legates and McCabe, 1999).

2.13 Literature Review Summary

Out of the different types of hydrologic models in the model classification, a lumped model was selected for the study. The applicability of hydrologic models under different temporal resolutions was studied and the daily resolution was selected for the research. Considering the objectives of the research, the modified ABCD model was selected which a lump monthly model having four parameters plus one snowmelt factors is making it to five parameters.

The model structure and the function of the parameters were identified in detail by reviewing different applications of the ABCD model. For the interpolation of rainfall, the Thiessen polygon method was selected considering its simplicity in application and wide usage among hydrologists around the world even for distributed hydrologic models.

In the model application, as initial values of soil moisture and groundwater, arbitrary values can be used as used in the two-parameter model application by Xiong and Guo (1999) and in the ABCD model by Thomas (1981). When the arbitrary values are used for initial soil moisture and groundwater storages, warm up period must be handled, not affecting the model performance. For that, the model can be run for a number of cycles until it reaches the quasi- steady state as Thomas (1981) had done in applying ABCD model by incorporating one of the methods proposed later by Robinson (2004). For the parameter optimization, Pearson r, R^2 and RMSE were selected as the objective function, considering its suitability for the performance evaluation.

3. METHODOLOGY AND MATERIALS

The research problem was identified by conducting a background study on the current modelling practices in Bhutan for river basins and the main objective was defined based on those information and findings. The specific objectives were defined benchmarking the overall objective, by showing the intermediate milestones that must be passed to achieve the overall objective.

After finalizing the objectives, a literature survey was conducted following the identification of the key aspects to be studied according to the defined specific objectives. First, an appropriate lump monthly model with an appropriate number of parameters was selected based on the literature review, considering the research question, time constraints, data availability, cost and model simplicity. For the selected model, a further refined literature survey was carried out to find an appropriate data period for the data collection. Subsequently, the literature survey was conducted to select an appropriate objective function to evaluate the model performance and a suitable method for the calculation of potential evapotranspiration. In addition, previous modelling work related to ABCD model was studied, and model parameter ranges were identified which were helpful in model calibration and parameter sensitivity analysis. The literature regarding model warm up period was studied to set the initial soil moisture and groundwater storages for the model.

The data collection was undertaken considering the input requirements of the model and checked by using recommended methods. The data set was divided into two sets, as old half for calibration and the latest half for validation and the ABCD hydrologic model was developed and checked, accordingly. The initial parameters were selected by using the values in the literature. Then the model was calibrated and validated by using appropriate data sets and parameter sensitivity analysis was conducted by using the methods identified in the literature review. Relevant water resources investigation applications were identified, and the applicability of the model was demonstrated for water resources investigation.

3.1 Methodology Flow Chart

Figure 3-1 depicts the methodology flow chart of the research.

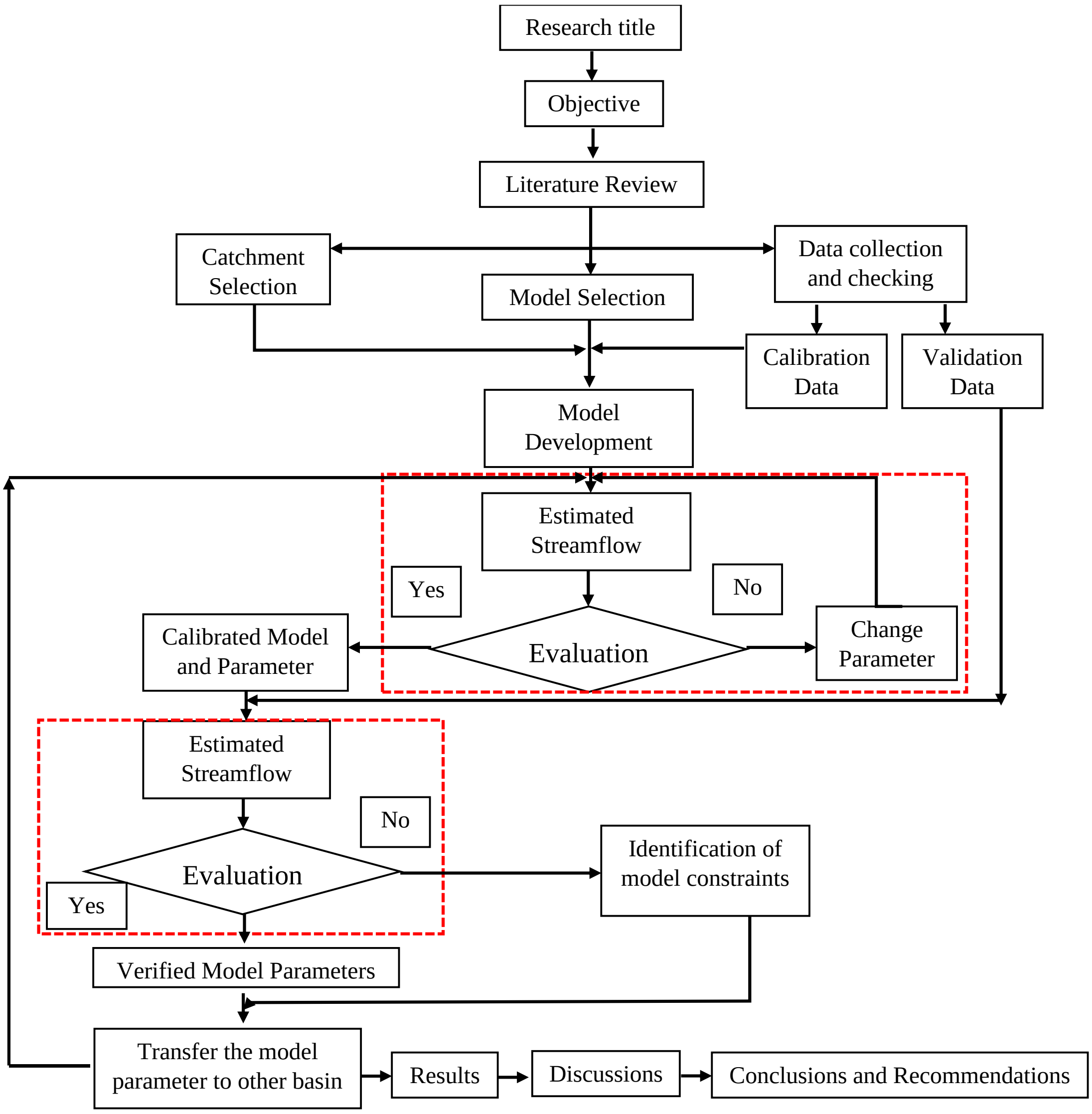

Figure 3-1: Methodology flow chart

3.2 Regionalization of Parameter

3.2.1 Introduction

The classical approach to relate the parameters of a conceptual rainfall-runoff model with the physical catchment descriptors follows a two-step procedure. The model is calibrated for several sub-catchments within the area of interest independently and a set of optimum parameters is estimated for each sub-catchment. The relationship between each of the model parameters and the physical catchment attributes is then estimated using a regression approach. This approach has been implemented for different conceptual rainfall-runoff models (Waylen and Woo, 1984; Weeks and Ashkanasy, 1985; Abdulla and Lettenmaier, 1997; Sefton and Howarth,1998; Post and Jakeman, 1999).

The regionalization of the parameters was tested further by applying the parameters derived for the Mo Chhu basin to the Pho Chhu basin through ABCD model with the incorporation of the same snow parameter.

There are two types of studies that use regionalization techniques for ungauged catchments. One type estimate parameters of streamflow statistics, flood quantiles in most cases. The other type estimates parameters of a rainfall-runoff model for simulating continuous streamflow or estimates continuous streamflow without using a model.

The derivation of relationships between the rainfall over a catchment area and the resulting flow in a river is a fundamental problem for the hydrologist.

3.2.2 A transfer function approach for parameter regionalization

The classical approach of regionalization of the parameters of a model doesn’t generally lead to a strong relationship between the model parameters and the catchment character. Calibration of the model against observed discharge doesn’t lead to a unique set of parameters. There could be a high degree of parameter interaction and as a consequence, many different sets of parameters may lead to similar model performance. The parameter set obtained through calibration is therefore a single realization among a large number of equally competing parameter sets in terms of their performance.

The parameters estimated in this way may not properly reflect the dependency they have with the catchment character. Therefore, the relationship established is likely to be weak. In addition, the catchment characteristics that may not have any influence on a given parameter may be included in deriving the regional relationships, as there is no indication from the ‘optimum’ parameter which descriptors are important in describing it.

Recently, a modelling paradigm that rejects the idea of an ‘optimum’ parameter set has been in use. Instead of trying to get a single set of parameters through model calibration, many sets of parameters that lead to acceptable model performance are used with their corresponding likelihood weights determined based on pre-specified likelihood functions to make a prediction by the model. Such a methodology referred to as a Generalized Likelihood Uncertainty Estimation (GLUE), is outlined by Beven and Binley (1992) and takes implicitly into account all the uncertainties resulting from the model structure and the data used for model calibration and enables quantification of the total uncertainty in the model prediction. It is based on randomly sampling a parameter set from the feasible parameter space and making a model run using the parameter set thus sampled. Whether to accept or reject the parameter set is decided based on a pre-defined threshold value of a model performance measure and if it is accepted a likelihood weight is assigned to it based on the defined likelihood function. The procedure is repeated many times so that the entire parameter space is well sampled. The required number of samples increases with the number of model parameters and the associated requirement of computing resources usually limits the applicability of the methodology for models with many parameters.

The intention in this work is to solve the problem of identifying a unique optimum set of parameters and fitting the relationship between the parameters and the catchment descriptors that is inherent in the classical method of parameter regionalization by implementing a different approach. Instead of calibrating the model for the individual sub-catchments separately and then trying to fit a relationship between the parameters and the catchment descriptors, the calibration process is begun by first expressing the model parameters as functions of the catchment descriptors using functions whose form is assumed a priori. The model is then calibrated for many sub-catchments simultaneously. The model calibration is performed without making any direct reference to the model parameters. Instead, the calibration yields another set of parameters that are used to relate the model parameters with the catchment descriptors in the initially assumed function.

3.2.3 Defining the transfer function

The model parameters are categorized into two groups. The first group of parameters are related to the runoff generation processes in different zones within the sub-catchments. These parameters are estimated based on the soil type or the land use class of the zones or both, depending on which of these catchment attributes influence the parameter values. For the runoff generation processes, the attributes that have a major influence are usually known from physically based models developed to model different components of a catchment process separately.

3.2.4 Estimation of the parameters of the transfer function

The parameters of the transfer function are the characteristic values that relate the different catchment attributes with the model parameters and each of them has a constant value throughout the study area. The actual value of each of the model parameters corresponding to a given sub-catchment depends solely on the catchment attributes, which are usually available in digital form. The objective of model calibration is therefore to estimate the parameters of the transfer function that lead to optimum performance of the model in all sub-catchments within the study area.

In order to estimate the parameters of the transfer function that can be applied to the entire study area, the model should be calibrated simultaneously for many sub-catchments within the study area with contrasting catchment attributes so that all possible ranges of the different catchment attributes are considered. Thirty sub-catchments from different parts of the study area were selected in this study as a set of calibration sub-catchments to estimate the parameters. The parameters estimated by calibrating the model for this set of sub-catchments As calibration of rainfall-runoff models is a process to seek a set of model parameters that leads to the best matching between the model simulated and the observed catchment responses, the objective of the model calibration was to minimise the sum of the square of the differences between the model simulated and the observed discharges from each of the sub-catchments that constitute the calibration set.

3.2.5 Validation of the regionalized model

Validation of the regionalized model was performed in two ways. The first approach follows the standard split sampling method, in which the available discharge observation is split into two series and model calibration is performed on one of the series while the other series is latter used to validate the calibrated model. This approach was used to validate the model in the calibration set of other catchments for which there is enough observed discharge data beyond the calibration period. The validation result shows that the performance of the regionalized model measure is more or less similar to that of the calibration period. However, the mean daily discharge appears to be a bit overestimated in the other neighbour catchment, while the mean annual peak discharge is more underestimated in the validation period.

The second approach of validating the regionalized model consists of applying the regional relationship between the model parameters and the catchment descriptors derived in the calibration set of one catchment to the other catchments within the study area that were not used to derive the regional relationship. These catchments constitute a validation set of another catchment. This approach is the most important part of the model validation exercise in this particular work. As the core objective of the methodology implemented here is to derive a regional relationship between the model parameters among two catchments which can later be used to predict the runoff from ungauged catchments. This approach, therefore, is a crucial step in validating the methodology as a whole. Performance of the regionalized model in the validation set of catchments was evaluated separately for the calibration and validation periods used in the calibration set of neighbouring catchments so that comparison of the performance of the model in the calibration set and the validation set of other catchments can be compared over similar periods of model simulation.

3.2.6 Methods of regionalization

The calibration parameters of the routines described were regionalized based on catchment characteristics for two reasons:

- Calibrating a model with a significant number of free parameters for every grid cell is not reasonable for meso-scale catchments.
- If the model is to reflect changes in catchment properties, then the parameters must be linked to natural features of the basin since calibration for future scenarios is not possible.

Four different regionalization approaches were used. The idea behind all four is to reduce the parameter space available for optimization by some form of constraint and therefore be able to find reasonable regression relationships, avoiding the problem of equifinality which often leads to weak correlations between model parameters and catchment properties.

3.3 Study Area

The study area (Figure 3-2) is in the upper region of the Puna Tsang Chu basin covering three 3 districts: Gasa, Punakha, and Wangdue Phodrang (partially), with a total area of 5,636.95 sq. km encompassing the geographical area between 28° 14' N and 27° 27' N and 89° 19' E and 90° 22' E, is dissected by a discharge gauging station located at latitude 27° 27' N and longitude of 27° 27' N and 89° 54' E from the overall basin.

Puna Tsang Chhu river basin is one of the biggest river basins in Bhutan. It originates in northern Bhutan and empties into the Brahmaputra in the state of Assam in India. The two largest tributaries are the Mo Chhu and Pho Chhu, which confluences at Punakha. After it enters in India, it flows on the border of Assam and West Bengal. At Wangdue Phodrang at elevation 1,364 m (4,475 ft), the river is joined by the west-flowing Tang Chu river and it enters a precipitous gorge. Near the town of Takshay is the confluence with the west-flowing Hara Chhu. The last major Bhutanese tributary is the Daga Chhu in the main basin.

The total catchment area of the Puna Tsang Chhu river is 13,263 km² and the ground elevation ranges from 330 m MSL to 7,011 m MSL above sea level; however, the gauging station on the river is located upstream of the confluence at Mo Chhu. The catchment areas of Mo Chhu basin and Pho Chhu basins are 2,363.064 km² and 2,331.126 km², respectively. For the third basin namely Wangdi basin the area is 1,371.69 km². The location of the study catchment and its stream drainage network is shown in Fig. 3-2. The study area is situated in the northern part of Bhutan and covers the area from the permanently snow-covered high Himalayan peak in the north to the green forest hills in further downstream. The snowcapped Himalayan Mountains contribute to a major portion of streamflow by snow and ice melt. The average annual temperature for the upper basin is 10.3°C while the average rainfall is 1,093 mm. The average annual temperature in downstream is 18.2°C while the average rainfall is 3016 mm. Winter low flow is sustained by baseflow from the groundwater storage and peak flow in spring is generated by snowmelt. In summer, rainstorm induced secondary runoff peaks to occur and floods are one of the major disasters affecting the downstream valleys in the area.

All major rivers in Bhutan depend on snowmelt for discharge. Therefore, changes in snow cover (Table 3-1) due to climate change can influence the distribution and availability of water. Pho Chu sub-basin with 19.5% of the total average Snow cover area had the highest average snow cover area.

Table 3-1: Mean extent of seasonal snow cover in Bhutan

Season	Snow Extent (sq.km)	Snow Extent (%)
Winter	14,485	37.7
Summer	4,326	11.2
Spring	7,411	19.3
Autumn	7,788	20.2

Bhutan has witnessed flash floods and glacier outburst floods which devastated acres of agriculture lands and infrastructure properties, destruction to historical monuments and caused a threat to people living downstream in the Puna Tsang Chu basin in the years 1957, 1960, and 1994.

Table 3-2: Summary Details of Mo chhu basin

Mo chhu basin (km^2)	2,347 km^2
District	Gasa
Mainstream Length (km)	5,834.135 km
Drainage density (km/km^2)	2.48 km

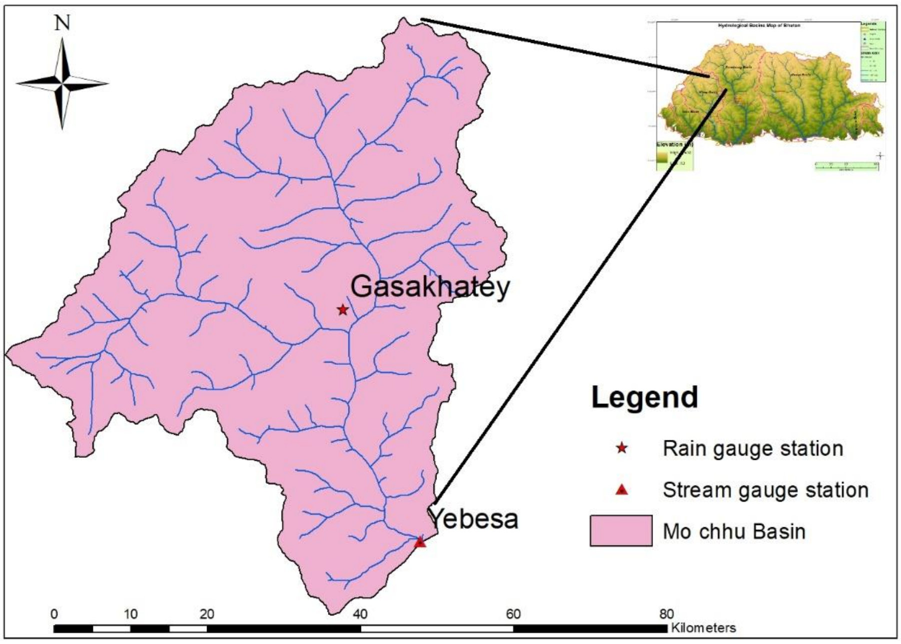

Figure 3-2: Mo chhu Basin

Table 3-3: Summary of Pho chhu Basin

Pho chhu basin (km^2)	2,331 km^2
District	Gasa, Punakha
Mainstream Length (km)	6,406.958 km
Drainage density (km/km^2)	2.75 km

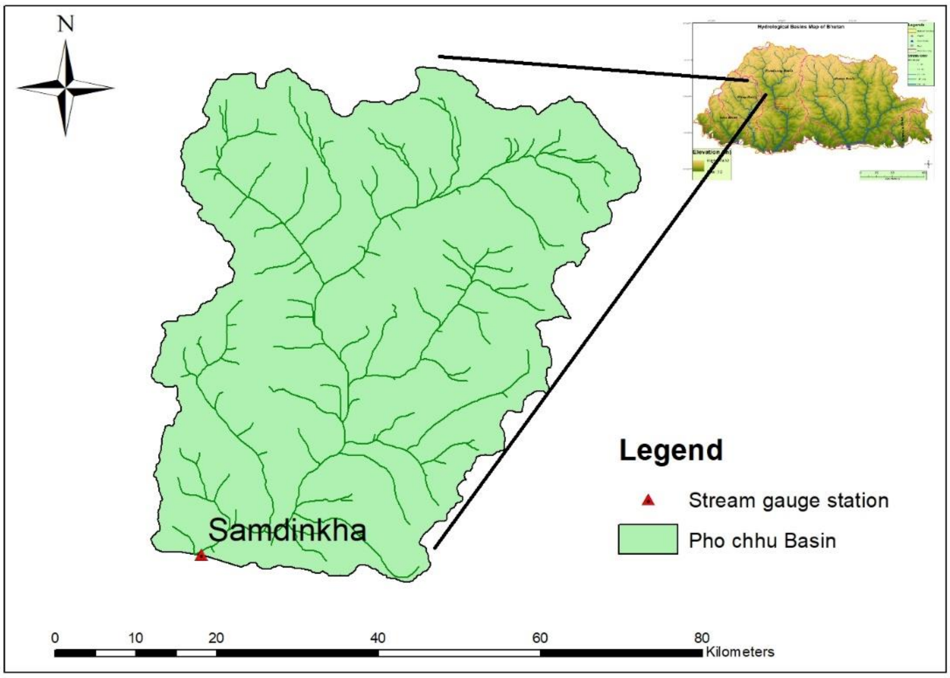

Figure 3-3: Pho chhu Basin

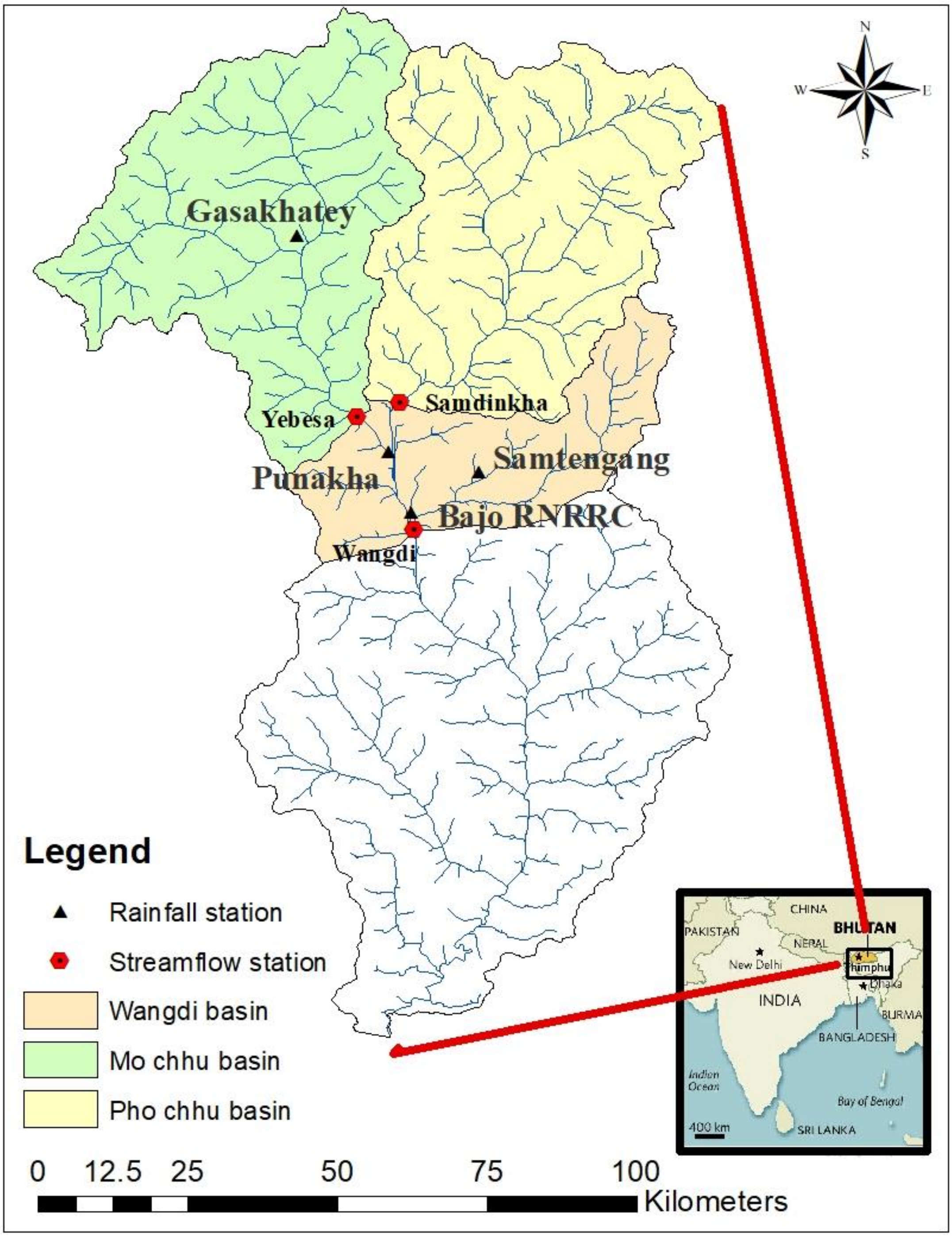

Figure 3-4: Study area

3.4 Topography for Mo Chhu and Pho Chhu Basins

Both basins lie within the same isohyets (Figure 3-3). The basin is characterized by rugged mountainous topography with high internal relief in most of the basin, especially in the north. The altitude in the basin ranges from about 90m above mean sea level in the south to over 7,000 m above mean sea level in the north. This huge elevation gradient affects precipitation and temperature values in the basin. The northern periphery of the Basin maintains an annual snowpack and approximately 4.4% of the area is covered by glaciers or permanent snow (Beldring et al., 2013). The basin has an average slope of 26.5 º. Of the total 677 glaciers and 2674 glacial lakes in Bhutan, Mo Chu basin comprises 118 glaciers and 380 lakes while Pho Chhu consists of total 154 glaciers and 549 lakes.

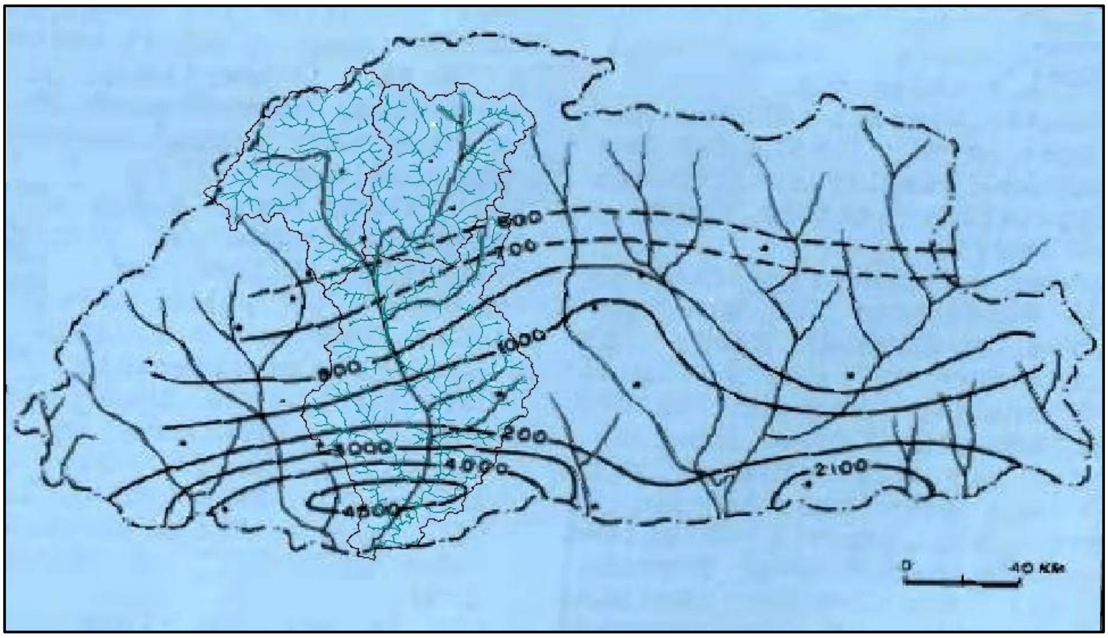

Figure 3-5: Isohyetal map of Bhutan (Modified from Sharma 1985)

3.5 Climate for Both Basins

The climate in the basin is as varied as its altitude and is affected by the summer monsoon from the Bay of Bengal. The monsoon season starts from June and lasts up till September and the dry season from October till May. The climate of the basin is divided into three zones, sub-tropical in the Southern foothills, warm temperate in the mid hills and arid alpine in the extreme north of the basin, with mean annual temperature varying from 15 ^{0} C to 30^{0} C in the southern foothills. Mean annual rainfall varies from 2,500 to 5,500 mm in the southern foothills, 1,000 to 2,500 mm in the mid valleys and 500 to 1,000 mm in the northern part of the basin.

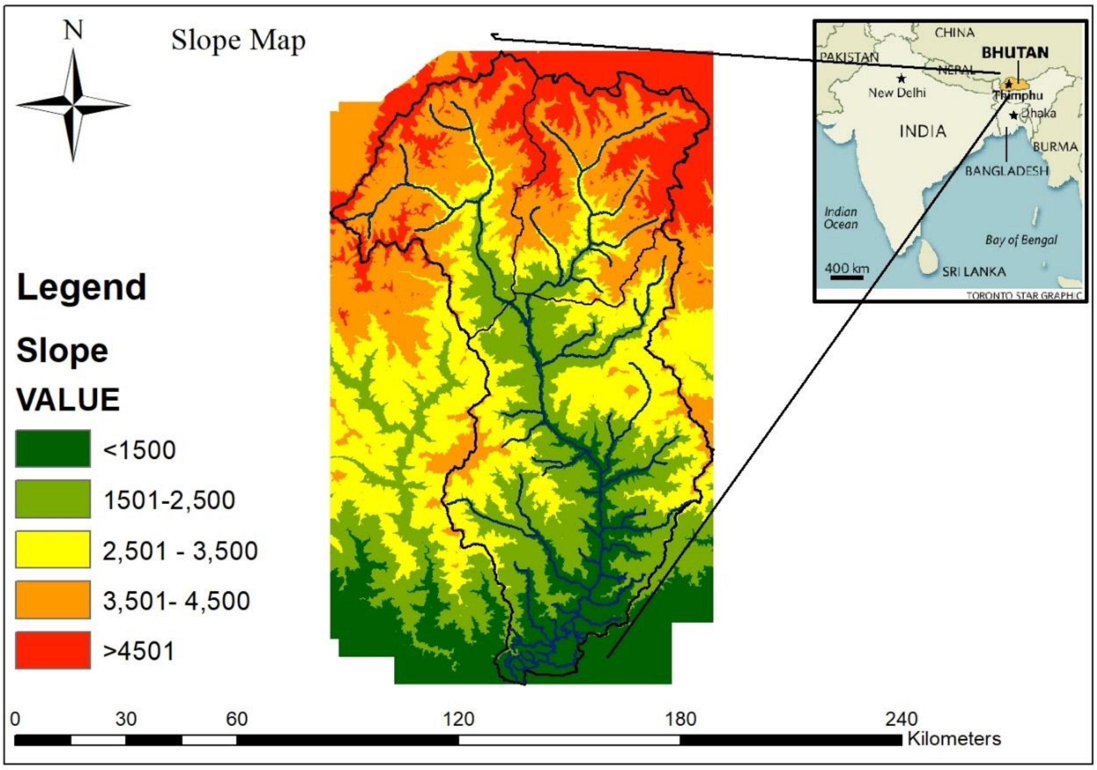

Figure 3-6: Slope map of study area

3.6 Landcover and Landuse for the Basins

The mainland cover type in the basins are forest, covering approximately 45% of the basin area. The other land cover types include woodland (17.8%), open shrubland (9.7%), wooded grassland (8.2%), grassland (7.6%) and other land-use types (less than 10%). The farming system in the basin includes agriculture, horticulture and livestock. The basin has a total arable land of 32,489 acres. Forest degradation is one of the major issues in the basin, the major reasons being the construction of roads and infrastructure development and also forest fires (MoAF, Bhutan, 2011).

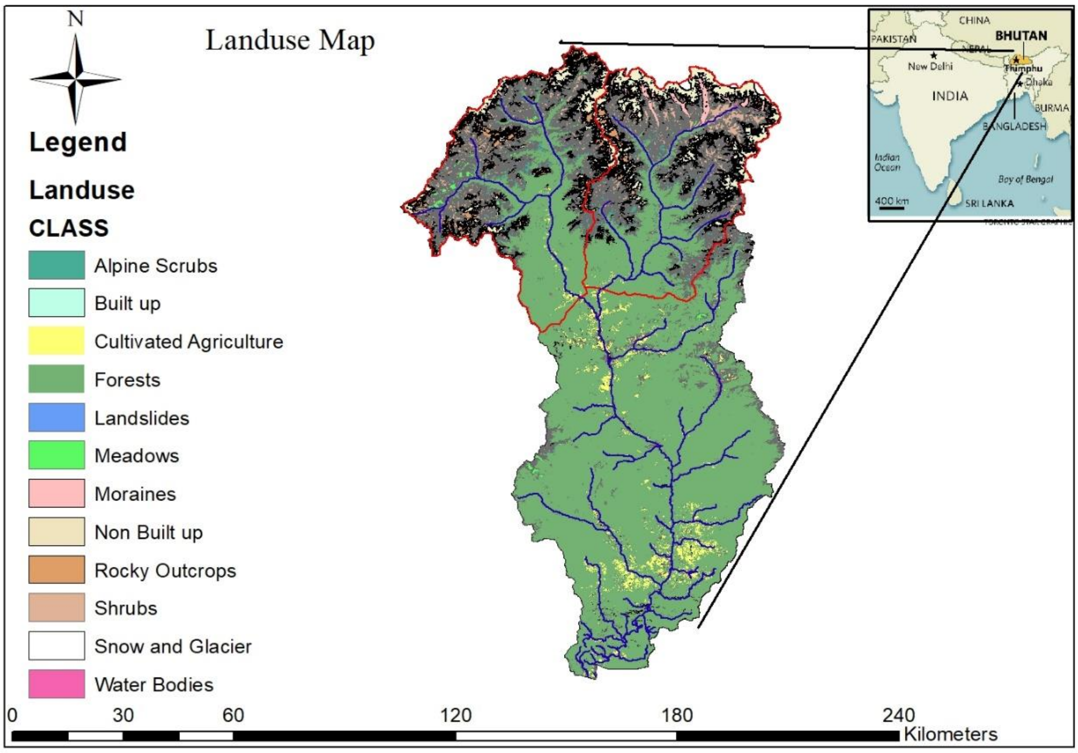

Figure 3-7: Landuse map of study area

3.7 Selection of appropriate model for the study

The following criteria had to be considered in choosing the model to be used in this study:

- Since the study is carried out on a large-scale catchment, the model should not be complex and data intensive. Its data requirement should be addressed by the available observations and measurements within the study area.

- The model structure should schematize the most important runoff generating processes in a scientifically reasonable way.

- The model should not have too many parameters.

- The model should be known to be applicable to the study area. This should be evidenced by previous application of the model to parts of the study area.

3.8 Data Collections

Precipitation and temperature are by far the most important meteorological variables driving the hydrological processes in a catchment. Precipitation, either in a liquid or snow form is the main input in a rainfall-runoff model. The model tries to simulate its movement within the catchment and its final transformation into the runoff. Temperature is another input to a model that influences the amount of evapotranspiration and snowmelt. Proper assessment of their distribution within a catchment under study is, therefore, a crucial step in a rainfall-runoff modelling practice.

Both precipitation and temperature are normally measured at a point scale by conventional measurement gadgets at observation stations. In a rainfall-runoff modelling exercise, however, the amount of precipitation and the magnitude of temperature are required at areal scales, with the areal extent depending on whether a lumped or distributed model is used. For lumped models, average values of precipitation and temperature over the whole catchment area are often sufficient. For grid-based distributed models, on the other hand, average values at grids of a few hundred meters to a few kilometres are required. The feasibility of establishing reasonable estimates of areal averages for small grid sizes depends on the availability of sufficient measurement points around each grid.

The quality of the model output is directly depending on the input data (Beven, 2001). Hydrological models are driven, in part, by hydrometeorological data, which contains hourly, daily, or monthly field observations. The resulting time series are never perfect and the data contains data errors (Beven, 2001). Data errors are divided into systematic errors and random errors. The first group contains errors which affect the measuring instrument systematically (Beven, 2001) and result in constant measurement bias. These errors can be caused, for instance, by false calibration of the instrument. Random errors, on the other hand, are caused by randomly occurring factors, such as interference of the automatic recording by animals. To achieve good modelling results it is crucial to control for data quality.

The Department of hydro-met services under the Ministry of Economic Affairs, Bhutan provides weather, water, climate and other related environmental services to a wide range of sectors, available hydro-meteorological data like precipitation, temperature, humidity, wind speed and river discharge for the study area were collected from the Department of Hydro met services. These collected data will be used as input and to calibrate the HBV model. During the field visit for data collection, it was explained by the officers in charge that the river gauges get submerged during the peak seasons and cause difficulty in reading them correctly and other factors like instrument breakdown and other technical problems sometimes causes days without observations. Therefore, the streamflow data is not free from observational errors. Other data like the land use, land cover maps were collected from the National Soil Service Center (NSSC), Bhutan.

Different methods of estimating areal average precipitation are used in practice. These include the simple arithmetic mean, the Thiessen polygon, and the inverse distance method. None of these methods, however, take into consideration the spatial structure of the variation of precipitation. The effect of additional variables that may affect the distribution of precipitation cannot also be integrated in the estimation. Besides, quantification of the uncertainty associated with the estimation is difficult and they do not necessarily lead to an estimate associated with the minimum uncertainty. Geostatistical methods have emerged as alternative approaches to estimate areal average precipitation or temperature from point measurement values. Such approaches incorporate the spatial structure of the variation of precipitation or temperature in estimating the areal average value and lead to minimum estimation uncertainty. There are also classes of Geostatistical methods that are adopted to include the effect of additional variables that have a close relationship with the variable of interest in the estimation process.

3.8.1 Rainfall Data

Rainfall data are measured as point observations and there are several potential sources of data errors associated with those measurements. The design of rain gauges can lead to a standard error between 3 to 30 % of the total annual measured rainfall sum (Dingman, 2002:P.115). These data errors can be corrected using an approach presented by Richter (1995). Rainfall time series might also include missing values. Here, Dingman (2002:P.115-117) suggests the following methods for data filling: station average method, normal ratio method, inverse distance weighting, regression analysis or the most common technique: the double mass curve between two stations.

The main criteria of selection of the stations were the availability of data for the selected period and the location with respect to the watershed. Four rainfall gauging station namely Gasakhatey, Punakha, Samtengang and Bajo RNRRC (Figure 3-4) are available for the desired study catchment. Daily data for 12 years' time period were collected from the National Center for Hydrology and Meteorology, Bhutan.

Table 3-4: Summary table for Missing Data

Station	**Number of missing values**	**% of missing values**
Rain Gauging Station		
Gasakhatey	100	27.78
Punakha	29	8.06
Bajo	3	0.83
Samtengang	33	9.17

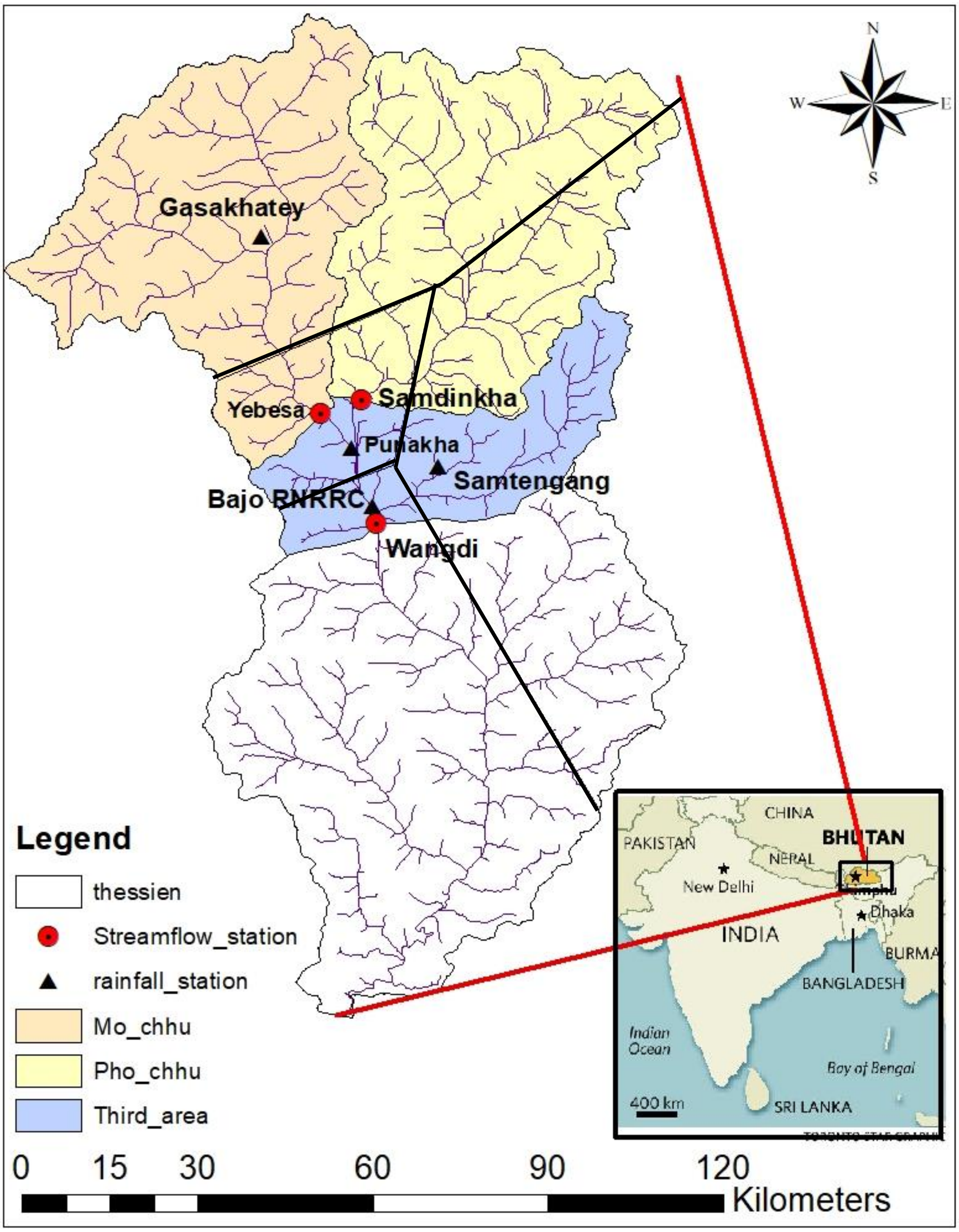

Figure 3-8: Study area showing Theissen Polygon

3.8.2 Streamflow Data

Streamflow records provide a measure of the response of a catchment to the time variable input and internal hydrological processes. Although model output may be a single or multiple outputs, the ability to predict stream discharge remains the most important objective of most models.

For the study, streamflow from the three stream gauge stations Yebesa, Samdinkha and Wangdi were collected for the time period of 12 years in daily time steps.

3.8.3 Temperature Data

The data sources used for the temperature data were provided by the NHCM That includes daily minimum and maximum temperature data for the time period 2006 to 2018 for the three districts that were covered by the basins.

3.8.4 Snow Data

The MODIS snow cover products, available at the public domain of the National Snow and Ice Data Centre, have been used for snow cover mapping of the study area. MODIS products are available as classified images based on normalized difference snow index (NDSI) including other test criteria. MODIS snow cover and ice mapping algorithm use the MODIS bands taken from visible to the infrared portion of the spectrum. The snow has high reflectance between the visible and mid-infrared region of the spectrum. The MODIS product downloaded was then processed using ArcGIS software to extract the snow cover map of the basin one by one from each product spectrum.

The snow was mapped using the Normalized Difference Snow Index (NDSI) method, with reflectance in bands 4 (0.545–0.565 μm) and 6 (1.628–1.652 μm). The NDSI was calculated using the following relationship.

NDSI = (Band 4 – Band 6)/ (Band 4 + Band 6)

In general, there are two approaches for snow and ice melt modelling. The energy balance approach explicitly models all components of the surface energy balance, and temperature-indexed-modelling considers temperature as the main variable controlling melt (Hock, 2003; Tobin *et al.*, 2013). Numerous studies have attempted to model the meltwater discharge using a positive degree day approach (Kayastha *et al.*, 2000a, 2005). Several studies have incorporated shortwave radiation to improve sub-daily melt totals (Hock, 1999; Pellicciotti *et al.*, 2005). Although the energy balance approach best describes the effects of debris cover on melt totals (Hock, 1999, 2003), input data availability is a significant constraint. Uncertainty in the hydrological models might arise due to errors in input data, inappropriate parameter selection and modelling approach used (Hughes *et al.*, 2010). The snow cover map of the basin is given in the Figure 3-5. And Table 3-4 represents the summary of the data collection of the basins.

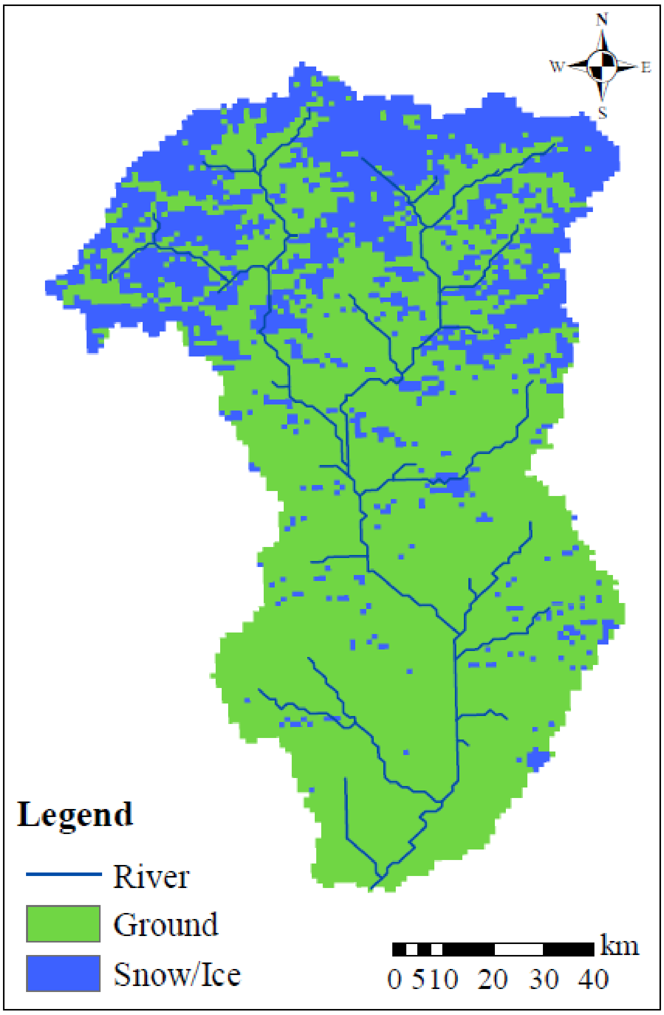

Figure 3-9: Snow cover for Puna Tsang chhu

Table 3-5: Summary of data collected

Data Type	Station Name	Resolution	Year	Source
Rainfall	Gasakhatey	Daily	2006-2017	NCHM, Bhutan
	Punakha	Daily	2006-2017	NCHM, Bhutan
	Samtengang	Daily	2006-2017	NCHM, Bhutan
	Bajo RNRRC	Daily	2006-2017	NCHM, Bhutan
Streamflow	Yebesa	Daily	2006-2017	NCHM, Bhutan
	Samdinkha	Daily	2006-2017	NCHM, Bhutan
	Wangdi	Daily	2006-2017	NCHM, Bhutan
Temperature	Gasa	Daily	2006-2017	NCHM, Bhutan
	Punakha	Daily	2006-2017	NCHM, Bhutan
	Wangdi	Daily	2006-2017	NCHM, Bhutan

3.9 Data Checking

3.9.1 General

The data checking method adopted in the present study includes both Graphical Checking (Visual Checking) and Statistical Checking. For the considered data period in both Mo chhu and Pho chhu, rainfall data, streamflow data and temperature data were checked by using standard data checking methods. Under data checking, visual data checking, missing data identification and filling, consistency check, annual water balance, seasonal water balance, runoff coefficient checks were performed.

3.9.2 Visual data checking

The main purpose of visual data check in Figure 3-6 and Figure 3-7 is to check the response of the flow to the rainfall which is considered as the most important aspect in water balance modelling.

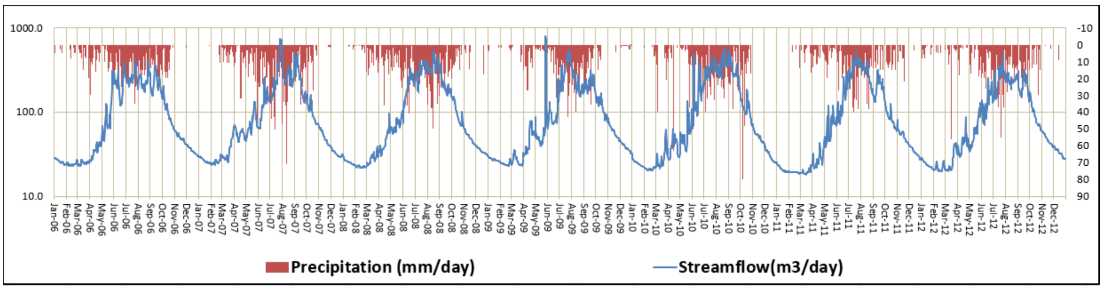

Figure 3-10: Comparison of Rainfall and Streamflow for Gasakhatey Station for Mo chhu basin for calibration period (2006-2012)

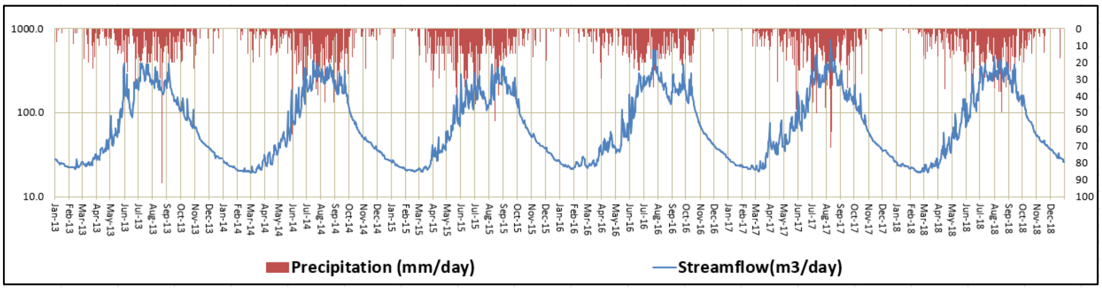

Figure 3-11: Comparison of Rainfall and Streamflow for Gasakhatey Station for Mo chhu basin for Validation period (2013-2017)

3.9.3 Co-relation between streamflow and rainfall data

The correlation between observed streamflow and Thiessen averaged rainfall was checked for Mo chhu is as shown in Figure 3-8 and Figure 3-9.

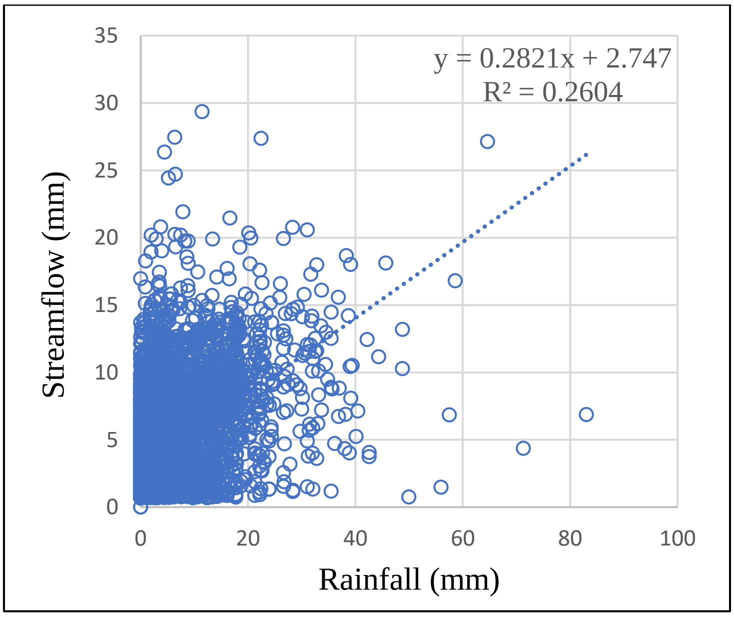

Figure 3-12: Correlation between Streamflow (Yebesa) and precipitation (Punakha)

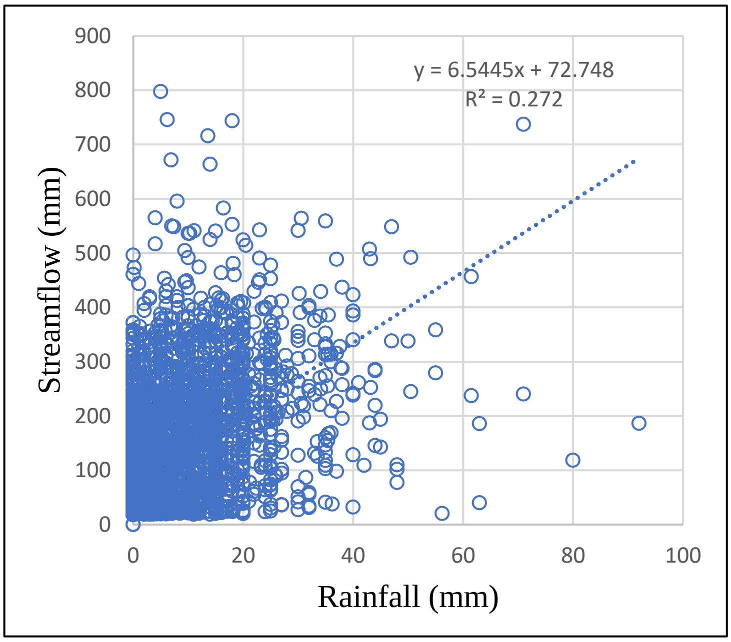

Figure 3-13: Correlation between Streamflow (Yebesa) and precipitation (Gasakhatey)

3.9.4 Single mass curve analysis

Single mass curve analysis as shown in Figure 3-10 was carried out for the rainfall, streamflow and evaporation data considering the consistency in annual cycles, which is the same concept of linear regression, which is used successfully to estimate the missing rainfall (Sharifi, 2015; Caldera, Piyathisse, & Nandalal, 2016).

Single mass curves were plotted for all the rainfall stations in one graph to check the consistency of rainfall data and to observe the relative variation for Mo chhu and Pho chhu watersheds. Further, the consistency was checked in the Thiessen averaged rainfall data, since it will directly affect the monthly water balance.

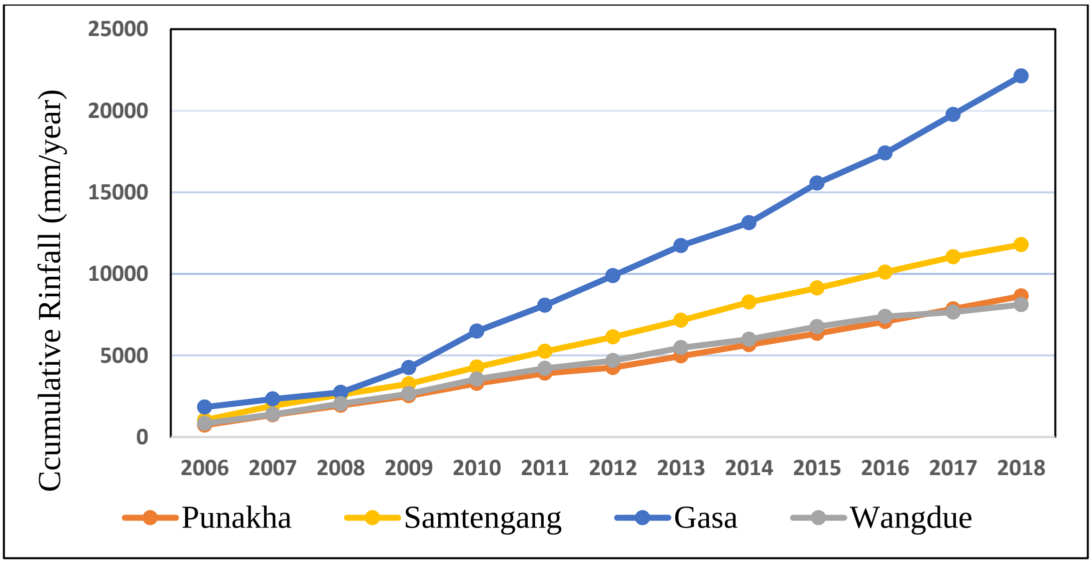

Figure 3-14: Single mass curve of all the rain gauging stations

3.9.5 Double mass curve analysis

If the conditions relevant to the recording of a rain gauge station have undergone a considerable change during the recording period, inconsistency would arise in the rainfall data of that station. The main reasons for an inconsistency may be due to a shifting of a rain gauge to a new location, changes in the neighbourhood of the station, changes in the ecosystem due to calamities and occurrence of an observational error from a certain date etc.

The check which is done to identify this inconsistency is the Double mass curve technique which is based on the principle that when each recorded data comes from the same parent population, they are consistent (Subramanya, 2008).

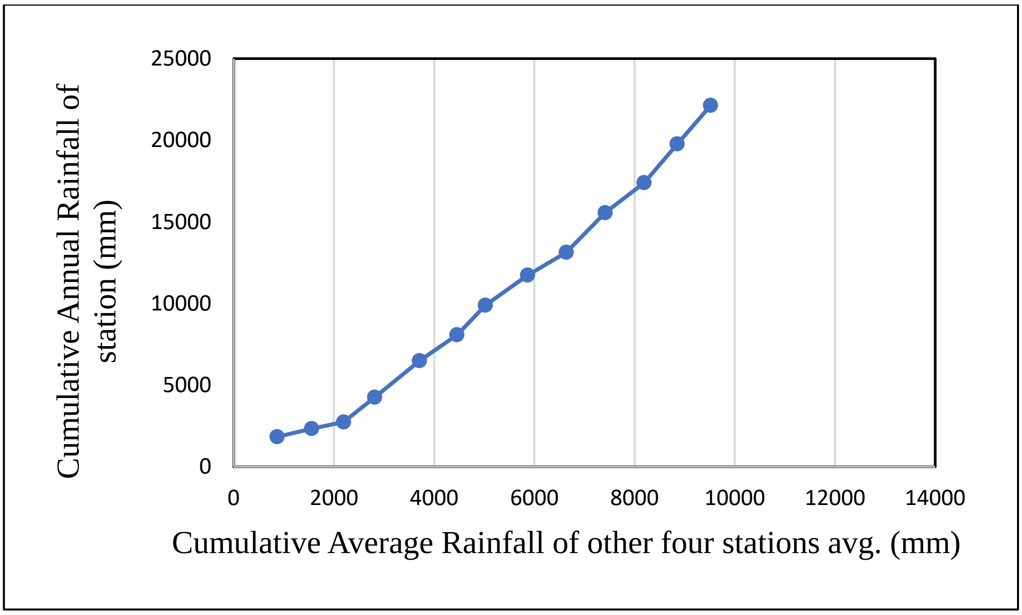

Figure 3-15: Double mass curve of all the Gasa stations

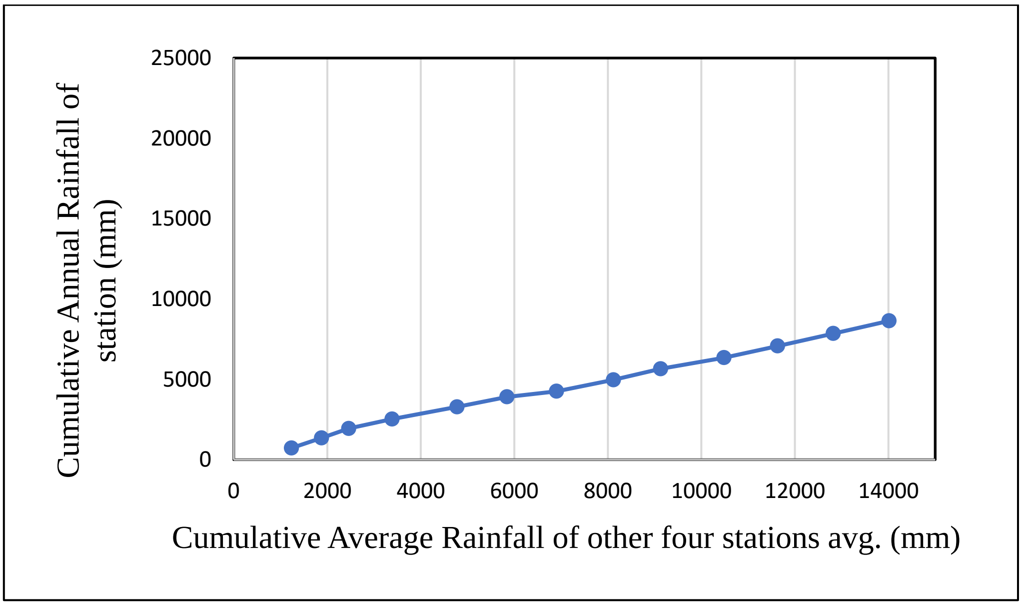

Figure 3-16: Double mass curve of Punakha stations

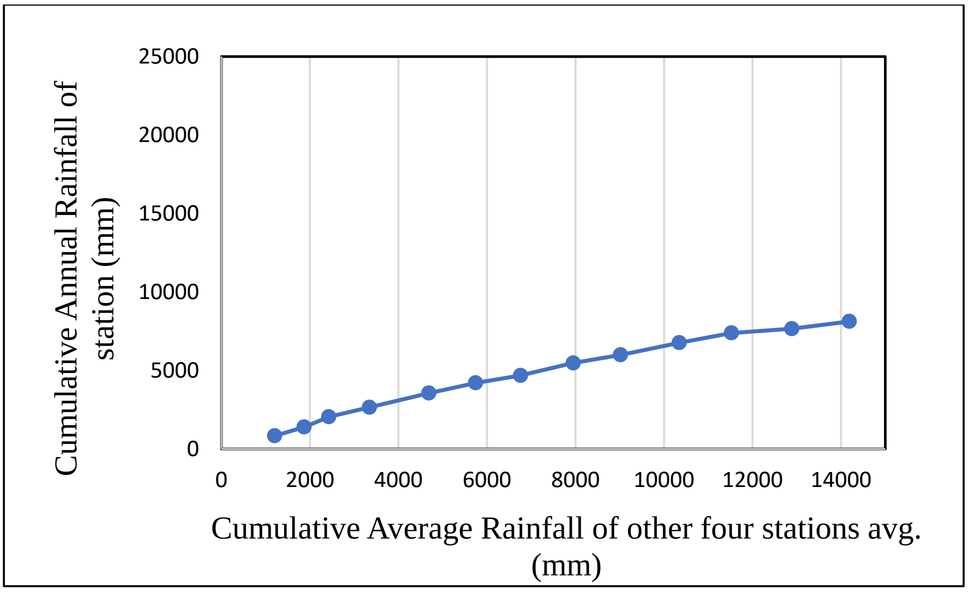

Figure 3-17: Double mass curve of Wangdi stations

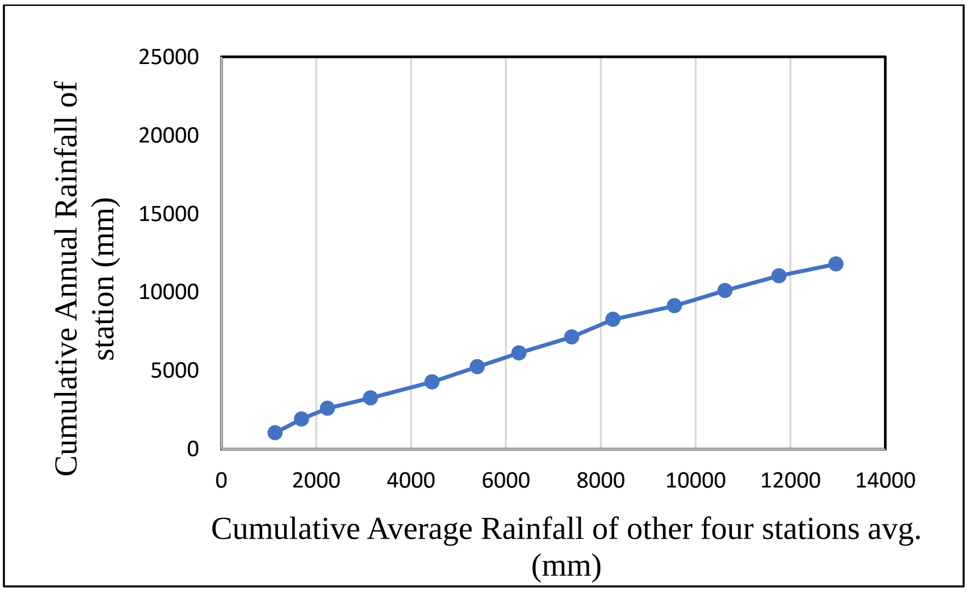

Figure 3-18: Double mass curve of Samtengang stations

4. RESULTS AND ANALYSIS AND DISCUSSIONS

The simulation results were compared using statistical criteria used as objective functions, RMSE, Pearson r and RSQ (R^2). The model performance during calibration and validation for both catchments are given in Table 4-1.

Table 4-1: Model efficiency at daily time step of calibration and validation periods on both basin

Objective Function	Mo Chhu		Pho Chhu
	Calibration	**Validation**	**Validation**
Pearson r	0.846	0.875	0.784
RSQ (R2)	0.715	0.766	0.615
RMSE	1.443	5.65	7.897

For Mo Chhu basin, runoff simulations were in good agreement with observed runoff yielding Pearson correlation values of 0.846 and 0.875 with R^2 values of 0.715 and 0.766. However, for Pho Chhu basin, a significant overestimation in simulated flow was observed while the objective functions also responded inadequately, indicating that parameter sets derived for the basins are transferable to other basins even with presumably similar basin characteristics. The relatively high RMSE values further indicate that model is in marginal agreement and not a perfect fit to the observed flow series (Figs. 4-1~4-3).

The present study explored the challenges involved in applying a water balance model for a basin with scarce rain gauge arrangement. A unique aspect of the study is the incorporation of snow component in ABCD model. For the snow-covered areas, consideration of snow component in the model has significantly improved the model performance as a major portion of the flow is from snowmelt in such basins. In the model without snow parameter, the simulated series showed a fairly lower value compared to the observed values.

The Pearson *r* value for the ABCD model with snow parameter for Mo Chhu basin was as low as 0.624 and 0.672 for calibration and validation runs, respectively. For the model with incorporation of snow parameter, the *r* increased to 0.846 and 0.875, respectively (Table 4-1). Snowmelt inexplicably plays a major role in streamflow contribution and is important to accurately simulate the snow processes in such Himalayan river basins, because their flow regime does not only depend on the precipitation amount while a certain percentage of snow is continuously melting to contribute to streamflow. Therefore, the basic ABCD model without any modification or any other model without snowmelt component will obviously fail to produce model results with reasonable efficiency.

The paper attempts to address the major concern as to why the parameters calibrated for Mo Chhu basin underperformed in Pho Chhu basin.

The climate in both basins are similar to the midstream region of the river is categorized as monsoon climate, which consists of the wet season during June to September and the dry season during October to May in general. Annual precipitation varies from 400 ~600 mm in the upstream region, 700 ~ 900 mm for midstream region where the data is collected and exceptionally more than 2,000 mm for steeply inclined topography in mid to downstream areas of the basin. The climate in the further downstream region near the border with India is categorized to be subtropical with annual precipitation of 3,000 to 5,000 mm where frequent floods occur (Dorji, 2003).

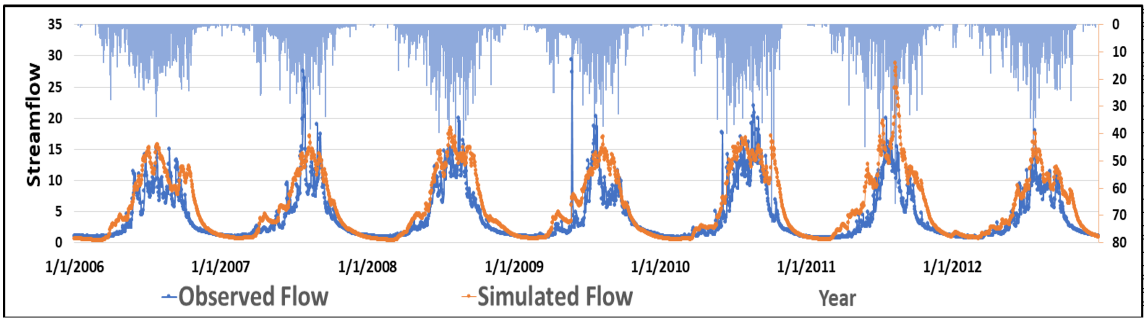

Figure 4-1: Calibration results for abcd with snow parameter for Mo Chhu

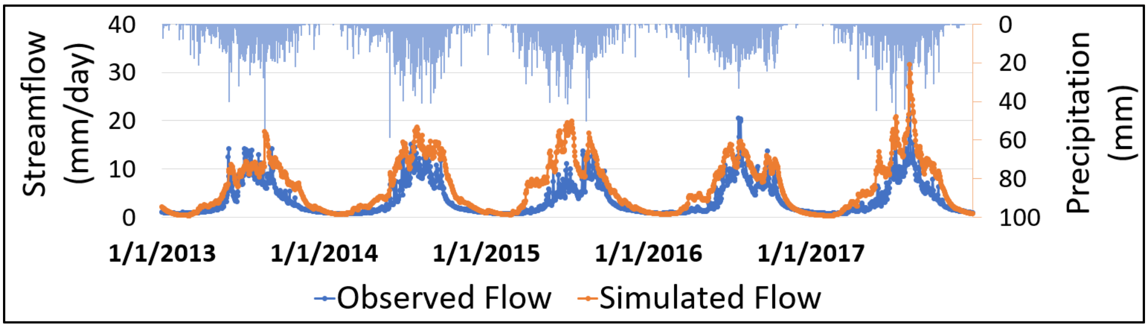

Figure 4-2: Validation results for abcd with snow parameter for Mo Chhu

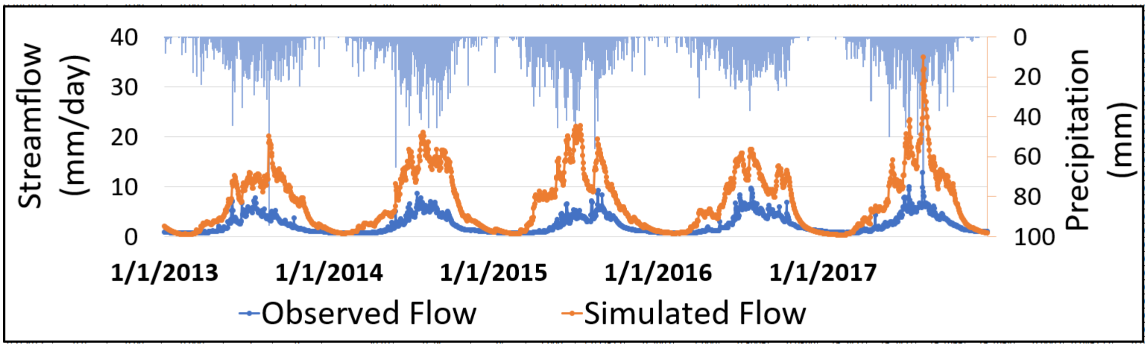

Figure 4-3: Validation results for abcd with snow parameter for Pho Chhu

The maximum and minimum streamflow for Mo Chhu river basin for calibration period (2006-2012) are 29.36 mm/day and 0.66 mm/day, and 27.13 mm/day and 0.72 mm/day, for validation period (2013-2017), respectively.

For Pho Chhu basin, the maximum streamflow recorded is 12.86 mm/day with a minimum 0.68 mm/day which clearly depicts the difference of observed streamflow hydrographs for the above two basins. It too explains the observed streamflow for Pho Chhu basin is comparatively lower than that of Mo Chhu basin which resulted in the observed difference in simulated flow.

4.1 Determination of Flow Duration Curves

A flow duration curve characterizes the ability of the watershed to provide flows of various magnitudes. The shape of a flow duration curve in its upper and lower regions is particularly significant in evaluating the watershed and stream characteristics. The shape of the curve in the high flow region indicates the type of flood regime the watershed is likely to have, and the shape of the low flow region characterizes the ability of the basin to sustain low flows during dry periods. A very steep curve, which shows high flows for short periods would be expected for rain caused floods on small watersheds.

In developing the flow duration curve, the monthly discharge values were rearranged according to the descending order and ranked starting from one. The exceedance probability was calculated as follows.

$P = 100 * [M / (n + 1)]$ where, P = the probability that a given flow will be equaled or exceeded (% of time)

M = the ranked position on the listing (dimensionless) n = the number of events for the period of record (dimensionless)

The probability of exceedance indicates how much percentage a discharge value has been exceeded.

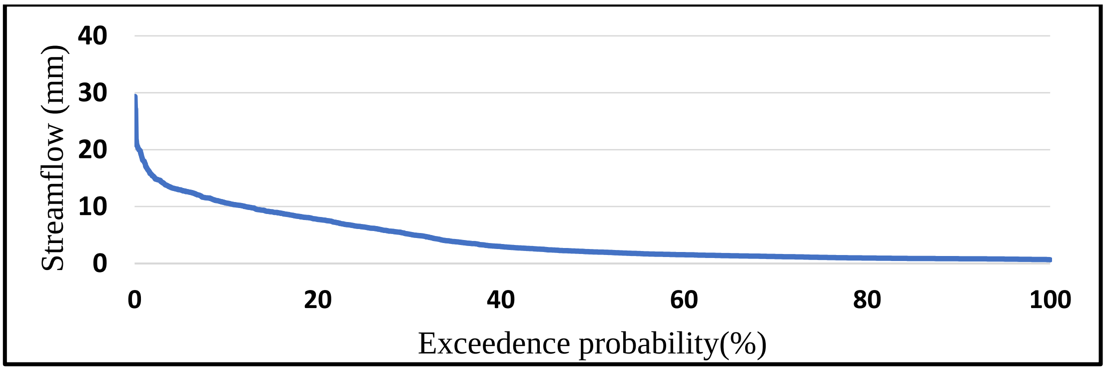

Figure 4-4: Flow duration curve for Calibration for Mo chhu (2013-2017)

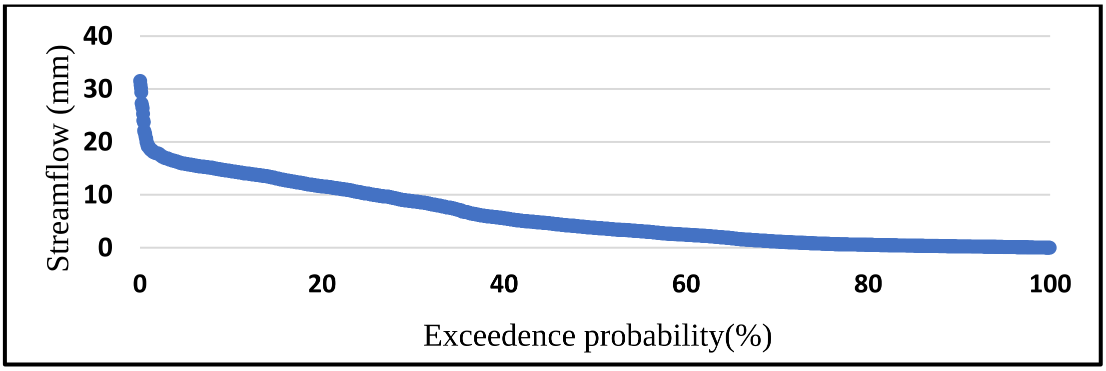

Figure 4-5: Simulated Flow duration curve for Calibration for Mo chhu (2006-2012)

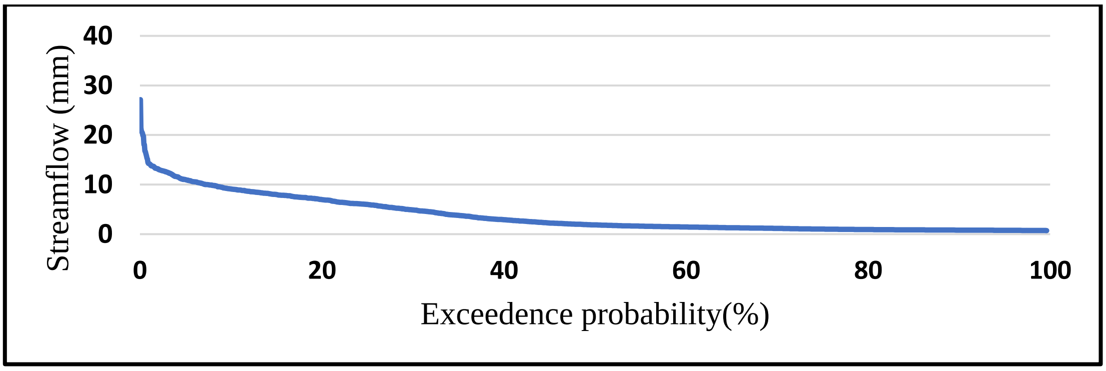

Figure 4-6: Flow duration curve for Validation for Mo chhu (2013-2017)

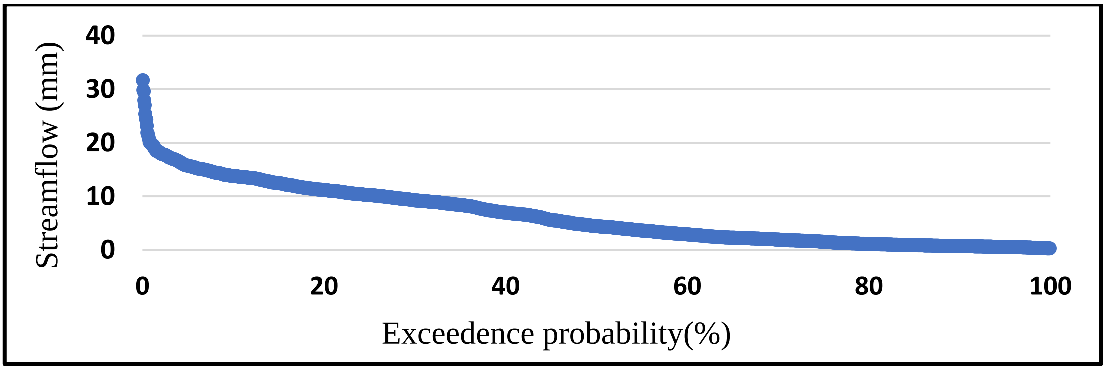

Figure 4-7: Simulated Flow duration curve for Validation for Mo chhu (2013-2017)

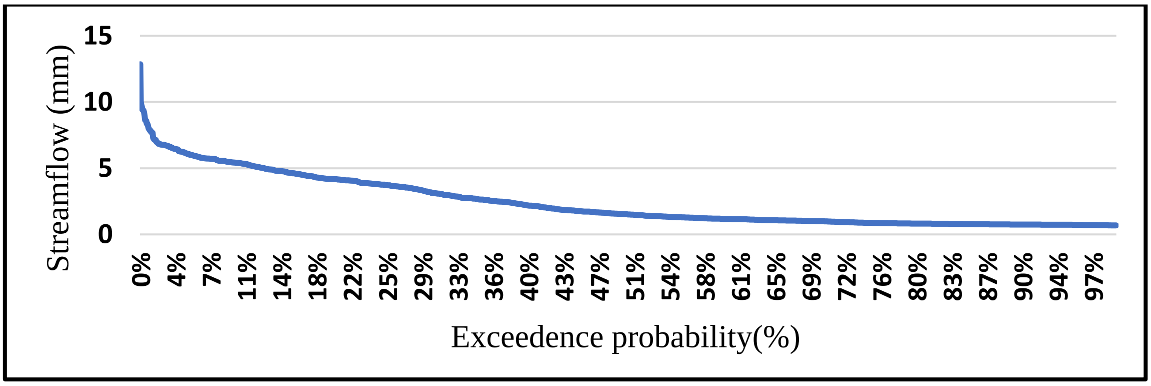

Figure 4-8: Flow duration curve for Validation for Pho chhu (2013-2017)

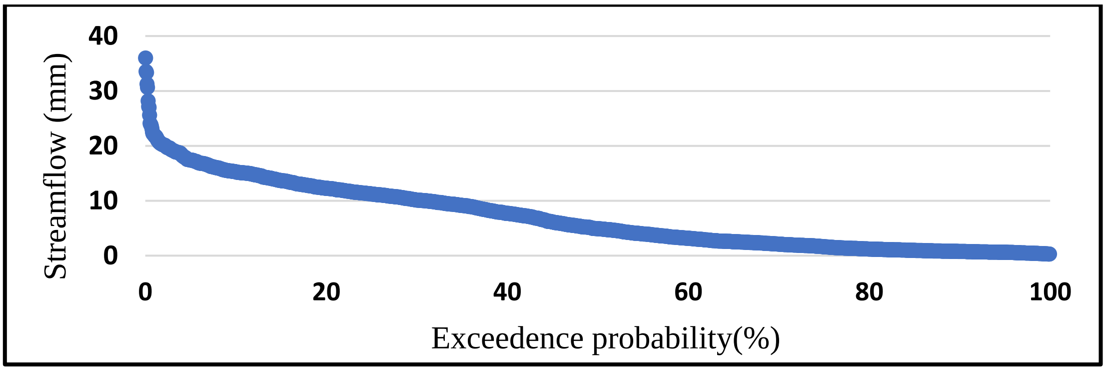

Figure 4-9: Simulated Flow duration curve for Validation for Pho chhu (2013-2017)

The annual daily average streamflow discharge in Mo Chhu basin is 4.38 ± 2.13 mm/day and 3.74 ± 3.64 mm/day for the calibration and validation periods, respectively, whereas it is only 2.90±9.22 mm/day in Pho Chhu basin (Figs. 14-15). It shows that the mean flow in Pho Chhu basin is significantly lesser than that of Mo Chhu basin (*t*-test; $p < 0.5$). The reason for such difference could be the presence of a large number of glacial lakes at the head source of Pho Chhu providing huge retention storage. Mo Chu basin comprises 118 glaciers and 380 lakes while Pho Chhu consists of total of 154 glaciers and 549 lakes.

4.2 Model Inputs

Rainfall is one of the main inputs of the ABCD 4-parameter model. For a better representation of rainfall, the number of rainfall stations was used considering WMO (2009) guidelines for both watersheds. In interpolation of rainfall, the Thiessen polygon method was used with the aid of Arc GIS as most of the modellers had used this method even for distributed models. With the modification to model, snowmelt is also one of the major factor affecting runoff generation process.

4.3 Model Performance

The overall performance of the model was measured by using the Root Mean Square Error (RMSE), Pearson correlation coefficient (r) and Coefficient of determination (R^2) as the objective functions.

The model performance was checked separating the high, medium and low flows in the data set separately for calibration and validation. The high, medium and low flow regimes were identified by using the sudden deflection points in the flow duration curves. The probability exceedance values of regime changing points were not the same for calibration and validation data sets even though it is expected from a parent data set but was in a satisfactory range.

Therefore, by considering the above facts, it can be concluded that the overall performance of the ABCD model is satisfactory for the considered watersheds.

4.4 Model Parameters and Behavior

The mean *a*, b, *c* and *d* parameter values from literature was taken as the initial parameter values for the model in the calibration and validation process and ended up with optimized parameters. No deviations in the optimized *a*, *b*, *c* and *d* parameters were observed with respect to the range from literature. According to the model structure of ABCD model, the parameter "*a*" reflects the propensity of runoff to occur before the soil is fully saturated. According to Thomas (1981) the parameter "*a*" will reduce with the urbanization and deforestation while reaching unity in flat terrains with low drainage density. The parameter ‘*b*’ is an upper limit on the sum of actual evapotranspiration and soil moisture storage in each month. This parameter reflects the ability of the catchment to hold water within the upper soil horizon.

The parameter ‘*c*’ is equal to the fraction of groundwater recharge and the balance (1-*c*) for the direct runoff. The timely changes in the land use and the slope will affect the magnitude of “*c*”. In the case of urbanization and deforestation, the value of parameter “*c*” will reduce while increasing the fraction for surface runoff which is (1-*c*). In considering the optimized “*c*” values for both watersheds, those are lesser than 0.1 which shows a lower recharge while showing a high fraction for runoff. The reason might be the mountainous terrain existing in both watersheds. In comparing both watersheds. Parameter “*d*” is relevant to the groundwater discharge.

4.5 Model Parameter Sensitivity

The study of the impact of changes in the model parameters and other variables used in a model on the model output is an important phase of the modelling practice. All parameters and variables used in a model do not have a similar level of effect on the sensitivity of the model simulation. A slight change in some parameters or variables may lead to a significant change in the model simulation result. The model is said to be sensitive to such parameters or variables. On the other hand, no noticeable change is felt due to a change in others and they constitute a group of parameters or variables to which the model is insensitive. Study of the sensitivity of the model simulation results to changes in the model parameters or other input variables gives an insight to the model user into which parameters or variables contribute most to the variability of the simulation result and which are insignificant in terms of their influence on the uncertainty associated with the model prediction.

4.6 Challenges Faced in Modelling

Models are a simplification of reality, so it is necessary to build assumptions into the model. Therefore, modelling is one of the most difficult tasks and time-consuming beginning from the data collection and checking, model development and data input to simulations. Data collection and checking are challenging, and it requires a lot of time and effort to make sure that the data resolutions are enough, relevant and uniform in order to use for model simulations. With regarding the model development, calibration and validation, difficulties were found regarding data and to set the initial conditions of the model which can affect the model performance.

It is difficult to assume an initial value during data input. Parameter optimization is also very difficult since the parameters can be very sensitive, and small changes may cause large changes in the simulated results while some parameter is very robust and insensitive to the initial values of the parameters. Moreover, model development is a complex process and the complexity of each process representation is constrained by observations, computational resources and knowledge. Thus, model development requires vast knowledge, experiences and skills.

4.7 Limitations of Model

According to Martinez and Gupta (2010), the model does not perform well with its conventional model structure for the catchments which has snow falling and the model structure need to be modified accordingly. After the modifications and considering the snowmelt factor also the behaviour and response of streamflow is not strong. Consideration this water balance model formulation, modelling of snow sublimation or other, more complex, spatiotemporal dynamics of the snow accumulation/ablation process is important. Further, by assuming that the effects of sub monthly distribution of timing and intensity of precipitation events, potential evapotranspiration and temperature variations, and other factors are negligible, the model may gives a better response. McCabe and Wolock (1999) and Hay and McCabe (2002) have used similar approaches.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

- ✓ In this study, comparative evaluation of the performance of the ABCD model with and without snow component was carried out for simulating streamflow behaviour of two snowmelt dominated catchments.
- ✓ The catchment lies at very high altitude with complex terrain in the Himalayan region with very limited observed data. It is emphasized that caution must be exercised when applying model parameters derived from one basin for modelling the hydrology of another, as transferability depends on the considerations of climate, topography, land cover type, surface storage and compatibility of scale.
- ✓ The Pearson r value for the ABCD model with snow parameter for Mo Chhu basin was as low as 0.624 and 0.672 for calibration and validation runs, respectively, without snow component.
- ✓ For the model with incorporation of snow parameter, the r increased to 0.846 and 0.875, respectively, indicating that snowmelt inexplicably plays a major role in streamflow contribution and is important to accurately simulate the snow processes in such Himalayan river basins.
- ✓ For Mo Chhu basin, runoff simulations were in good agreement with observed runoff yielding Pearson correlation values of 0.846 and 0.875 with R^2 values of 0.715 and 0.766. However, for Pho Chhu basin, a significant overestimation in simulated flow was observed while the objective functions also responded inadequately, indicating that parameter sets derived for the basins are transferable to other basins even with presumably similar basin characteristics.
- ✓ The annual daily average streamflow discharge in Mo Chhu basin is 4.38 ± 2.13 mm/day and 3.74 ± 3.64 mm/day for the calibration and validation periods, respectively, whereas it is only 2.90±9.22 mm/day in Pho Chhu basin.
- ✓ This conclusion parallels the view expressed by past research that a parameter set is often and only valid for the conditions (catchment scale and area characteristics) for which it is defined when the basins have unique conditions.

5.2 Recommendations

This study presents very promising results for hydrological modelling. However, uncertainties still exist, from which key areas for further research can be derived.

• Energy and temperature variations in snow can be more complex than assumed in the present model. However, a more comprehensive approach would need very accurate temporal and spatial observations of snow depth, water content, temperature, as well as energy fluxes, which in practice are usually not available especially in mountainous regions. Certainly, such data can be achieved by satellite data and remote sensing techniques. Hence, the method presented can be a useful tool for simulating snowpack processes and snowmelt but should be verified in the field and improved provided more comprehensive datasets become available.

• Slope and aspects played an important role in the spatial distribution of snow cover at the beginning of the winter, too. At the time of maximum accumulation, elevation gradients seem to have a dominant effect on the spatial distribution of snow.

• Estimation of the model parameters and their corresponding regional relationships with the catchment attributes was done by calibrating the model based only on simulating the runoff observed at the outlet points of the subcatchments. Simulating the runoff at the outlet needs consideration of all the catchment processes simultaneously and this leads to an interaction of the model parameters pertaining to the different hydrological processes. This obviously increases the freedom of the individual model parameters and parameter values spanning over a wide range can lead to similar model performance. This consequently reduces identifiability of the model parameters. Although the regionalization approach implemented in this work imposes constraints on the parameters, further improvement of estimation of the parameters may be achieved by incorporating other catchment responses or state variables corresponding to different phases of the runoff generation process, if it is feasible to obtain such data. This may suggest a direction for future parameter regionalization works.

• The large number of small to large surface water bodies (glacial lakes) affect the model accuracy and thus, special consideration of storage effect is required.

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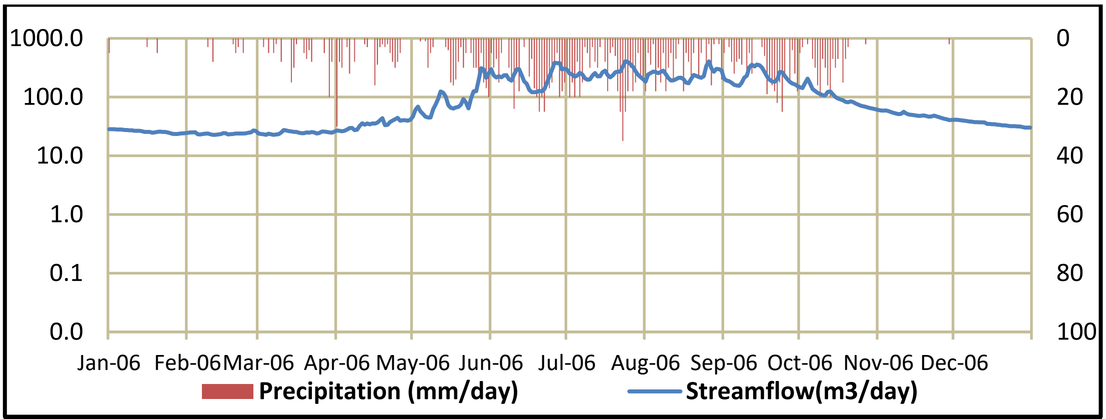
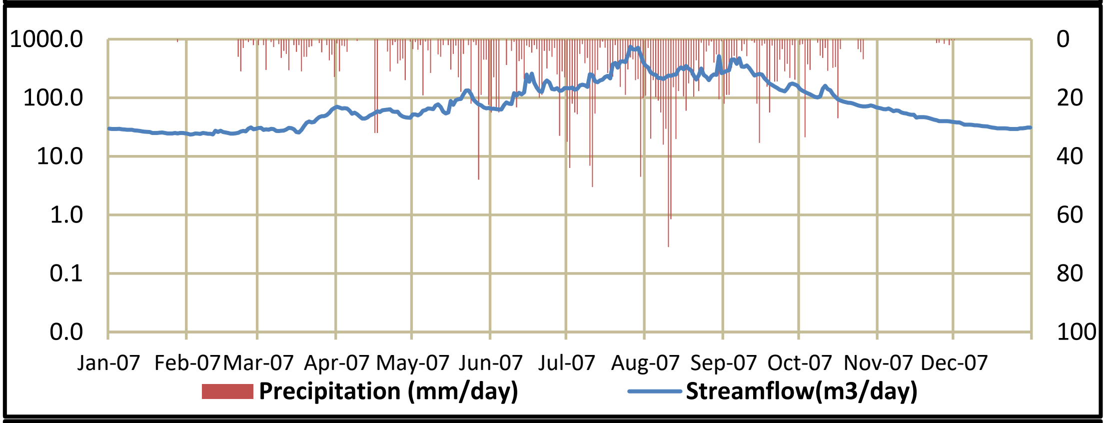
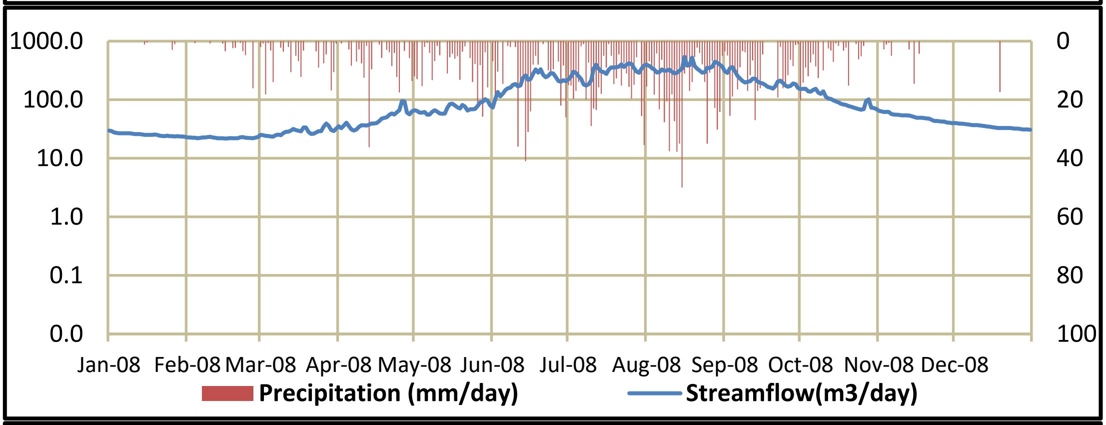
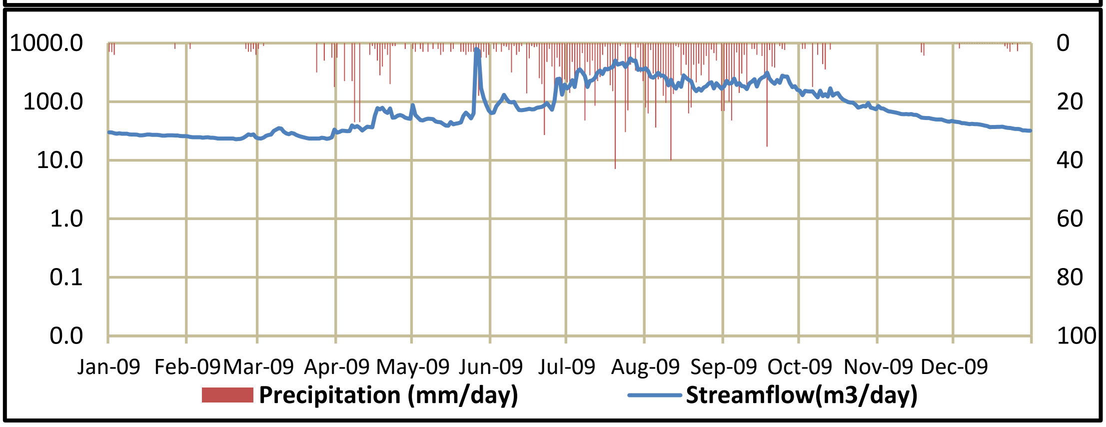
APPENDIX A- Data Checking

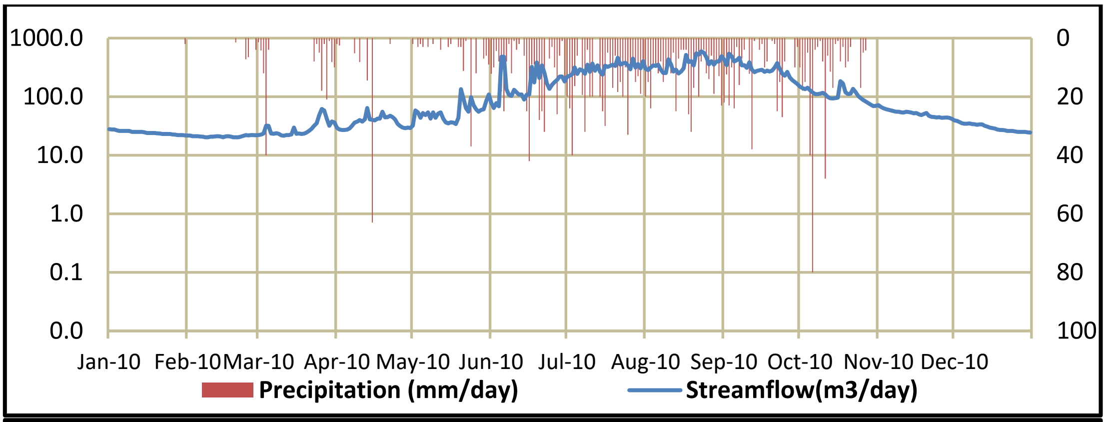
Streamflow vs precipitation for Mo chhu basin Gasakhatey







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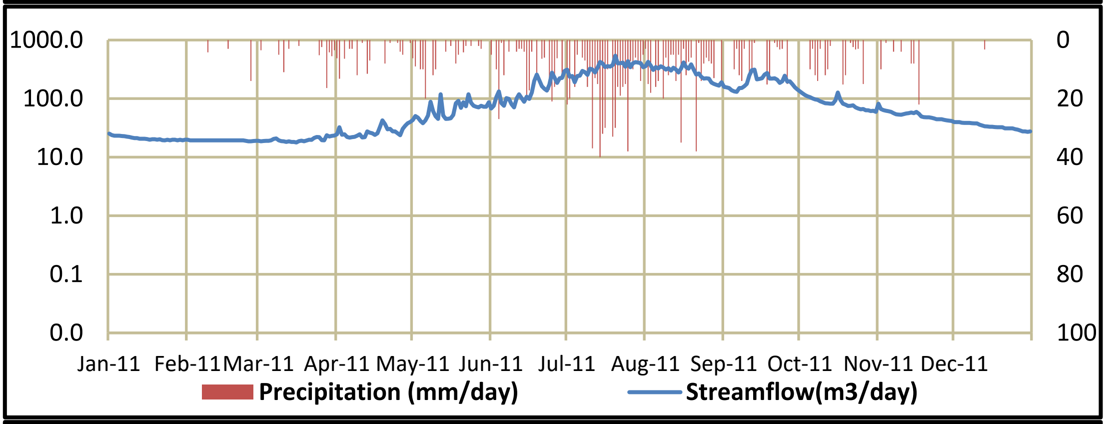
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Precipitation (mm/day)
Streamflow(m3/day)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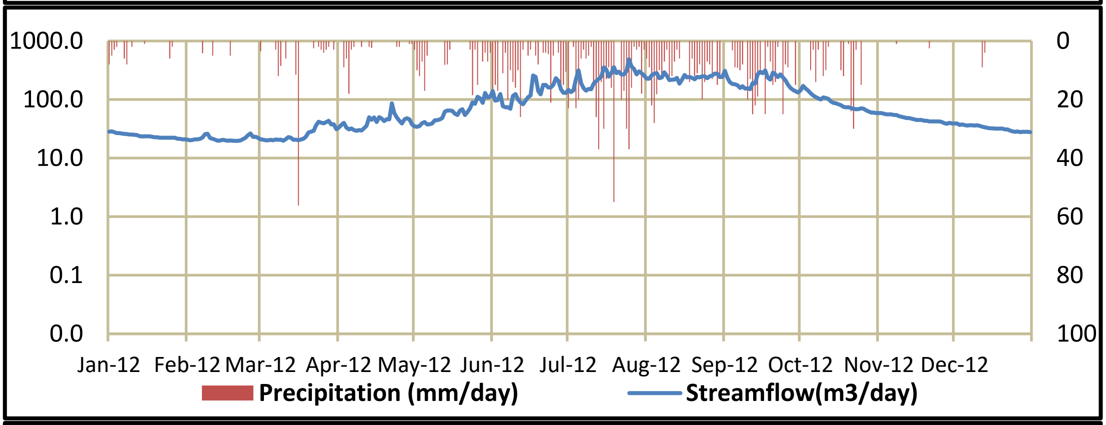
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Precipitation (mm/day)
Streamflow(m3/day)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100
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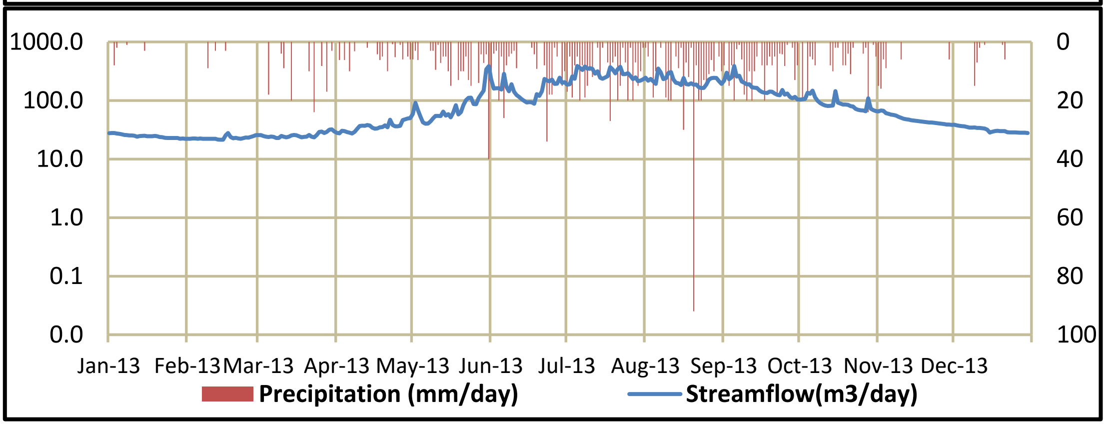
Precipitation (mm/day)
Streamflow(m3/day)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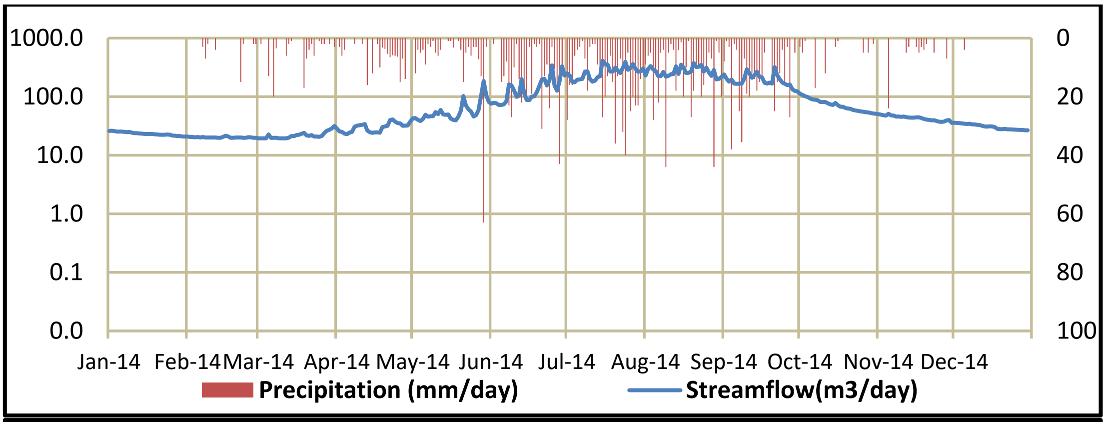
Precipitation (mm/day)
Streamflow(m3/day)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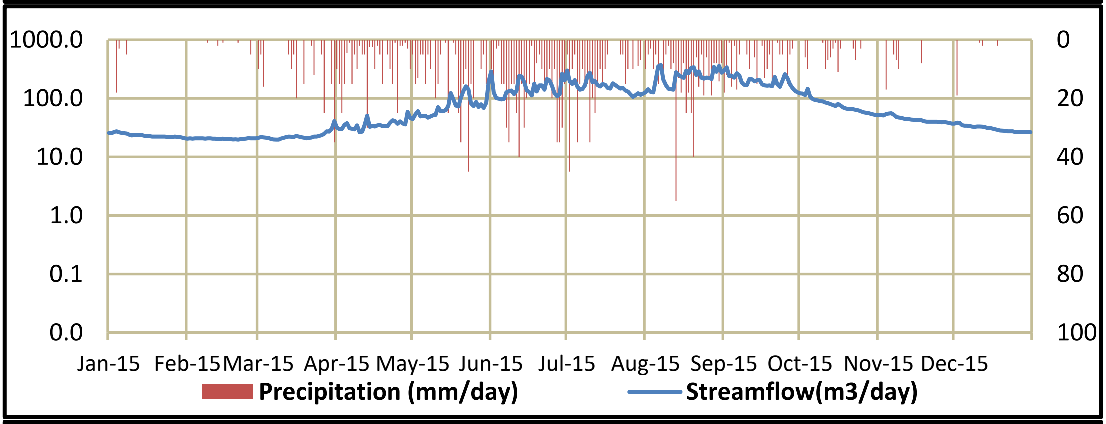
Precipitation (mm/day)
Streamflow(m3/day)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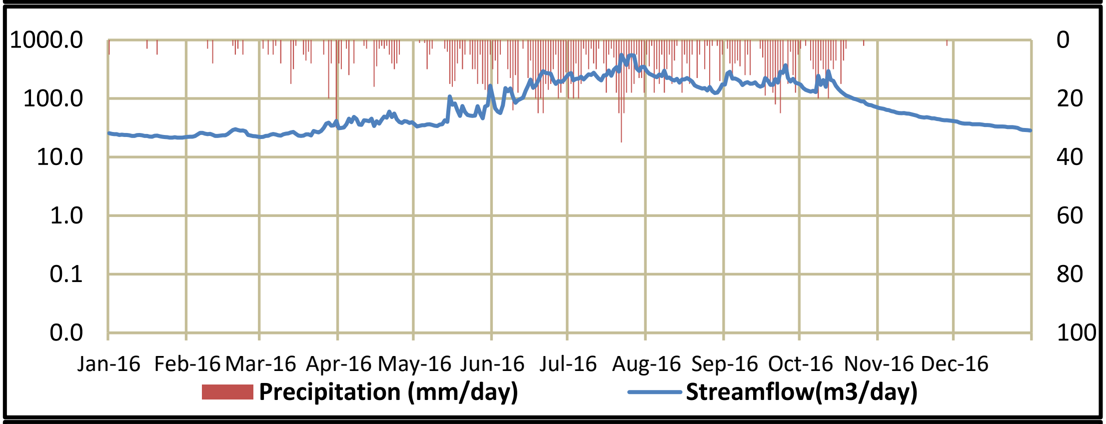
Precipitation (mm/day)
Streamflow(m3/day)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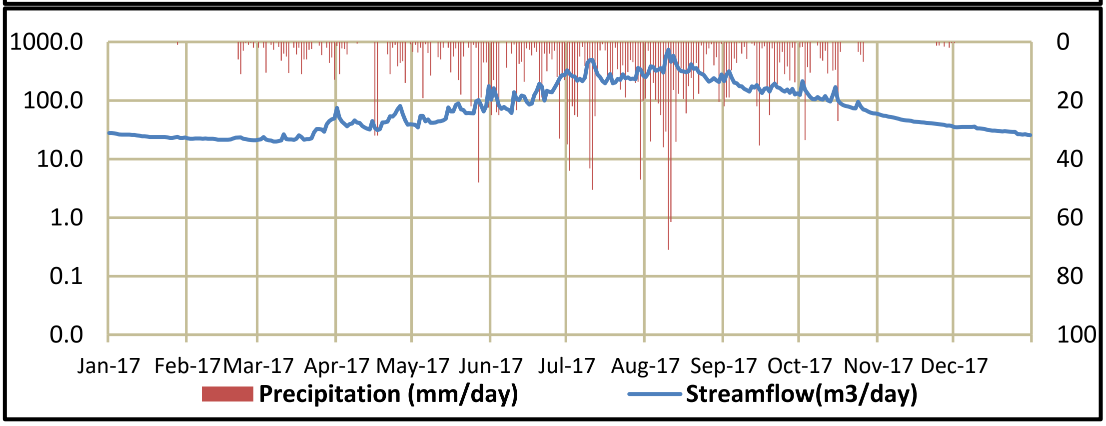
Precipitation (mm/day)
Streamflow(m3/day)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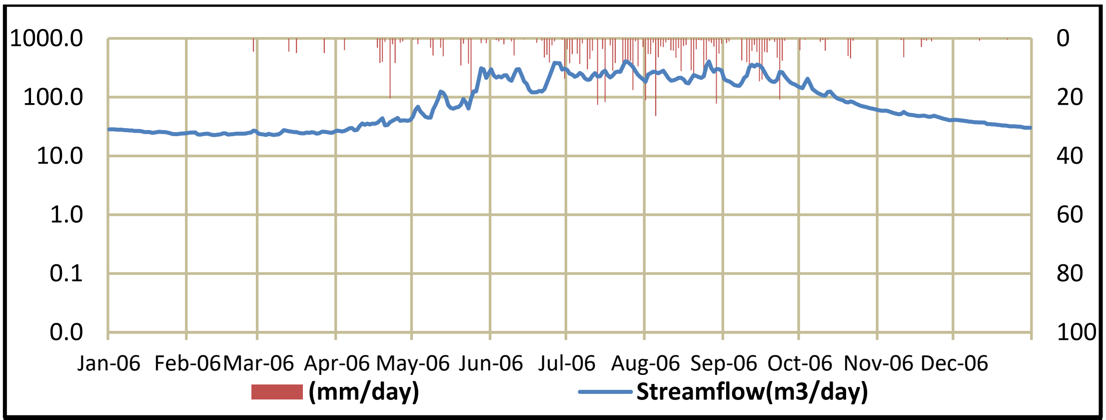
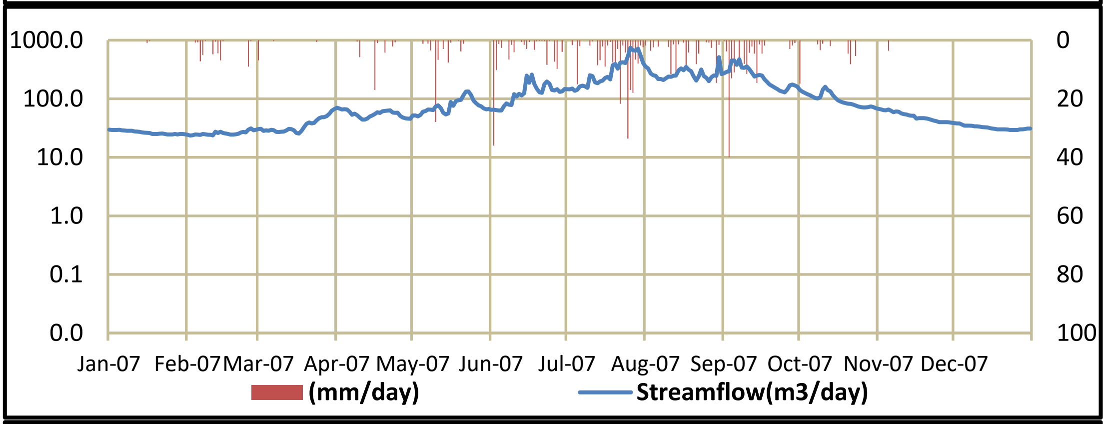
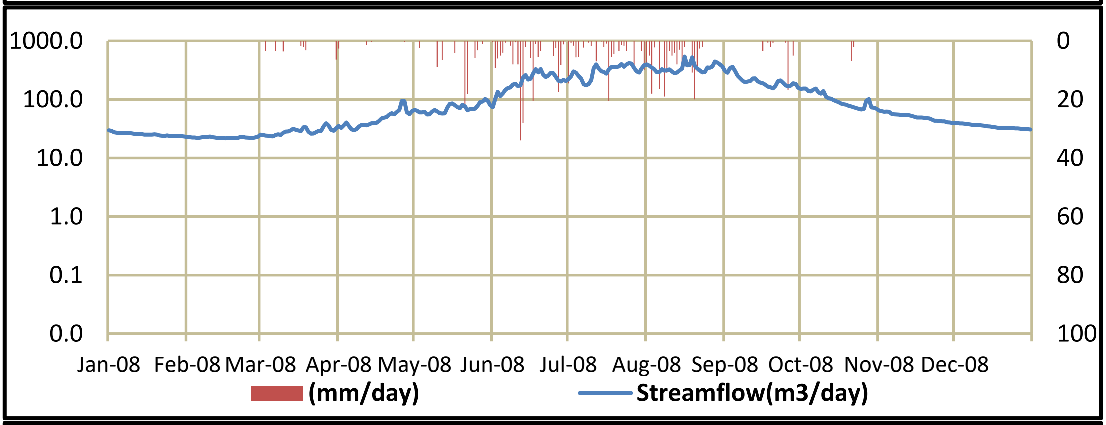
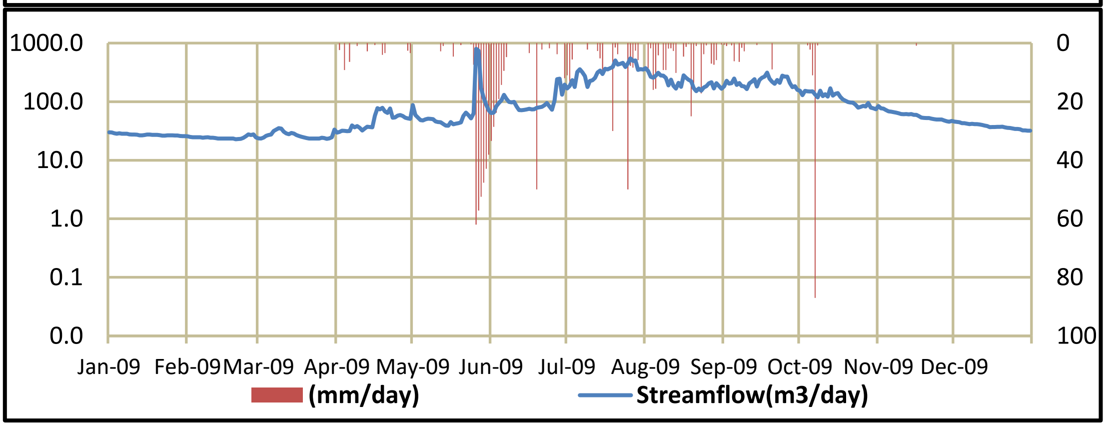
100
Jan-17 Feb-17 Mar-17 Apr-17 May-17 Jun-17 Jul-17 Aug-17 Sep-17 Oct-17 Nov-17 Dec-17
Precipitation (mm/day)
Streamflow(m3/day)

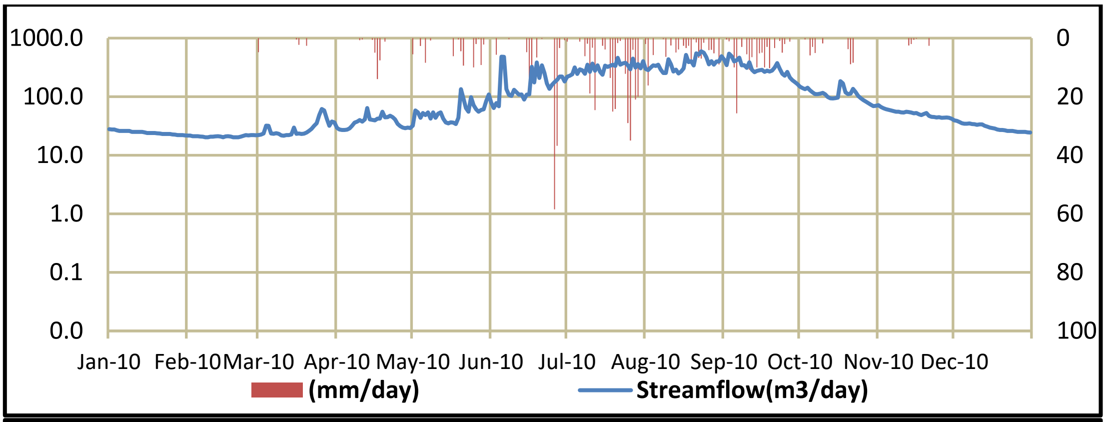
Streamflow vs precipitation for Mo chhu basin for Yebesa and Punakha







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40
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80
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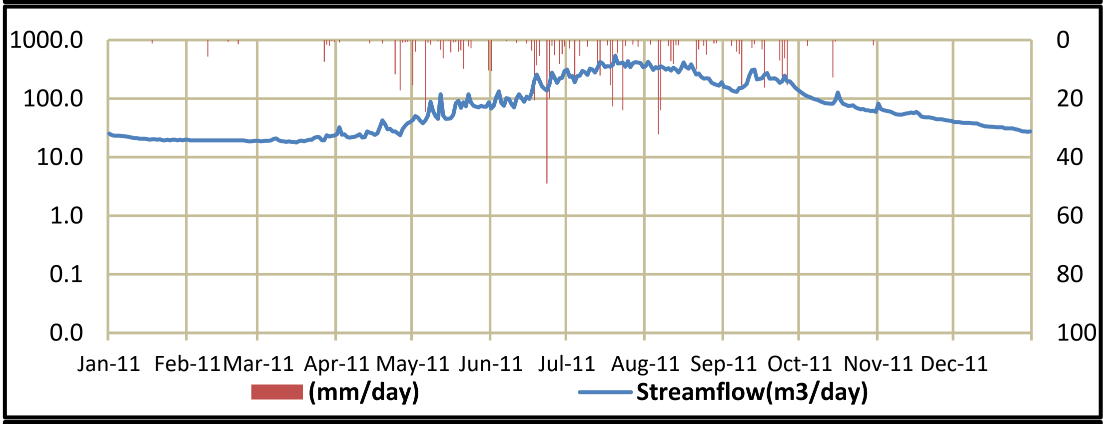
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
(mm/day)
Streamflow(m3/day)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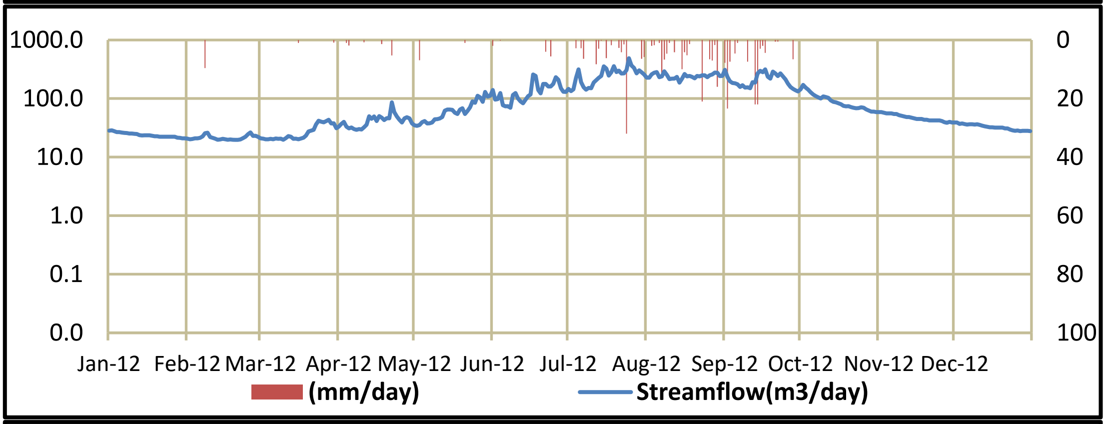
(mm/day)
Streamflow(m3/day)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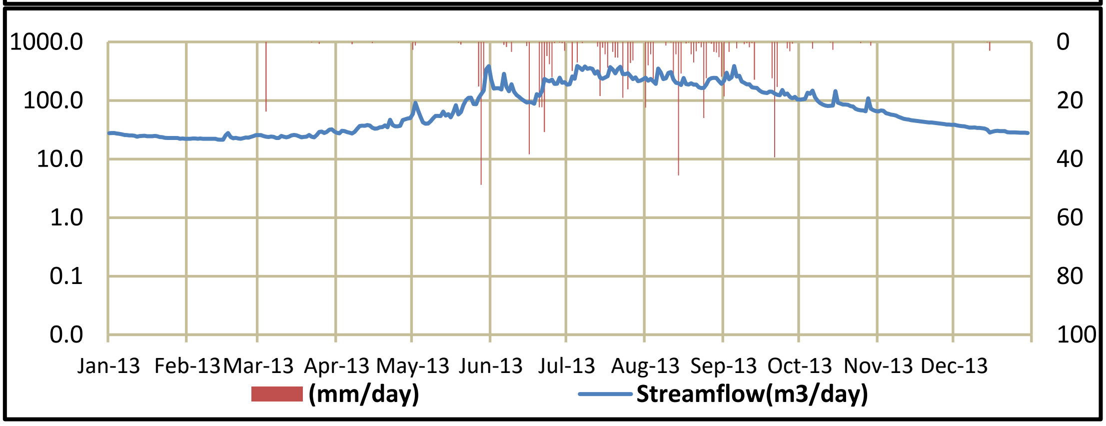
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
(mm/day)
Streamflow(m3/day)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40
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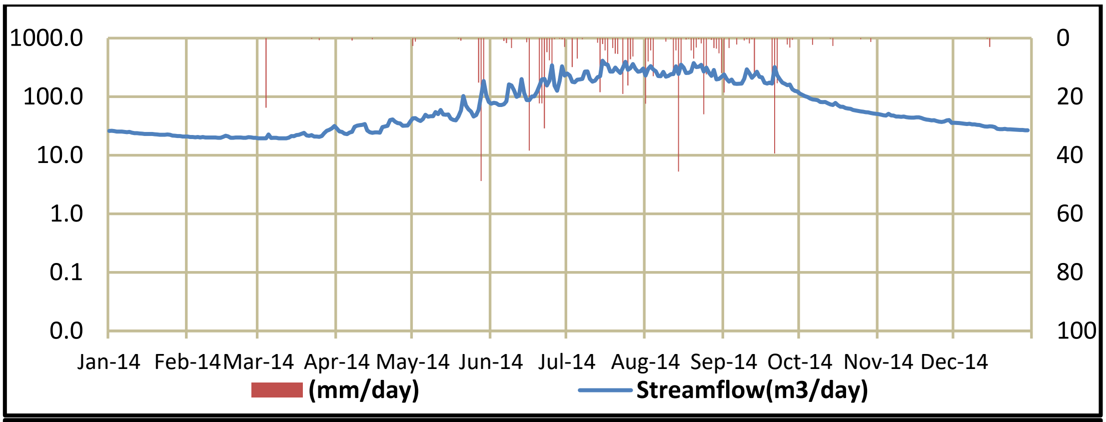
80
100
Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13
(mm/day)
Streamflow(m3/day)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0
20
40
60
80
100
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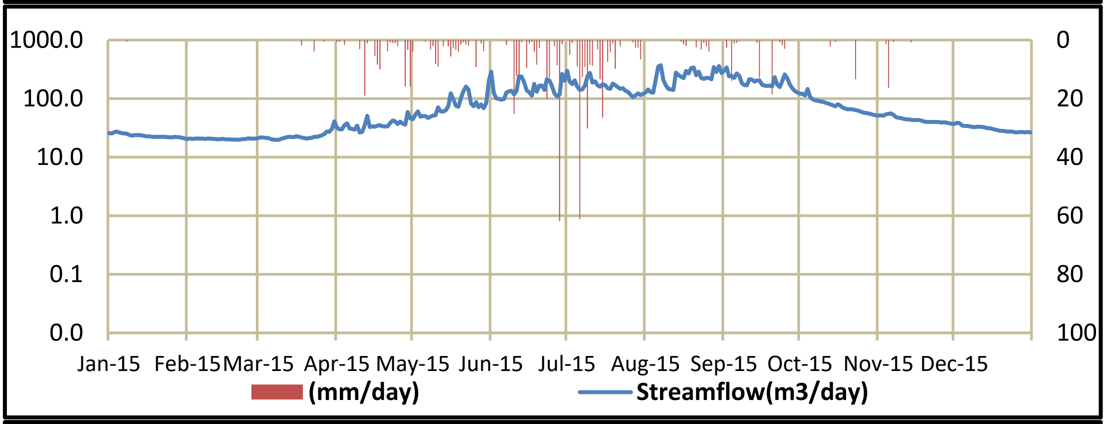
(mm/day)
Streamflow(m3/day)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40
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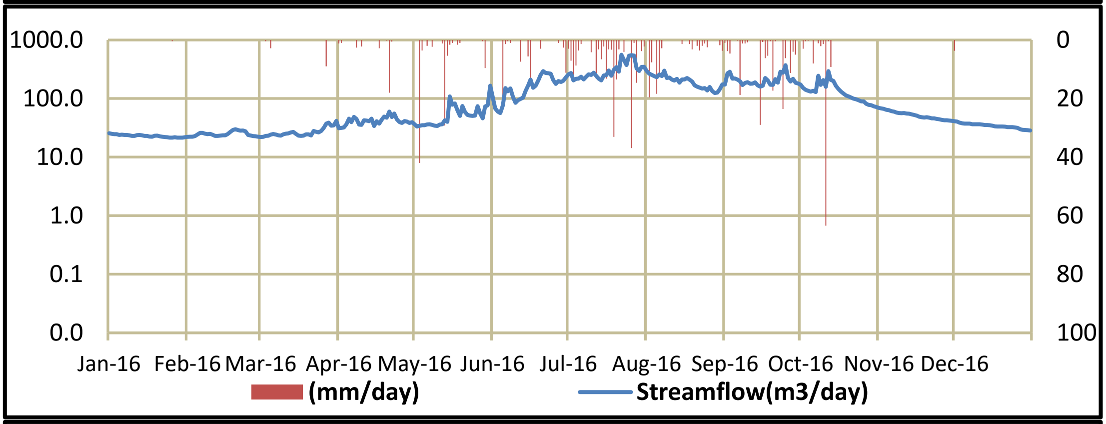
100
Jan-15 Feb-15 Mar-15 Apr-15 May-15 Jun-15 Jul-15 Aug-15 Sep-15 Oct-15 Nov-15 Dec-15
(mm/day)
Streamflow(m3/day)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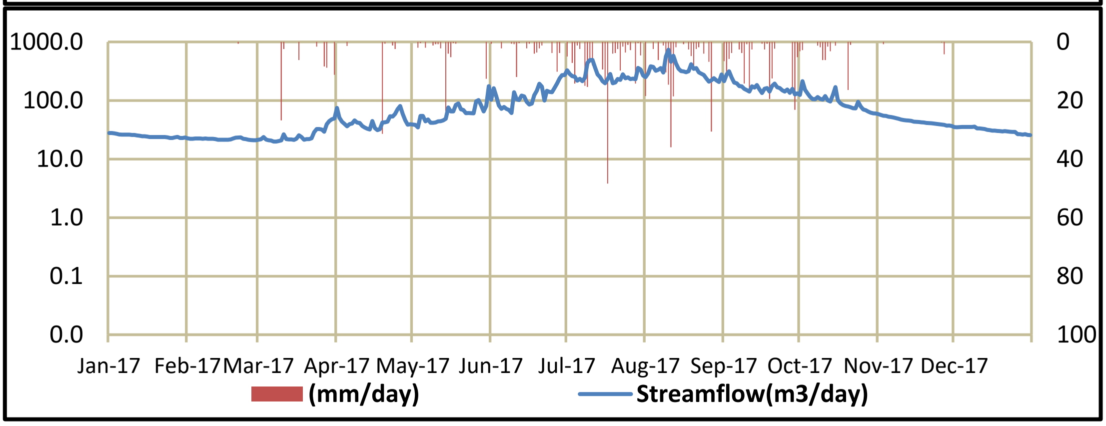
0
20
40
60
80
100
Jan-16 Feb-16 Mar-16 Apr-16 May-16 Jun-16 Jul-16 Aug-16 Sep-16 Oct-16 Nov-16 Dec-16
(mm/day)
Streamflow(m3/day)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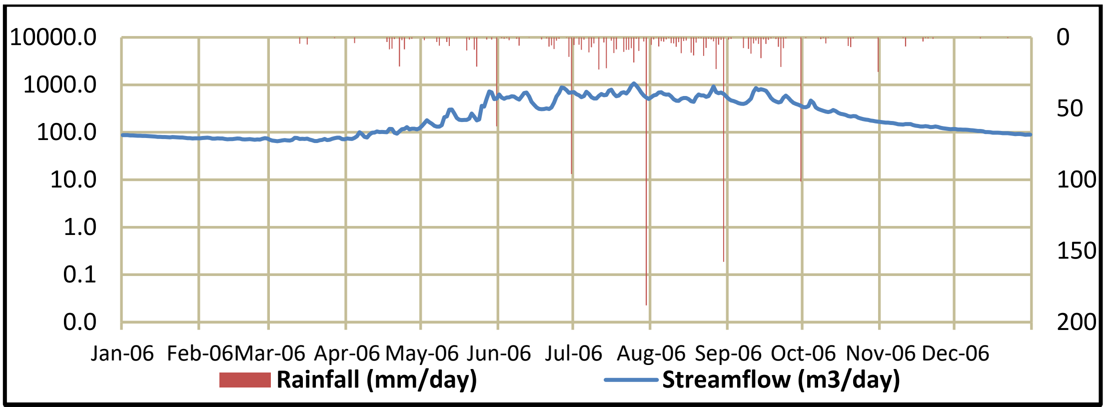
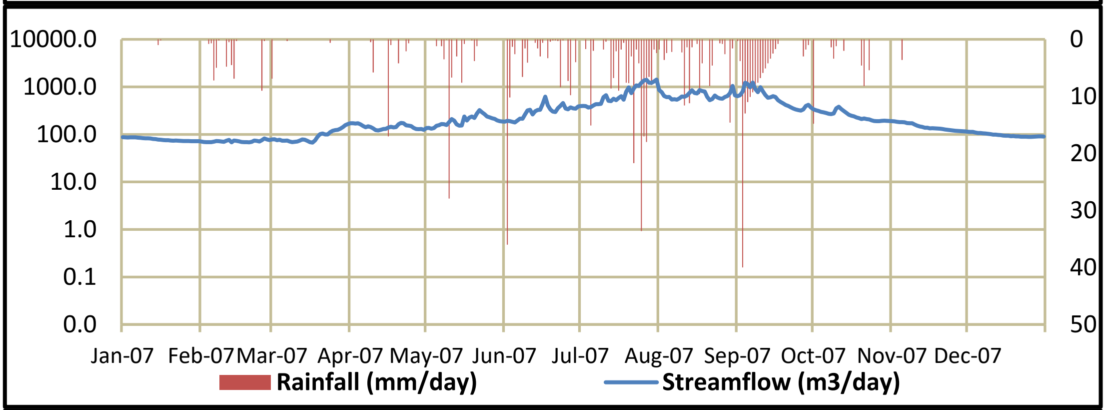
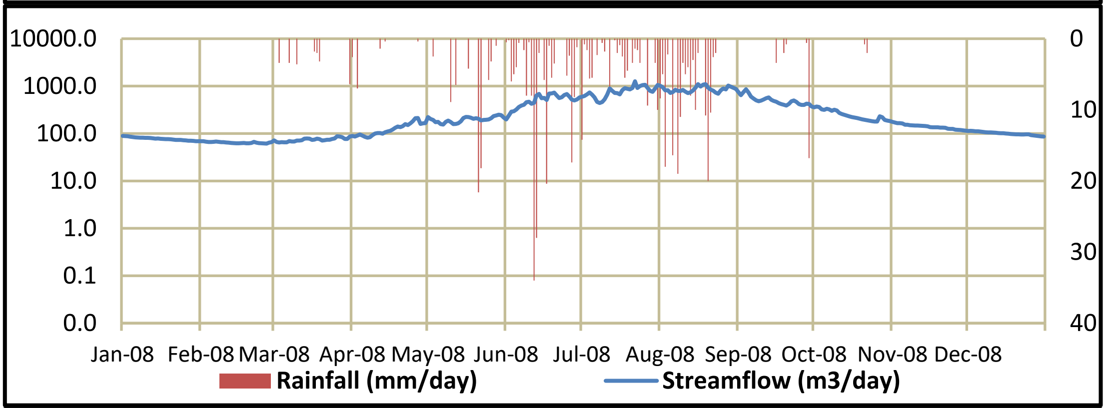
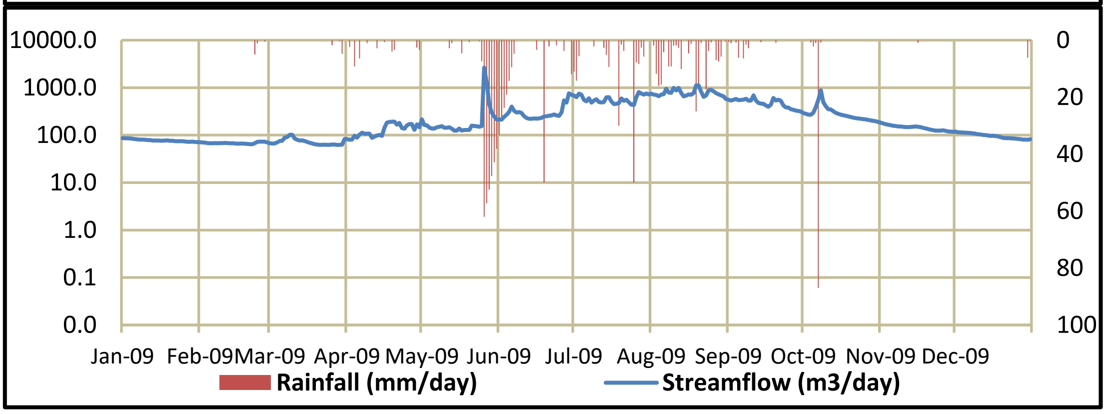
0
20
40
60
80
100
Jan-17 Feb-17 Mar-17 Apr-17 May-17 Jun-17 Jul-17 Aug-17 Sep-17 Oct-17 Nov-17 Dec-17
(mm/day)
Streamflow(m3/day)

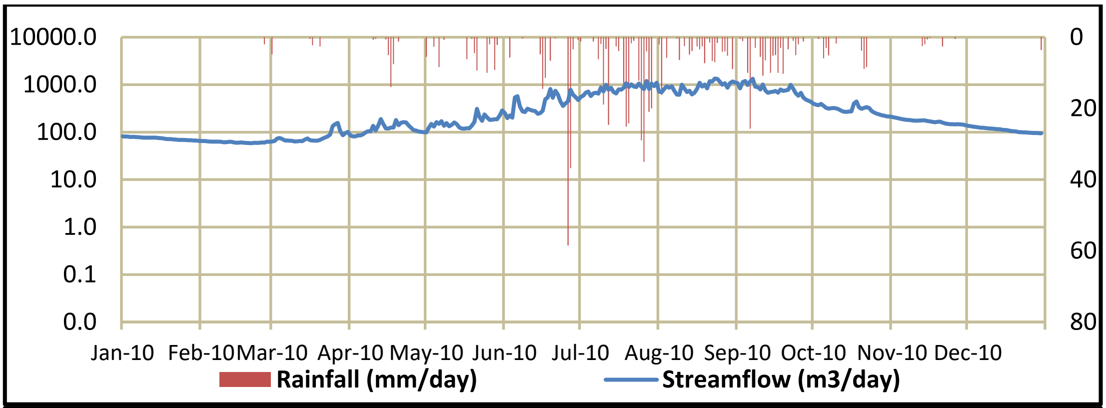
Streamflow vs Rainfall for Wangdi Rapid and Punakha







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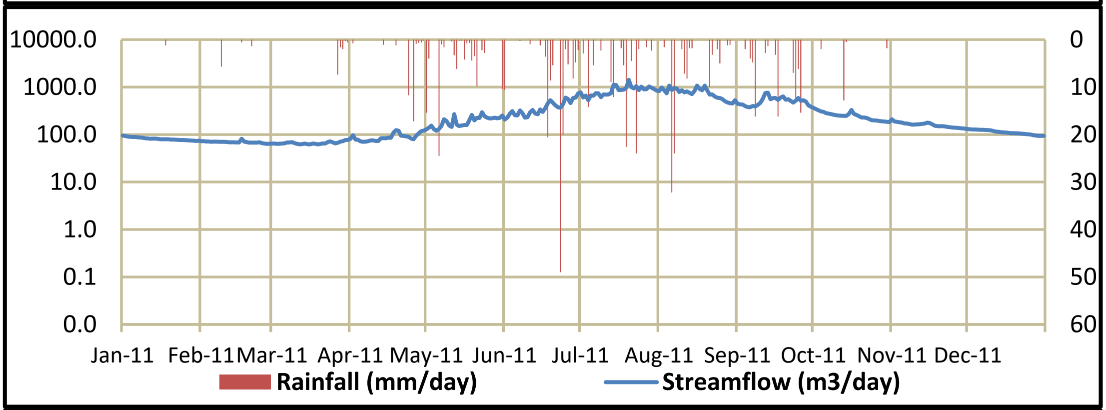
20
40
60
80
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Rainfall (mm/day)
Streamflow (m3/day)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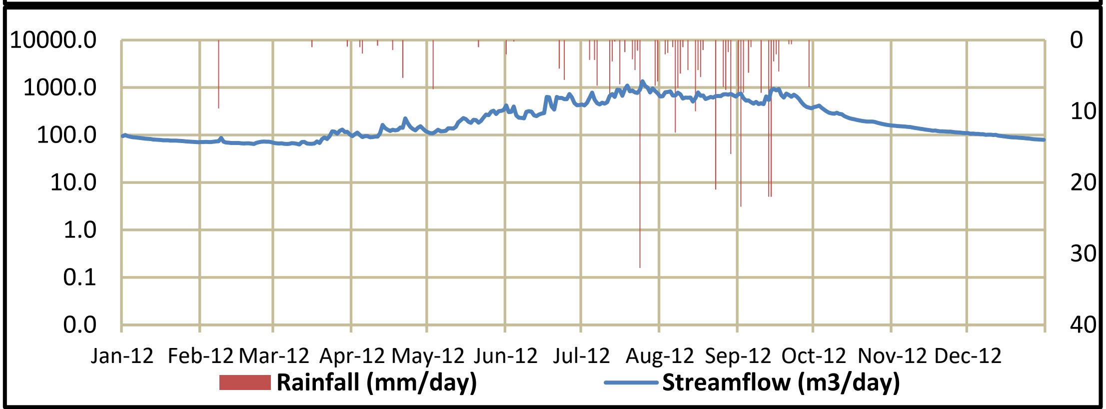
10
20
30
40
50
60
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Rainfall (mm/day)
Streamflow (m3/day)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20
30
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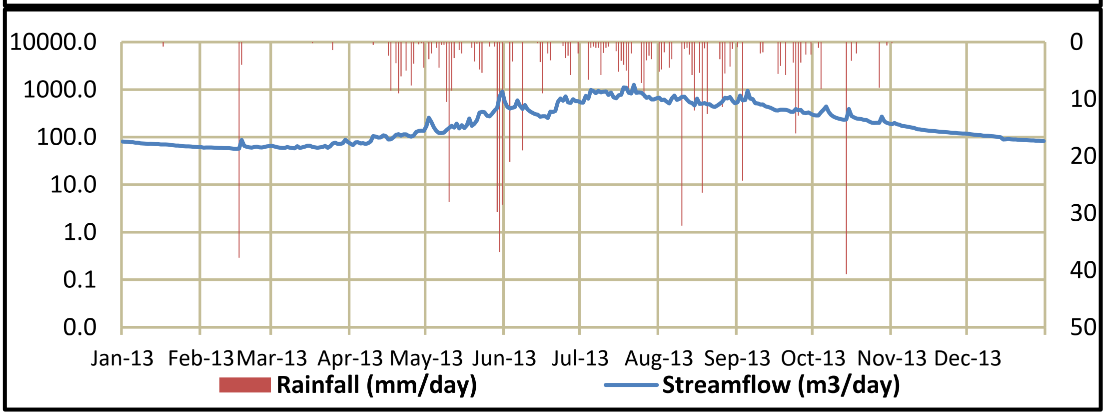
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
Rainfall (mm/day)
Streamflow (m3/day)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30
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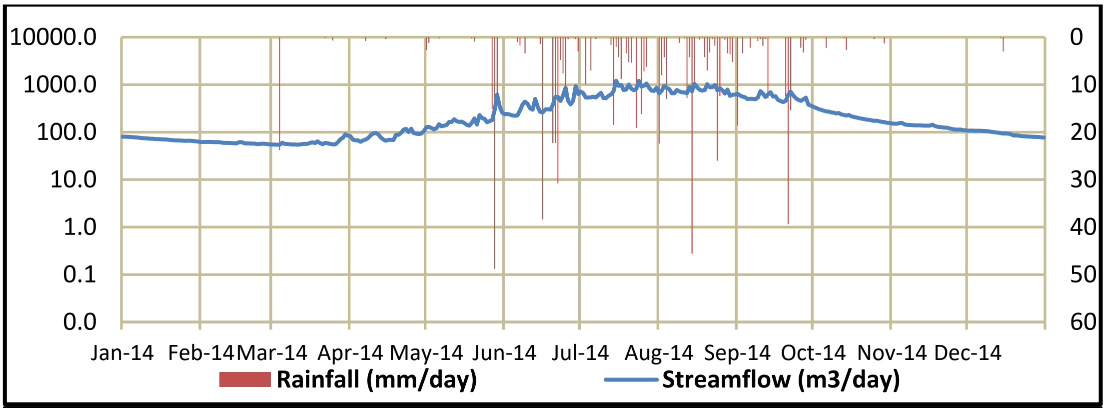
Rainfall (mm/day)
Streamflow (m3/day)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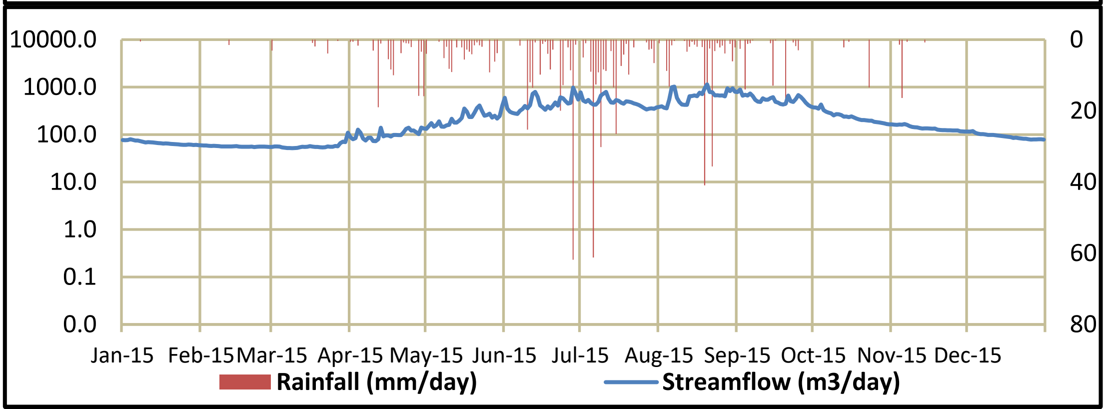
Rainfall (mm/day)
Streamflow (m3/day)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60
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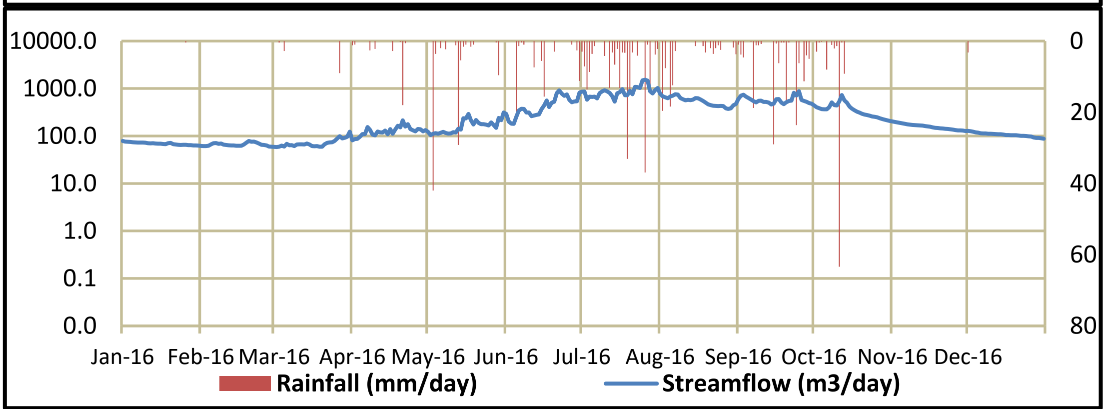
Rainfall (mm/day)
Streamflow (m3/day)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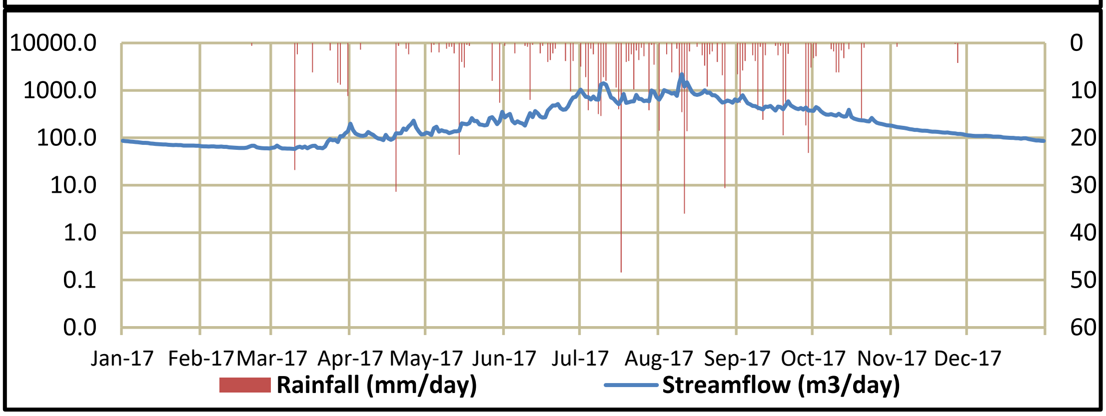
20
40
60
80
Jan-16 Feb-16 Mar-16 Apr-16 May-16 Jun-16 Jul-16 Aug-16 Sep-16 Oct-16 Nov-16 Dec-16
Rainfall (mm/day)
Streamflow (m3/day)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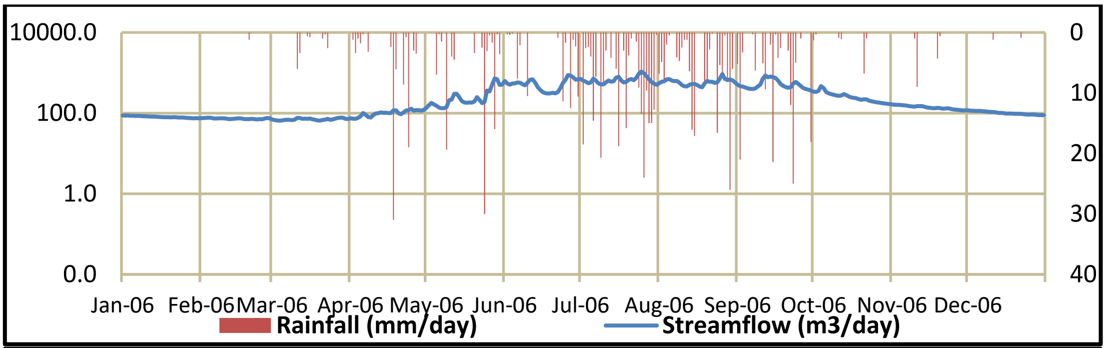
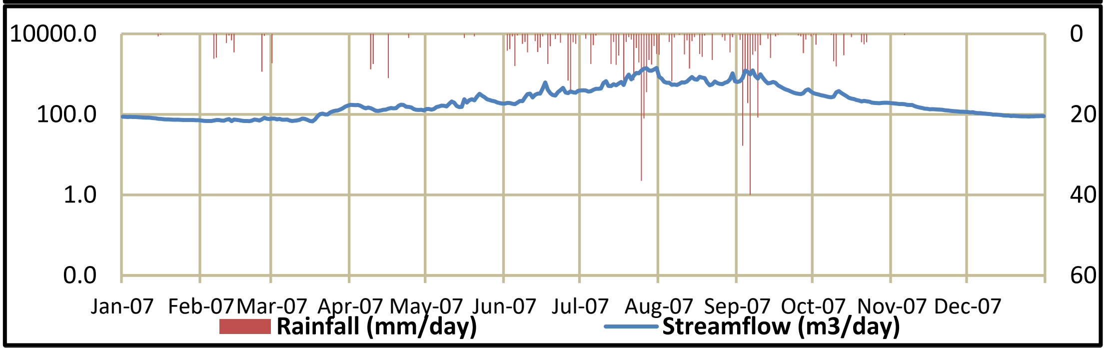
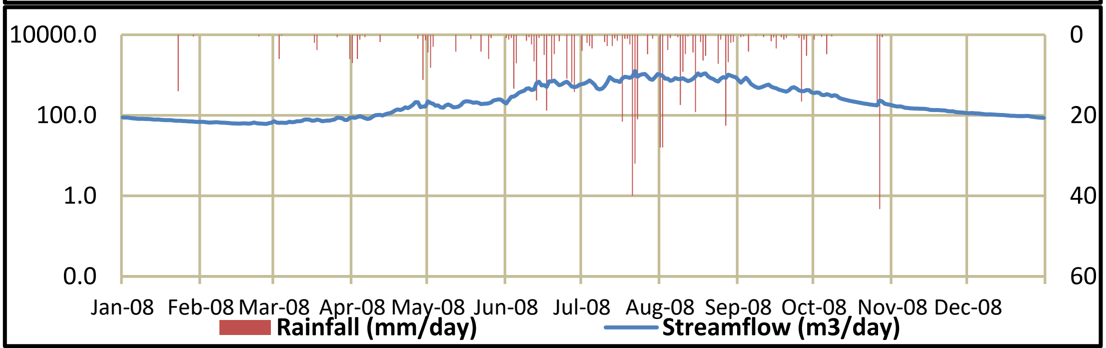
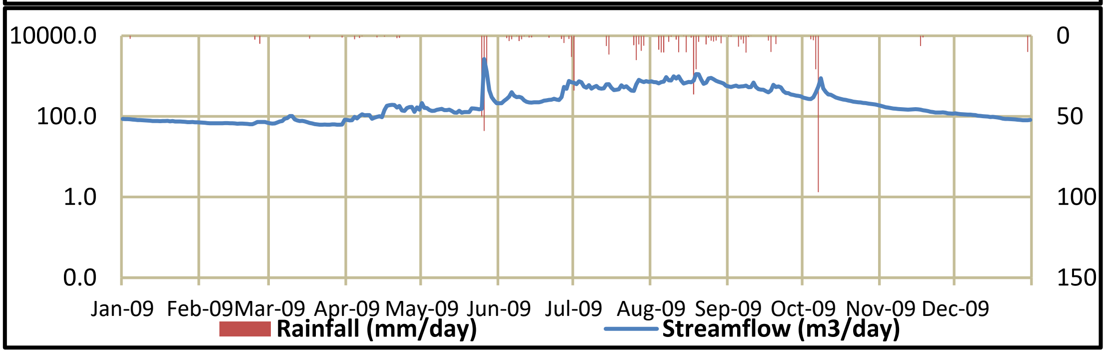
20
30
40
50
60
Jan-17 Feb-17 Mar-17 Apr-17 May-17 Jun-17 Jul-17 Aug-17 Sep-17 Oct-17 Nov-17 Dec-17
Rainfall (mm/day)
Streamflow (m3/day)

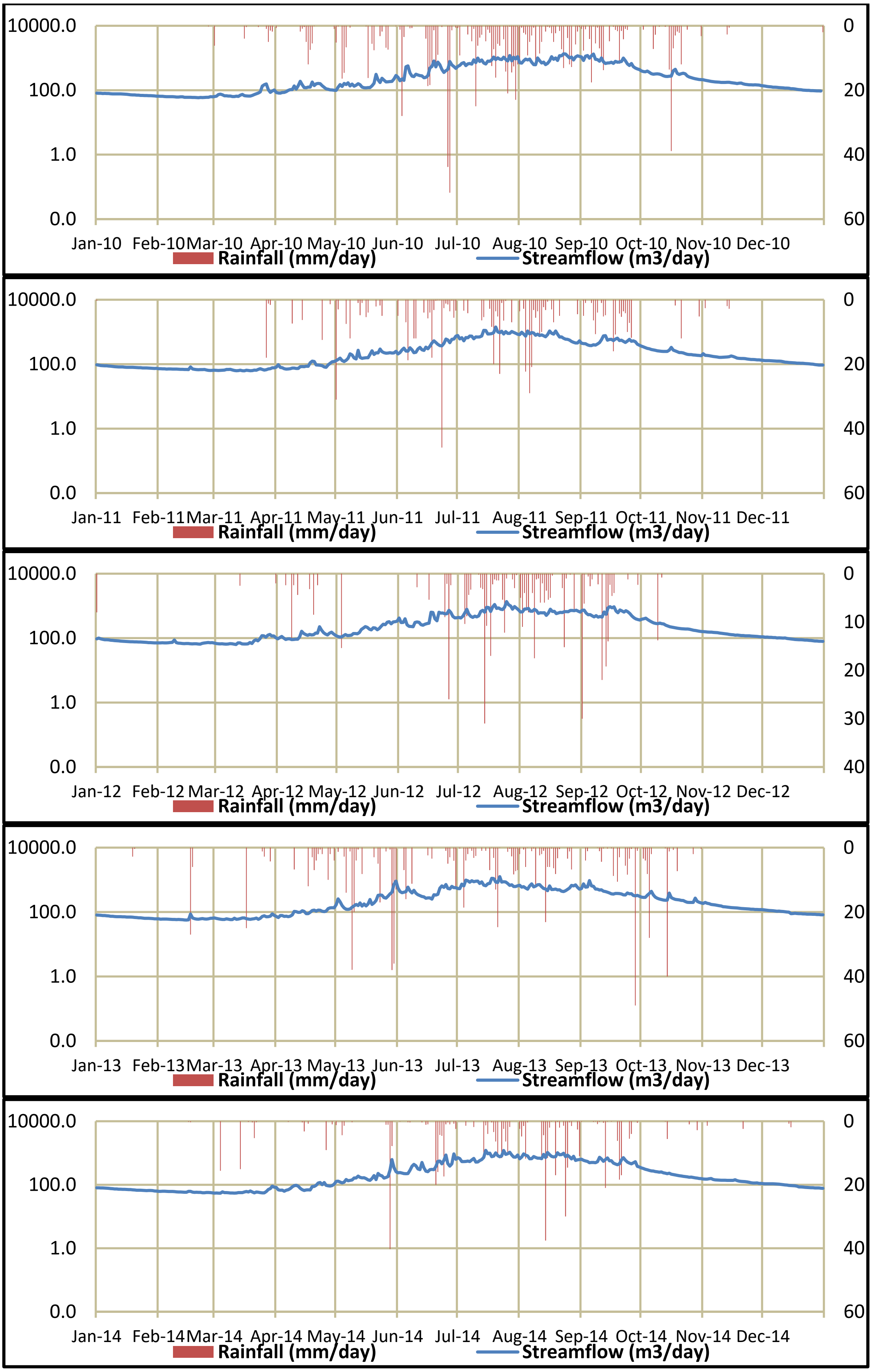
Streamflow vs Rainfall for Wangdi Rapid and Bajo







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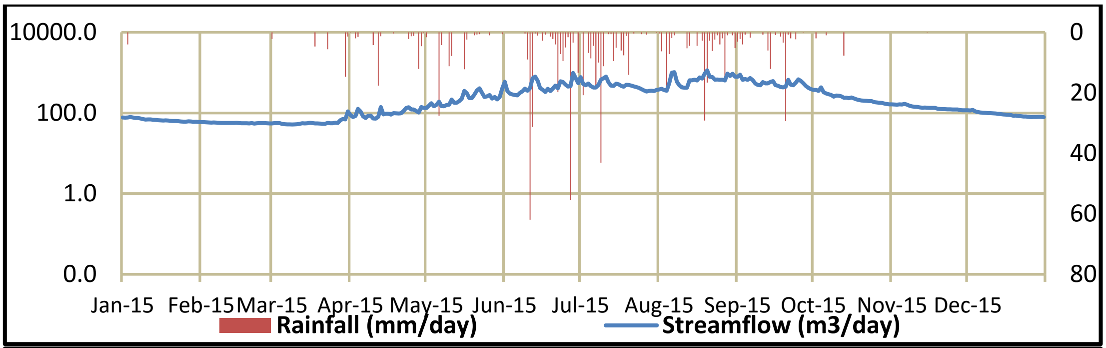
1.0
0.0
0
20
40
60
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
10
20
30
40
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
Jan-14 Feb-14 Mar-14 Apr-14 May-14 Jun-14 Jul-14 Aug-14 Sep-14 Oct-14 Nov-14 Dec-14
Rainfall (mm/day)
Streamflow (m3/day)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60
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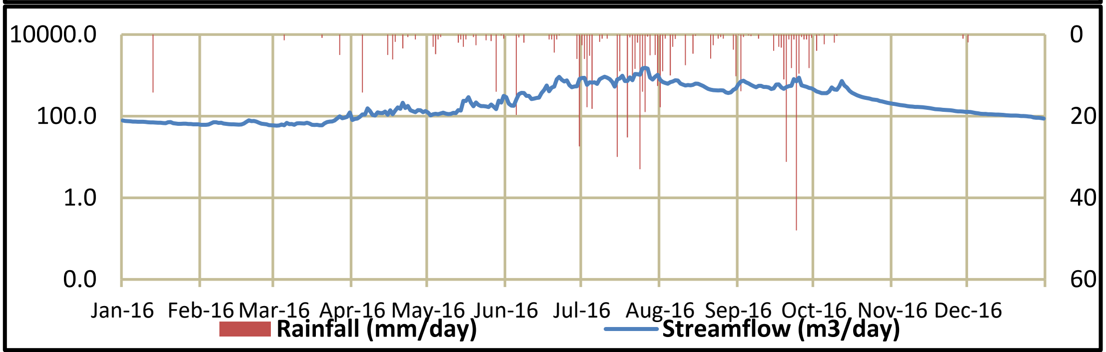
Jan-15 Feb-15 Mar-15 Apr-15 May-15 Jun-15 Jul-15 Aug-15 Sep-15 Oct-15 Nov-15 Dec-15
Rainfall (mm/day)
Streamflow (m3/day)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60
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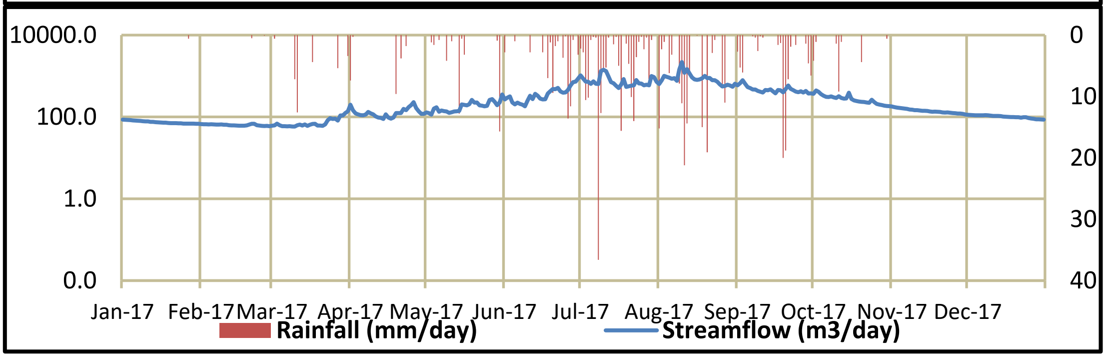
Rainfall (mm/day)
Streamflow (m3/day)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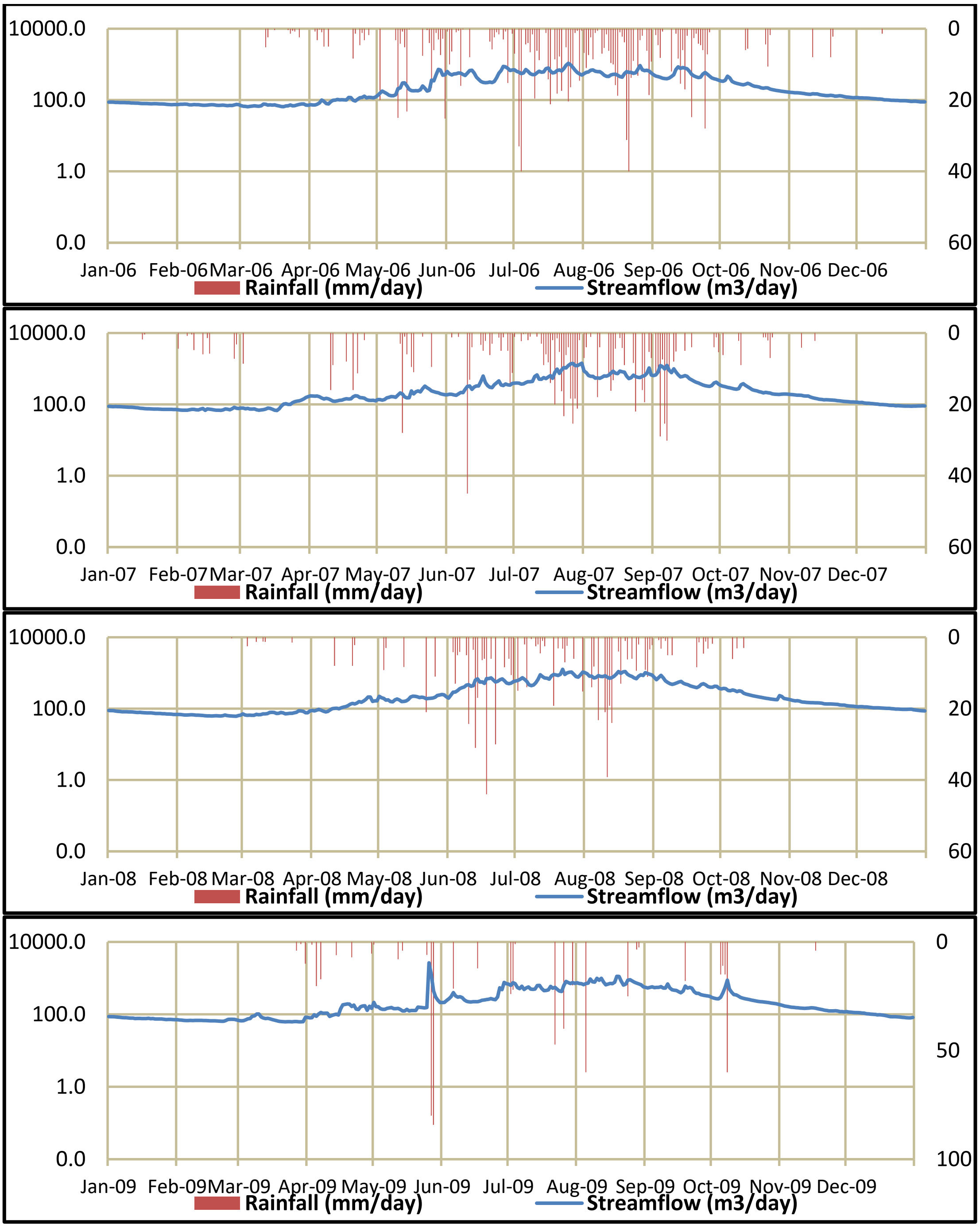
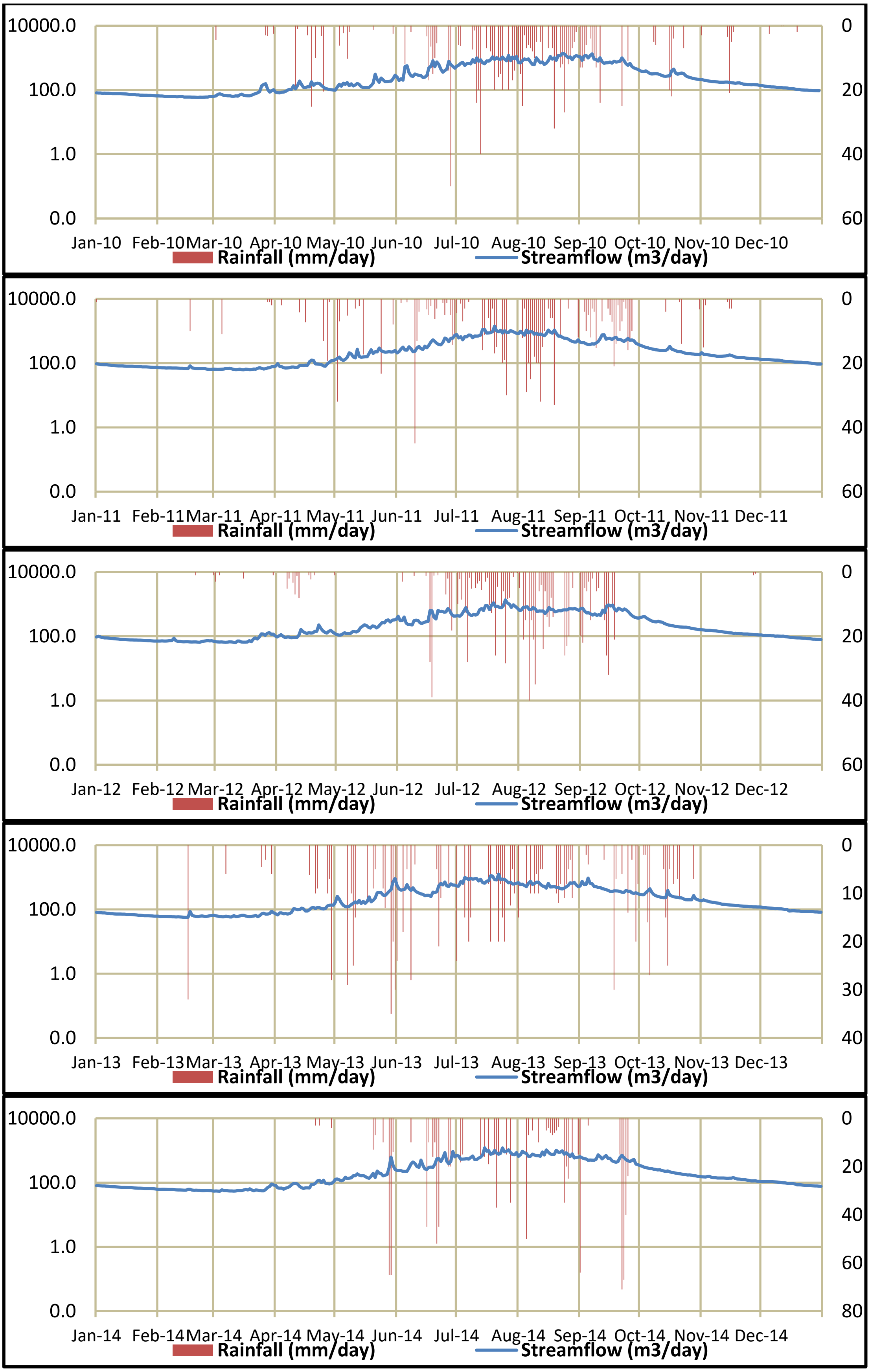
20
30
40
Jan-17 Feb-17 Mar-17 Apr-17 May-17 Jun-17 Jul-17 Aug-17 Sep-17 Oct-17 Nov-17 Dec-17
Rainfall (mm/day)
Streamflow (m3/day)

Streamflow vs Rainfall for Wangdi Rapid and Samtengang

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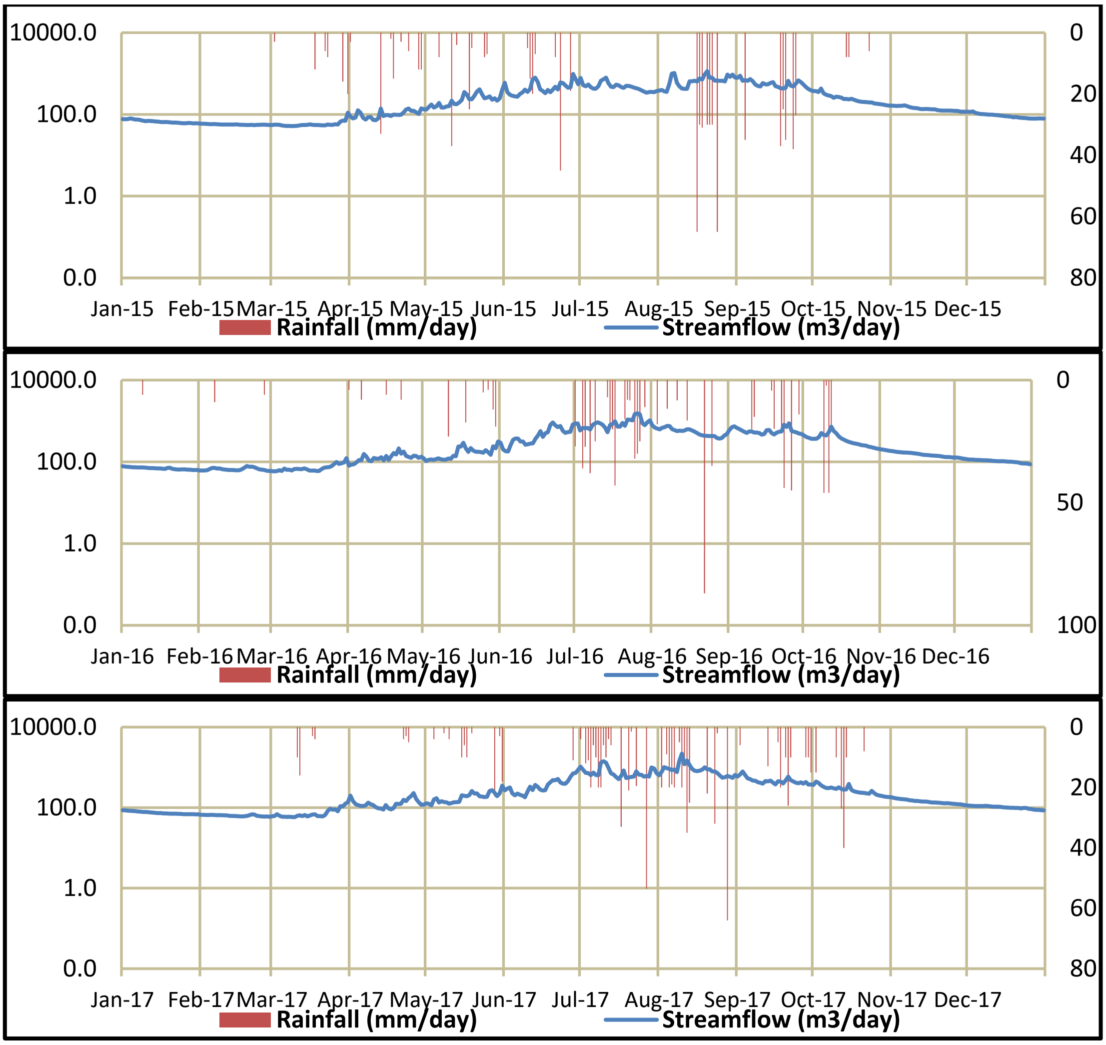
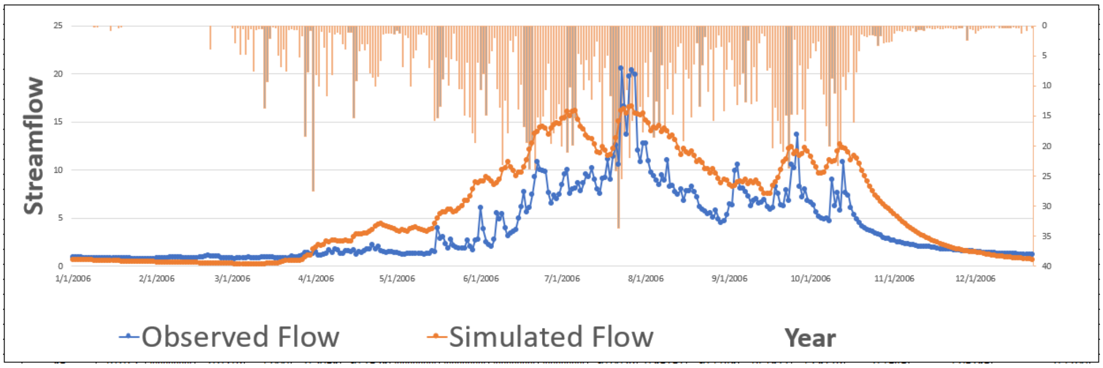
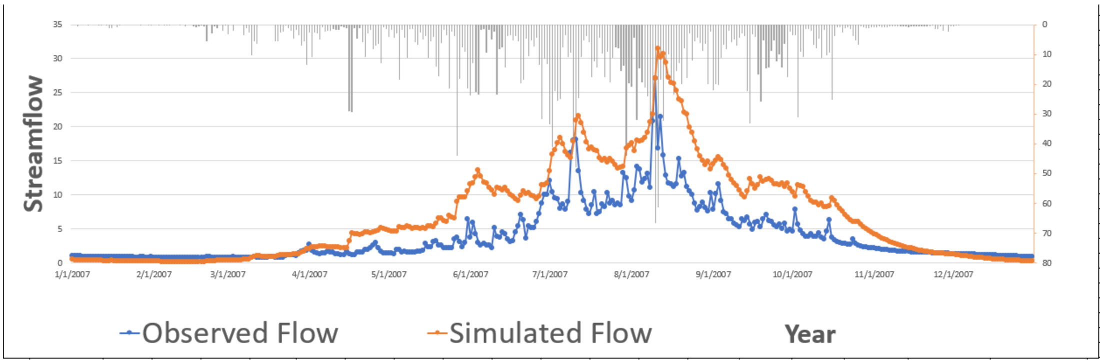
100.0
1.0
0.0
0
20
40
60
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
10
20
30
40
Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
80
Jan-14 Feb-14 Mar-14 Apr-14 May-14 Jun-14 Jul-14 Aug-14 Sep-14 Oct-14 Nov-14 Dec-14
Rainfall (mm/day)
Streamflow (m3/day)

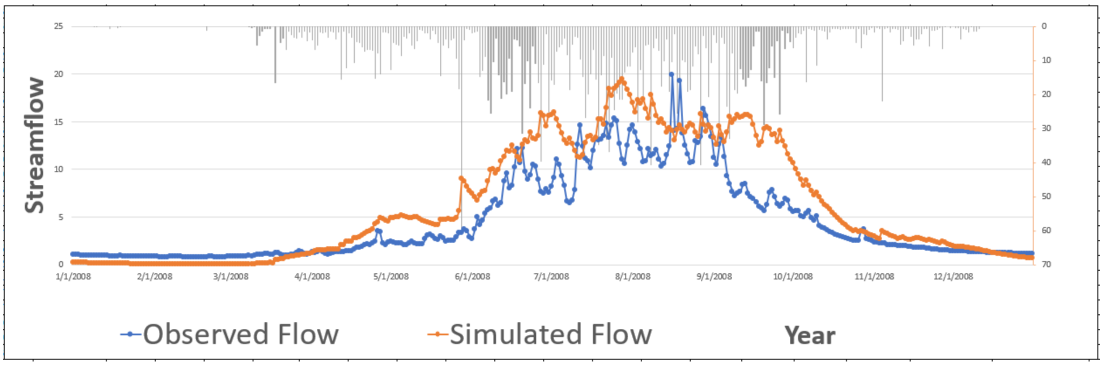

10000.0
100.0
1.0
0.0
0
20
40
60
80
Jan-15 Feb-15 Mar-15 Apr-15 May-15 Jun-15 Jul-15 Aug-15 Sep-15 Oct-15 Nov-15 Dec-15
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
50
100
Jan-16 Feb-16 Mar-16 Apr-16 May-16 Jun-16 Jul-16 Aug-16 Sep-16 Oct-16 Nov-16 Dec-16
Rainfall (mm/day)
Streamflow (m3/day)
10000.0
100.0
1.0
0.0
0
20
40
60
80
Jan-17 Feb-17 Mar-17 Apr-17 May-17 Jun-17 Jul-17 Aug-17 Sep-17 Oct-17 Nov-17 Dec-17
Rainfall (mm/day)
Streamflow (m3/day)

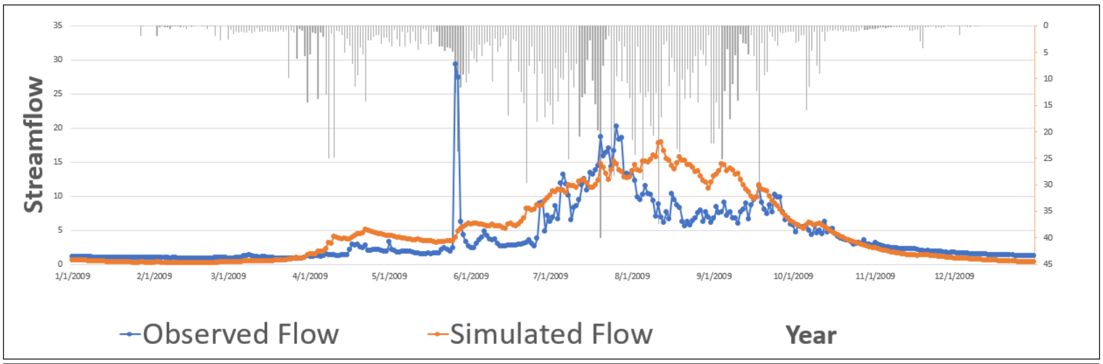
APPENDIX B: Results of Model Runs

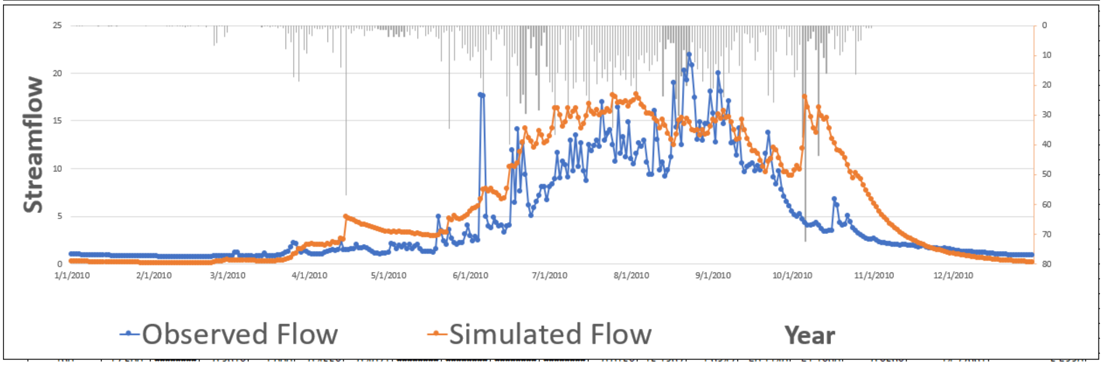
Calibraton results for abcd model with snow on yearly basis

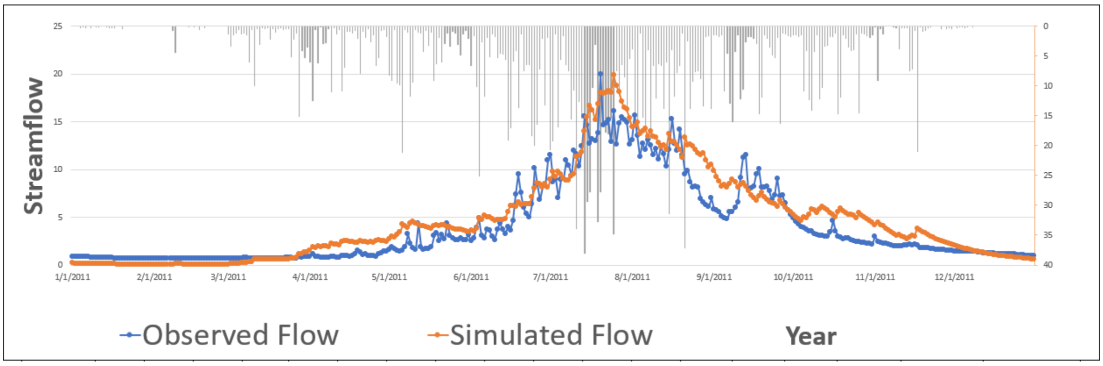


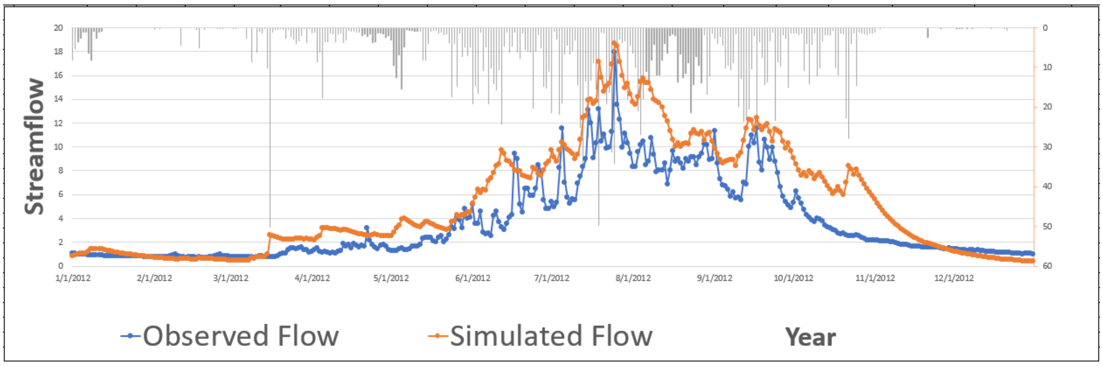




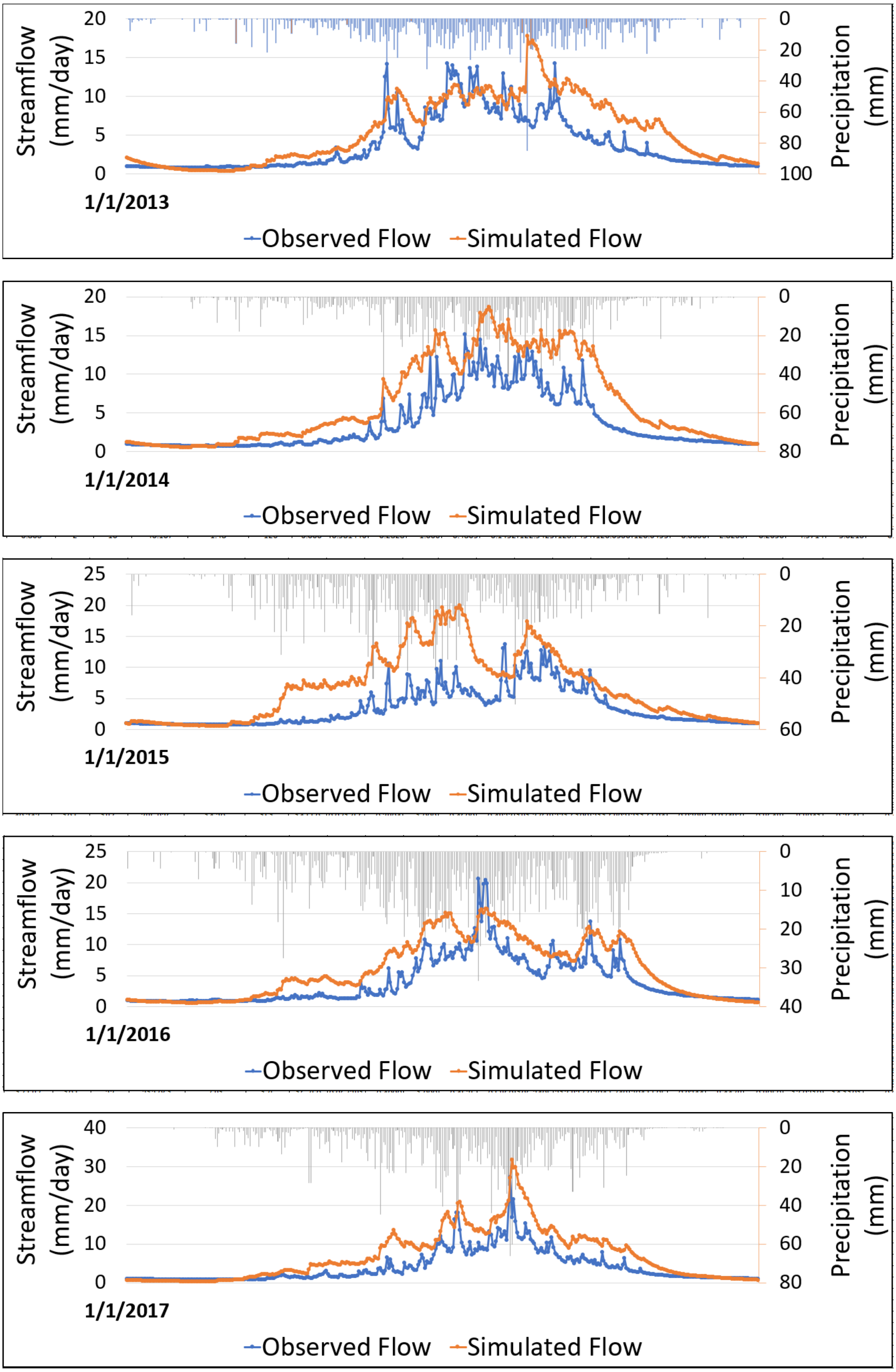

Streamflow
1/1/2009
2/1/2009
3/1/2009
4/1/2009
5/1/2009
6/1/2009
7/1/2009
8/1/2009
9/1/2009
10/1/2009
11/1/2009
12/1/2009
Observed Flow
Simulated Flow
Year


Streamflow
1/1/2010
2/1/2010
3/1/2010
4/1/2010
5/1/2010
6/1/2010
7/1/2010
8/1/2010
9/1/2010
10/1/2010
11/1/2010
12/1/2010
Observed Flow
Simulated Flow
Year

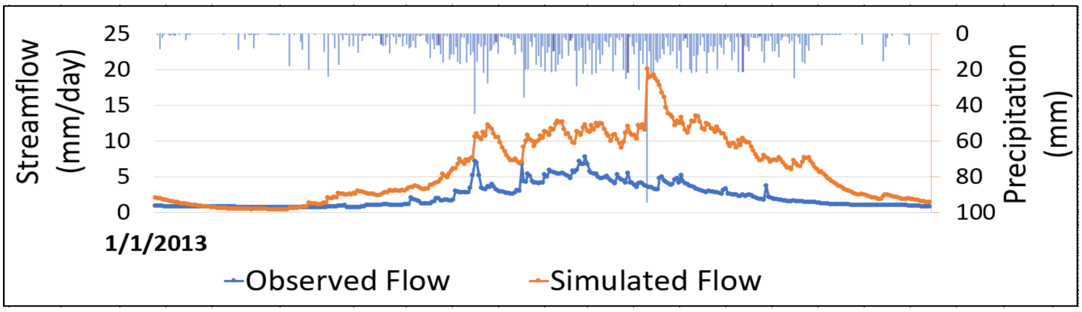

Streamflow
1/1/2011
2/1/2011
3/1/2011
4/1/2011
5/1/2011
6/1/2011
7/1/2011
8/1/2011
9/1/2011
10/1/2011
11/1/2011
12/1/2011
Observed Flow
Simulated Flow
Year

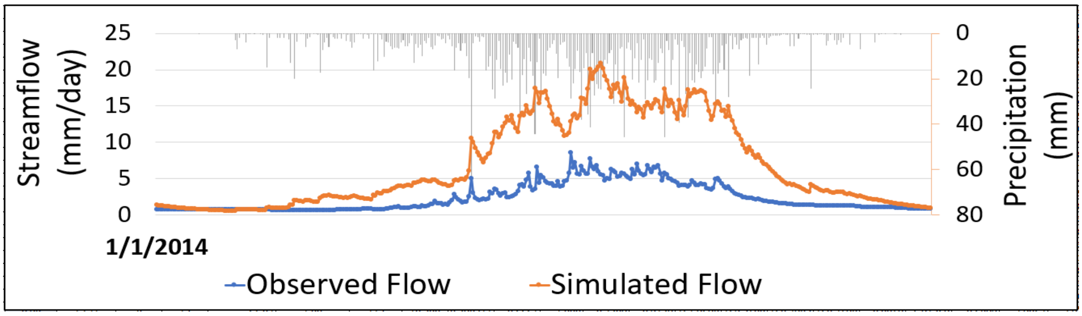

Streamflow
1/1/2012
2/1/2012
3/1/2012
4/1/2012
5/1/2012
6/1/2012
7/1/2012
8/1/2012
9/1/2012
10/1/2012
11/1/2012
12/1/2012
Observed Flow
Simulated Flow
Year

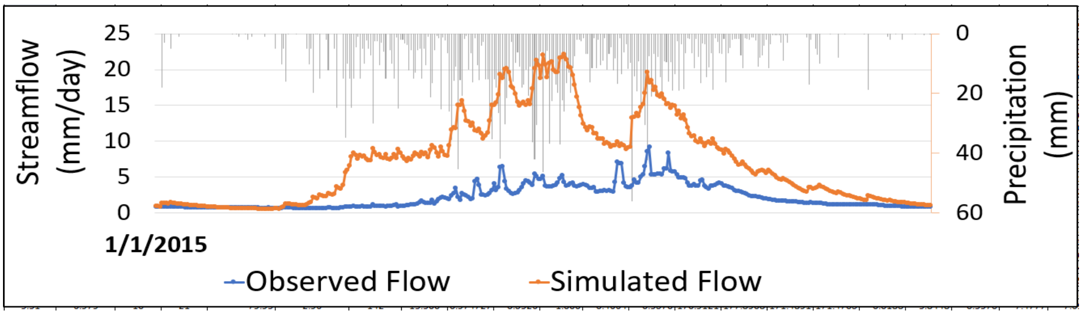
Validation results for abcd model with snow on yearly basis for Mo chhu

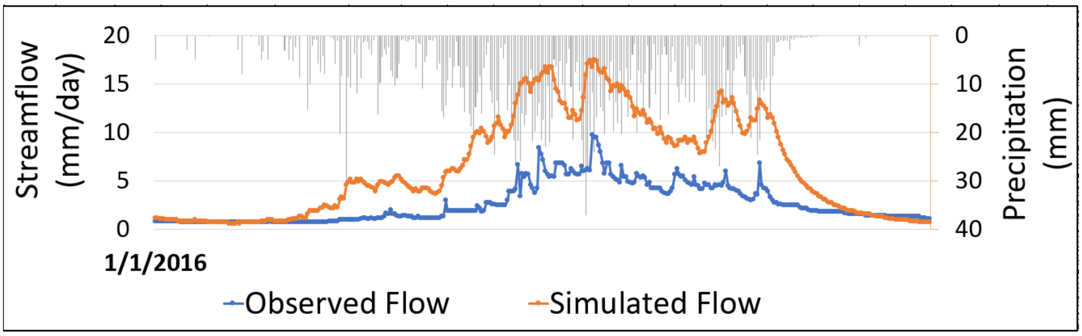


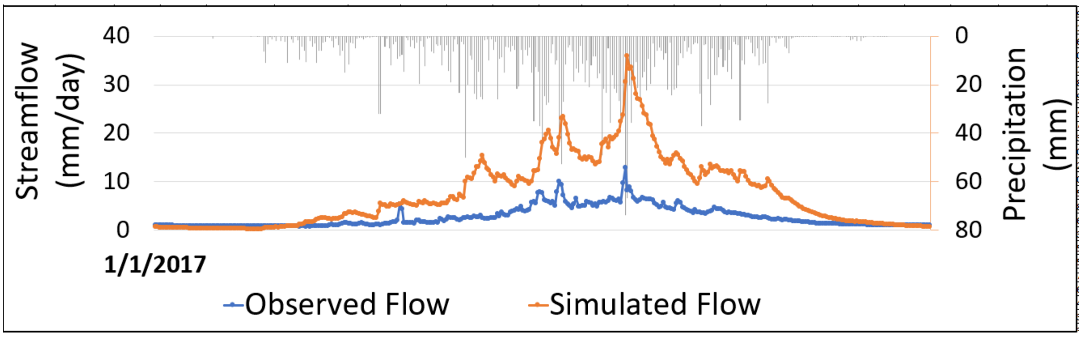
Validation results for abcd model with snow for Pho chhu











The findings, interpretations and conclusions expressed in this thesis/dissertation are entirely based on the results of the individual research study and should not be attributed in any manner to or do neither necessarily reflect the views of UNESCO Madanjeet Singh Centre for South Asia Water Management (UMCSAWM), nor of the individual members of the MSc panel, nor of their respective organizations.