Development of Daily, Monthly, Inter-annual, and Mean Annual Hydrological Models Based on a Unified Runoff Generation Framework

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DEVELOPMENT OF DAILY, MONTHLY, INTER-ANNUAL, AND MEAN ANNUAL HYDROLOGICAL MODELS BASED ON A UNIFIED RUNOFF GENERATION FRAMEWORK

by

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ABSTRACT

The main goal of this dissertation develops a unified model structure for runoff generation based on observations from a large number of catchments. Furthermore, obtaining a comprehensive understanding of the physical controlling factors that control daily, monthly, and annual water balance models. Meanwhile, applying the developed Unified model on different climate conditions, and comparing it with different well-known models.

The proposed model was compared with a similar timescale model (HyMOD, and abcd) and applied on 92 catchments from MOPEX dataset across the United States. The HyMOD and abcd are a well-known daily and monthly hydrological model used on a variety of researchers. The differences between the new model and HyMOD, and abcd include 1) the distribution function for soil water storage capacity is different and the new distribution function leads to the SCS curve number method; and 2) the computation of evaporation is also based on the distribution function considering the spatial variability of available water evaporation.

The performance of all models along with parameters used is examined to understand the controlling factors. The generated results were calibrated and validated using the Nash-Sutcliffe efficiency coefficient (NSE), indicating that the Unified model has a moderate better performance against the HyMOD at a daily time scale, and abcd model at a monthly timescale. The proposed model using the SCS-CN method shows the effect of improving the performance.

I dedicate this dissertation to my wife, Ashjan Bakhsh. We got married not long time ago. She was always the ease in hardship, the calm in a stormy day, and the support in stressful moments. I do not think of someone else to dedicate this work to but only her, because she is worth it and deserves better.

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CHAPTER 1 INTRODUCTION

The Hydrologic cycle is one of the most important phenomena in the earth environment and it is a fundamental concept in hydrology. The hydrological systems are complex, mainly at a catchment scale, it is controlled by climate (e.g. precipitation, evaporation, potential evaporation) and landscape (e.g. soil topography, vegetation). Those factors vary with time and space, which invokes a numerous type of questions for hydrologists on which they try to answer or understand. Some try to answer it analytically and some try numerical or empirical solutions with help of computer aid represented by models. Models are used as simplified understanding of hydrological processes. We use models due to our limited range of measurements in space and time particularly in ungauged catchments where observations are not available to assess the impact of future change. The complexity of hydrologic models varies with time scale at which the model is applied. For long-term water balance model, precipitation is partitioned into runoff and evaporation, soil moisture storage change is negligible, and runoff routing is not necessary. Hydrologic models at the daily scale need to simulate the processes of runoff generation and routing; and the soil moisture storage change is significant and controlled by the infiltration and evaporation processes. Monthly water balance model, instead is between the daily rainfall-runoff model and mean annual water balance model; and all the three components of hydrologic responses to precipitation, including evaporation, runoff and soil moisture storage change, may be not negligible. This complexity in hydrological problem in time and space with the increasing of demand on water resources throughout the world highlights the importance of improved decision making within a context of fluctuation weather patterns based on time scale.

There is a wide variety of catchments water balance models, as an example, Budyko-type models at the annual scale, the "abcd" model at monthly scale, and the Soil Conservation service (SCS curve number) model at an event scale, are based on different conceptual or physical mechanisms. The Budyko type models of mean annual water balance and interannual variability which are expressed in terms of climatic aridity index, which is defined based on the competition between water and energy availability. At the monthly time scale, the competition between seasonality of water and energy at varying soil water storage. At the event scale, the rainfall is partitioned into surface abstractions and runoff; and evapotranspiration is a less of significant contributor. At an event scale, antecedent wetness is considered as a parameter, however, in nature it is governed by long-time scale over several events, highlighting the linkage through seasonality. The inability to of previous developed water balance models to find a common organizing principle or unifying basis is the independency of current water balance models and finding the linkage to define some of the physical parameters. Therefore, the motivation is to link SCS-CN principle at an event scale with seasonal, interannual, and mean annual scales by finding a commonality and keeping it simple.

1.1 Rainfall-runoff Water Balance Model Using New Soil Moisture Distribution

Since the late 1960s, a widespread of developing hydrological models capable of describing the horizontal movement over the soil was not an easy task. It was found that due to the rapid horizontal movement on the top soil, it was highly challenging to adequately represent this phenomenon with a low number of parameters. The complex black-box concept with a large number of parameters (not less than 20) with no physical controlling factors was dominant. Later on, constrained liner systems (CLD) model [*Natale and Todini,* 1977] and conceptual models were

evaluated by the World Metrological Organization [*WMO,* 1975] and by [*Franchini and Pacciani,* 1991], which showed its incompetence to be significantly better and over parameterized than conceptual models. Therefore, the development of new conceptual models with a better understanding of the importance of the dynamic variation on the saturated zones in a catchment regarding the soil moisture content is highly responsible for the dynamic variation on those areas which contribute directly to direct runoff generation [*Beven et al.,* 1983*; Todini,* 1996]. Based on that concept, the development of new models presented the concept of the probability distribution function of the soil moisture capacity has appeared. The Xinanjiang model [*Zhao,* 1977*; Zhao,* 1992], ARNO [*Todini,* 1996], and Variable Infiltration Capacity (VIC) model (*Wood et al.,* 1992*; Liang et al.,* 1994), or the distribution of the topographic index as in TOPMODEL [*Beven and Kirkby,* 1979*; Beven et al.,* 1984] is part of the low number of parameters and physically meaningful. All models describe the soil moisture storage capacity as a cumulative probability distribution function using the power function to predict runoff in a grid or sub-catchment or parts of landscape as in the hydrological response unit (HRU). An advantage of the distribution function approach is that the signature of runoff generation process nonlinearities can be reflected in the distribution function but without introducing the large number of parameter values [*Beven,* 2012].

A conceptual hydrologic model is presented based on the newly proposed distribution function for describing the soil water storage capacity. The new distribution of soil moisture capacity is applied using the generalized proportionality scheme from the SCS-CN method [*Mockus*, 1972] to mean annual water balance by *Wang and Tang*, [2014], which has established a bridge to represent Unified model and VIC type model at an event scale type, derived from the soil moisture and precipitation, and soil moisture storage index as soil moisture capacity and precipitation. The differences between the new model and VIC type models include 1) the

distribution function for soil water storage capacity is different and the new distribution function leads to the SCS curve number method; and 2) the computation of evaporation is also based on the distribution function considering the spatial variability of available water evaporation.

1.2 Daily Water Balance Model

Hydrological models play a major role in many applications. The new proposed Unified model has a similar model structure with HyMOD [*Moore*, 1985, 1999; *Boyle*, 2001] based on the concept of saturation excess runoff generation. Hydrologic models at the daily scale need to simulate the processes of runoff generation and routing while taking into consideration the soil water storage change significance and how it is controlled by the infiltration and evaporation processes. In addition, the daily water balance models require more attention to the details due to its focus on soil moisture water storage change through hydrological processes. This applies a complexity to model daily water balance due to collecting a large number of data and the additional processes that are necessary to simulate with a greater degree of variability [*Xu and Singh*, 1998].The developed model was applied to 92 catchments in the United States for simulating daily streamflow. The performance of the model is quantified by Nash-Sutcliffe efficiency coefficient (NSE) [*Nash and Sutcliffe*, 1970] and is improved compared with the HyMOD model. The proposed model using the SCS-CN method shows the effect on improving the performance using the combination of new soil moisture capacity distribution and new approach of evaporation method. Also, implies a similar framework using the generalized proportionality relationship (SCS-CN) unifies the runoff generation framework at which it is useful at different time scales.

1.3 Monthly Water Balance Model

Monthly water balance model is between the event-based rainfall-runoff model and mean annual water balance model; and all the three components of hydrologic responses to precipitation, including evapotranspiration, runoff and soil water storage change, may be not negligible [*Wang and Tang*, 2014]. Therefore, monthly water balance model is expected to be more complex than event-scale surface runoff generation model and mean annual water balance model from the perspective of hydrologic response variables.

A variety of monthly water balance models have been developed in the literature [*Vandewiele et al*., 1992; *Makhlouf and Michel,* 1994; *Xu and Singh*, 1998]. The first well-known monthly water balance model was developed by *Thornwaite* [1948] and formally introduced in *Thornthwaite and Mather* [1955]. This model was later modified by adding a parameter to partition a fraction of precipitation into a direct runoff by *Alley* [1984]. Later on, *Palmer* [1965] developed a monthly water balance model for computing hydrologic drought index. The threshold concept has been used to model runoff in both Thornthwaite and Palmer models, i.e., runoff does not occur until the soil moisture layer is completely saturated. *Thomas* [1981] developed the abcd model with a similar structure to *Thornthwaite and Mather* model [1957], which has separated the model into a two-layer structure, one for soil moisture and the other for groundwater with similar treatment of evapotranspiration. The model has been applied in many studies [e.g., *Alley*, 1984]. Some of the models efforts has utilized the applicability of Budyko framework on smaller time scales such as seasonal [*Chen et al*., 2013, *Zhang et al*., 2008, *Takleab et al.*, 2011; *Du et al.*, 2016].

1.4 Inter-annual and Mean Annual Water Balance Model

The annual runoff water balance model is important because it can be measured with accuracy compared with e.g. precipitation, evaporation, soil moisture storage, and other components of the water balance model. Also, it is a critical component for a practical aspect because it is various uses to human and aquatic ecosystem.

Many studies have developed annual water balance models and studied the factors that affect the temporal and spatial variability. *Thornwaite* [1948] and *Budyko* [1955] used mean annual precipitation and mean annual potential evapotranspiration to identify soil moisture storage regimes on a global basis. In 1949, *Langbein* found that climate was the dominant factor that controls the spatial distribution of annual runoff in the conterminous United States. Following previous studies, *Eagleson et al.* [1987] and *Milly* [1994] found that precipitation, soil texture, vegetation type and density, and geomorphology are dominant factors that controls variability of annual runoff.

1.5 Comparison of Water Balance Model at Different Time Scales

Developing water balance models with time variability requires an investigation of the different attributes that controls each model. *Zhang et al.* [2008] improved the Budyko framework to accommodate the mean annual, annual, monthly, and daily timescales in Australia. The model has performed well in most of the catchments at mean annual and annual, however in shorter timescales the significance of soil moisture storage played a major role on the variability of the performance therefore it was concluded that more complicated models are in need for monthly and daily time scales. Consequently, different time scales of the water balance model using the SCS-

CN proportionality are compared at different time scales will show the affect and the controlling factors on runoff and performance of the model with time.

1.6. Research Objectives

The discovery of the generalized proportionality by *Wang and Tang* [2014] from SCS-CN method leads to Budyko type equation and the equation has the same functional form as the monthly abcd model by *Thomas* [1981], and VIC/ Xinanjiang type models. This implicates that the runoff generation at the different time scales could be modeled using same model structure [*Zhao et al*., 2016]. Therefore, the shown evidence from the literature indicates that there is a potential unification of models across time scales from daily, monthly to annual.

The objectives of the study can be summarized as follow:

1) To develop conceptual daily water balance model.

2) To develop conceptual monthly water balance model.

3) To develop conceptual inter-annual and mean annual water balance model.

4) Test the performance of the models.

5) Investigate the temporal scaling behavior of water balance

6) To understand the potential linkages of hydrologic processes among different time scales.

CHAPTER 2 DAILY WATER BALANCE MODEL USING SCS-CN METHOD

The description of the hydrologic models is provided by the probability distribution function models which are transforming the rainfall and potential evaporation data to runoff flow at the catchment outlet [*Institute of Hydrology*, 1992]. At a point scale, the runoff generation in a catchment is controlled by the soil moisture holding capacity. This can be described as a storing unit with a given storage capacity, and variable in space [*Moore*, 2007]. Specifically, the HyMOD [*Moore*, 1985, 1999; *Boyle*, 2001] is utilized and compared with a proposed SCS-CN method using a new distribution function by *Wang* [2018]. The partitioning of precipitation into surface runoff and soil wetting (i.e., infiltration). The partitioning is quantified by proportionality relationship from SCS-CN method to compute the direct runoff and by using the new soil moisture capacity distribution by *Wang*, [2018] to compute the soil wetting. Therefore, and from recent studies by *Wang and Tang* [2014], found that the generalized proportionality from SCS-CN plays a major role in unifying models framework in which it implies having unified model structure. The proposed daily hydrologic model is based on the distribution function of soil water storage capacity based on SCS curve number method is described in detail as follows.

2.1 Methodology

2.1.1 Data collection

The daily water balance model is applied to the Model Parameter Estimation Experiment (MOPEX) watersheds [*Duan et al.*, 2006]. The MOPEX data set provides daily precipitation in (mm), streamflow in (mm) maximum and minimum air temperature in (°C) data from 1948 to

2003. The daily potential evapotranspiration data during 1948 to 2003 were obtained from *Zhang* et al. [2010], and the potential evapotranspiration was estimated using Priestley-Taylor method [*Priestley and Taylor*, 1972] at the spatial resolution of 8 by 8 km. The daily precipitation and potential evapotranspiration during 1948 - 2003 are inputs for the daily water balance model, and the daily streamflow data is used for model calibration and validation. The daily water balance model is applied to 92 of the MOPEX watersheds as shown in Figure 1, where snow effect is not significant. The proposed models were applied on the selected catchments regardless of the snow effect and human perturbation on catchments. The snowy areas have been excluded by applying a snow effect occurring threshold of (-2 °C) for the months in between November to April [*Kottek et al*., 2006; *Kienzle*, 2008; and *Rajagopal*, 2015].

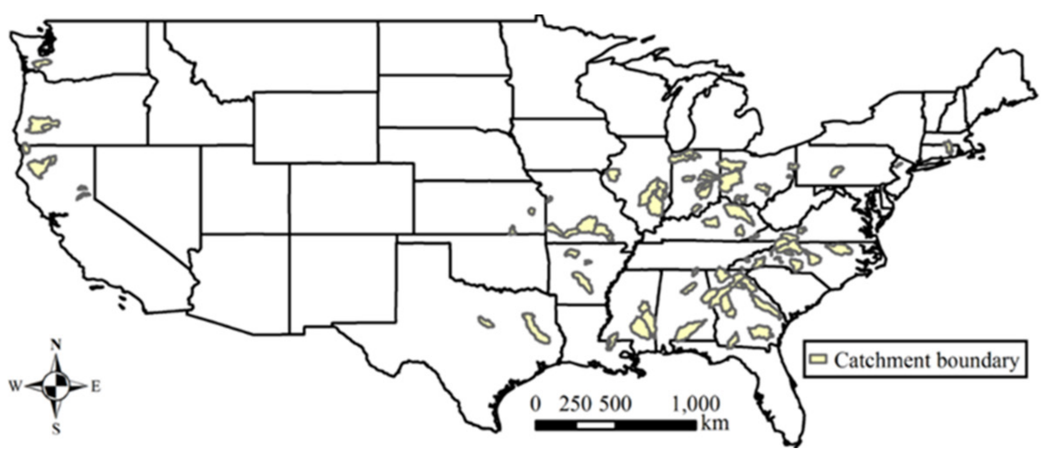

Figure 1: location map of the selected catchments from the MOPEX dataset.

<u>2.1.2 Daily hydrologic model</u>

The daily hydrologic model is essentially computed by the probability distribution function models which are transforming the rainfall and potential evaporation data to runoff flow at the

catchment outlet [*Institute of Hydrology*, 1992]. At a point scale, the runoff generation in a catchment is controlled by the soil moisture holding capacity. This can be described as a storing unit with a given storage capacity, and variable in space [*Moore*, 2007]. The description of the model is based on the partitioning of precipitation into surface runoff and soil wetting (i.e., infiltration) by proportionality relationship from SCS-CN method by *Wang and Tang* [2014] to compute the direct runoff and by using the new soil moisture capacity distribution by *Wang*, [2018] to compute the soil wetting.

<u>2.1.3 Soil wetting or infiltration</u>

The spatial variation of point-scale storage capacity (C) is represented by the following cumulative distribution function (CDF) proposed by *Wang* [2018]:

$$F(C) = 1 - \frac{1}{a} + \frac{C + (1-a)S_b}{a\sqrt{(C+S_b)^2 - 2aS_bC}} \tag{2.1}$$

where C is soil water storage capacity at a point scale and it is supported by a positive semi-infinite interval (i.e.,$C \geq 0$); $F(C)$ is the fraction of the catchment area for which the storage capacity is less than C; a is the shape parameter with a range of $0 < a < 2$; and S_b is the mean of the distribution, i.e., the average soil water storage capacity over the catchment.

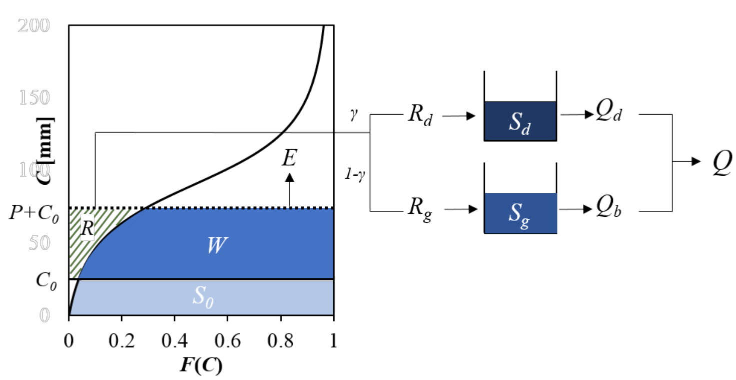

Figure 2: Daily water balance model scheme for the Unified model.

As shown in Figure 1, the initial average soil moisture is denoted as S_0, and the corresponding value of C is denoted as C_0. The precipitation depth (P) is partitioned into a runoff (R) and soil wetting (W) (i.e., infiltration). Soil wetting is computed by the integration (Moore, 1985):

$$W = \int_{C_0}^{P+C_0} (1 - F) dC \quad (2.2)$$

The computed integral is as the following equation [*Wang*, 2018]

$$W = \frac{P + S_b\sqrt{(m+1)^2 - 2am} - \sqrt{[P + (m+1)S_b]^2 - 2amS_b{}^2 - 2aS_bP}}{a} \quad (2.3)$$

Where;

$$m = \frac{S_0(2S_b - aS_0)}{2(S_b - S_0)} \quad (2.4)$$

If initial soil water storage is zero (i.e., $S_0 = 0$), equation (2.3) becomes the proportionality relationship of SCS curve number method [*Wang*, 2018]. Therefore, the computation of soil wetting by equations (2.3) is an extension of the curve number method by incorporating initial soil moisture explicitly.

2.1.4 Evaporation

Once W is computed by equation (2.3), the sum of soil wetting and initial soil water storage (S_0), denoted by Y, which is obtained:

$$Y = W + S_0 \quad (2.5)$$

Y is then partitioned into evaporation (E) and ending soil water storage (S_1):

$$Y = E + S_1 \quad (2.6)$$

E is computed using the integration of equation (2.1) for a given Ep

$$E = \frac{Y}{S_b} \int_0^{E_P} (1 - F) dC \tag{2.7}$$

The computed integration will result in the below equation (2.8).

$$E = \frac{Y}{S_b} \frac{E_P + S_b - \sqrt{(E_P + S_b)^2 - 2aS_bE_P}}{a} \tag{2.8}$$

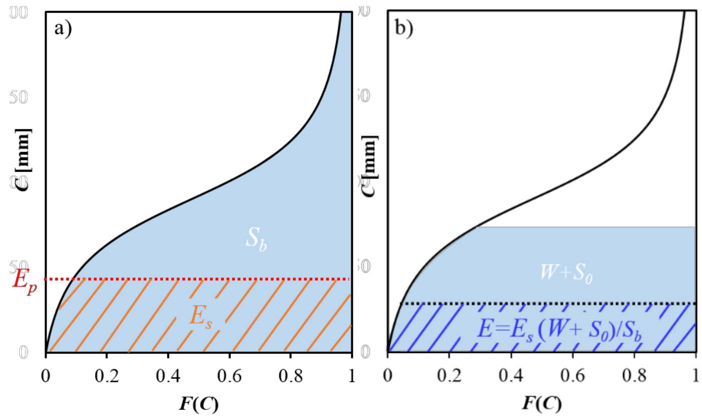

Figure 3: evaporation scheme when the soil storage is fully and partially saturated.

Equation (2.8) was simplified by multiplying the numerator by $S_b$as shown in equation (2.9). The evaporation scheme under fully and partially saturated soil moisture storage is demonstrated in Figure (2a, and 2b), respectively.

$$E = Y \frac{1 + \frac{E_P}{S_b} - \sqrt{\left(1 + \frac{E_P}{S_b}\right)^2 - 2a\frac{E_P}{S_b}}}{a} \tag{2.9}$$

Finally, the ending storage is computed as the difference between Y and E.

2.1.5 Surface runoff and baseflow:

It should be noted that direct runoff is computed by the proportionality relationship from the SCS-CN method. However, the difference between precipitation and soil wetting is a total runoff (R) like the HyMOD model [*Boyle*, 2001]:

$$R = P - W \tag{2.10}$$

The total runoff from equation (10) is partitioned into a surface runoff (R_s) and groundwater recharge (R_g):

$$R_s = \gamma R \tag{2.11}$$

The groundwater recharge is computed using equation (12)

$$R_g = (1 - \gamma)R \tag{2.12}$$

while γ represents the percentage of surface runoff to the total runoff. Surface runoff is fed into a quick storage tank for routing. The discharge from the quick storage tank is computed by a linear storage-discharge relationship:

$$Q_s = k_s(S_{d0} + R_s) \tag{2.13}$$

where S_{d0} is the initial storage in the quick storage tank, and k_s is the coefficient of storage-discharge relation. The ending storage at the quick storage tank (S_{d1}) is computed by:

$$S_{d1} = (1 - k_s)(S_{d0} + R_s) \tag{2.14}$$

Groundwater recharge is fed into a slow storage tank, and the discharge from the slow storage tank is computed by a linear storage-discharge relationship:

$$Q_b = k_b\left(S_{g0} + R_g\right) \tag{2.15}$$

where G_0 is the initial storage in the slow storage tank, and k_b is the coefficient of storage-discharge relation. The ending storage in the slow storage tank (S_{g1}) is computed by:

$$S_{g1} = (1 - k_b)\left(S_{g0} + R_g\right) \tag{2.16}$$

The total streamflow is computed by:

$$Q = Q_s + Q_b \tag{2.17}$$

2.1.6 State variables and parameters

There are three state variables (S, S_d, and S_g) representing the storages for soil water, surface water, and groundwater. There are five main parameters (a, S_b, γ, k_s and k_b) which describes the Unified model. a and S_b are parameters describing the spatial distribution of soil water storage capacity for estimating runoff generation. γ is used for the partitioning of runoff into surface runoff and groundwater recharge. k_s and k_b are parameters for surface runoff and baseflow routings. The ranges of these parameters for calibration are shown in Table 1.

Table 1. Daily water balance model parameter ranges.

SCS curve number		
Parameters	**Ranges**	**Units**
a	$0.01-2$	-
S_b	$50-1500$	mm
γ	$0.01-1$	-
k_s	$0.14-1$	day^{-1}
k_b	$0.01-0.14$	day^{-1}

2.1.7 Parameter estimation and model performance evaluation

Many of the hydrological models with multiple parameters incorporated exhibited a need to be calibrated before it is used in practice. In this paper, all included parameters above in each model have been estimated with fixed initial values (S_0, S_{d0}, and S_{g0}). The genetic algorithm is a function of optimization applied to find a set of values at a random initial values and objective function. This technique generates a new random population of values concentrated within the range of good values of the objective function [*Wang*, 1991]. The calibrated parameters predictions

have used [NSE, defined by *Nash and Sutcliffe*, 1970] as it approaches to 1, the best fit. Essentially, a single objective function has been applied to evaluate the performance of good fit by maximizing the NSE values and computed as the following:

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N}(Q_o - Q_m)^2}{\sum_{i=1}^{N}(Q_o - \overline{Q_o})^2} \tag{2.18}$$

The Root Mean Square Error (RMSE) is a frequently measurement of difference between modeled and observed values, which is called individually a residual.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Q_o - Q_m)^2}{n}} \tag{2.19}$$

The r^2 is the coefficient of determination which describes how much of the variance between the two variables is described by linear fit.

$$r^2 = \frac{\sum_{i=1}^{N}(Q_o - \overline{Q_o})(Q_m - \overline{Q_m})}{\sqrt{\left((\sum_{i=1}^{N}(Q_o - \overline{Q_o})^2 \sum_{i=1}^{N}(Q_m - \overline{Q_m})^2]\right)^2}} \tag{2.20}$$

The Kling-Gupta efficiency (KGE) (Gupta et al., 2009; Kling et al., 2012) is based on a decomposition of NSE into its three components (Pearson Correlation coefficient, ideal value r=1), $\alpha = \frac{\sigma_m}{\sigma_o}$ the standard deviation of the modeled and standard deviation observed values, ideal value=1, and $\beta = \frac{\mu_m}{\mu_o}$ is the ratio between mean of the modeled values (μ_m) and mean of the observed values (μ_o), ideal value =1.

$$\mathrm{KGE} = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_m}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_m}{\mu_o} - 1\right)^2} \tag{2.21}$$

The BIAS measures the values of ratio of bias from mean values of streamflow modeled to observed.

$$\mathrm{BIAS} = 1 - \left[max\left(\frac{\overline{Q_m}}{\overline{Q_o}}, \frac{\overline{Q_o}}{\overline{Q_m}}\right) - 1\right]^2 \tag{2.22}$$

where Q_o , $\overline{Q_o}$ and Q_m is the observed discharge, average discharge and simulated streamflow, respectively, at time step (i), and N is the number of days to be calibrated. The studied models share the same unified model concept and structure which is constructed based on two layers, each layer has a buffering storage, and parameters that deals with the storage residence time. Meanwhile, the collected historical observations have been split into three parts (warm-up, calibration, and validation). The warm-up period is from 01/01/1948 to 31/12/1953 (6 years), the calibration period is the from 01/01/1954 to 12/31/1973 (20 years) and the validation period is from 01/01/1974 to 12/31/2003 (30 years). The selected catchments were calibrated and validated for 50 years (1954-2003) at a daily time scale using split-sample test by *Refsgaard* et al. [1996].

2.2 Results and Discussion

As formerly described, the daily water balance model is applied to 92 watersheds shown in Figure 1, where snow effect is not significant. The catchments' areas range from 134 to 9886 (average 3220) km^2. The selected catchment mean daily values of temperature range from 9 to 21 °C, E/P range from 0.20 to 0.91, Ep/P range from 0.27 to 1.91, and Q/P range from 0.09 to 0.80.

2.2.1 Model performance

The developed Unified daily model is based on the generalized proportionality of the SCS-CN by *Wang and Tang* [2014], and the density distribution function for the soil moisture capacity by *Wang*, [2018]. The values of the daily Unified model parameters (a, S_b, γ, k_s and k_b) are estimated based on the available data of the daily precipitation, potential evaporation, and runoff during 1983-2003. The Unified model is applied on 93 catchment areas as shown in Figure 1.

The evaluation using the frequency distribution of NSE over 92 catchment locations across the United States is presented in Figure 5. In (Figure 5A), it shows the calibration values with 98% are higher than 0.5 at a 38 peak frequency of values between 0.6 and 0.7. In (Figure 5B), it shows the validation values with 76% of values are higher than 0.5 at a 37 peak frequency of values between 0.5 and 0.6.

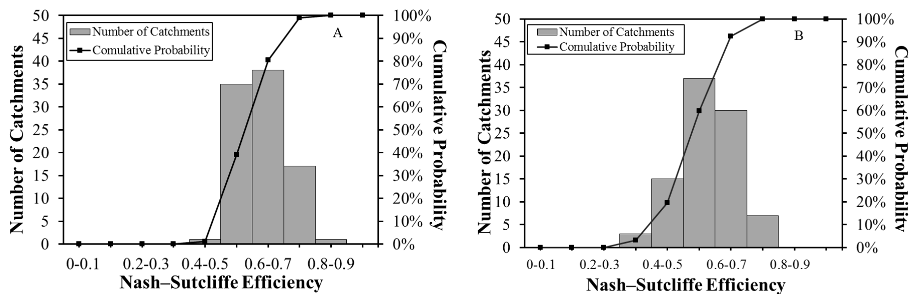

Figure 4: Histogram of Nash-Sutcliffe efficiency (NSE) for the daily Unified model for the calibration period (A) and validation period (B).

<u>2.2.2 Estimated model parameters</u>

The Unified daily model has five parameters that controls the runoff allocation. Parameter α is a shape parameter which controls the soil moisture capacity distribution function, while S_b is the upper bound of the soil moisture capacity. The model structure contains three main soil storages , total storage (S), surface storage (S_d), and ground water storage (S_g) as in it is described in Figure 2. Parameters (k_d) snd (k_b) for each model controls the degree of recharge to groundwater and its rate of release into the rivers base flow. The two parameters vary based on how the activity of the subsurface storage zone. For example, when k_d approach to 1 this corresponds to little or no surface runoff. Similarly, when k_b approach to 0 it corresponds to little or no base flow contribution, according to the feasible region in Table 1.

The distribution of each parameter over the 92 catchments is found in Figure 5. In Figure (5A), the parameters α frequency distribution is skewed to the left having most of the values between 1.9 and 2.0 with a peak frequency value of 91. However, in parameters S_b and k_s it is skewed to right having most of parameters between 150 and 300 (mm) for S_b with a peak of 31 frequency values and between 0.1 and 0.2 (mm/day) for k_s with a peak values of 38 frequency values in Figures (5B, and 5D). On the other hand, parameters k_b and γ have a u shape frequency distribution, having a peak of 36 frequency values between 0.0 and 1.0 for γ and a peak value of 30 frequency values ranging between 0.00 and 0.01 (mm/day) of k_b in Figures (5C, and 5E).

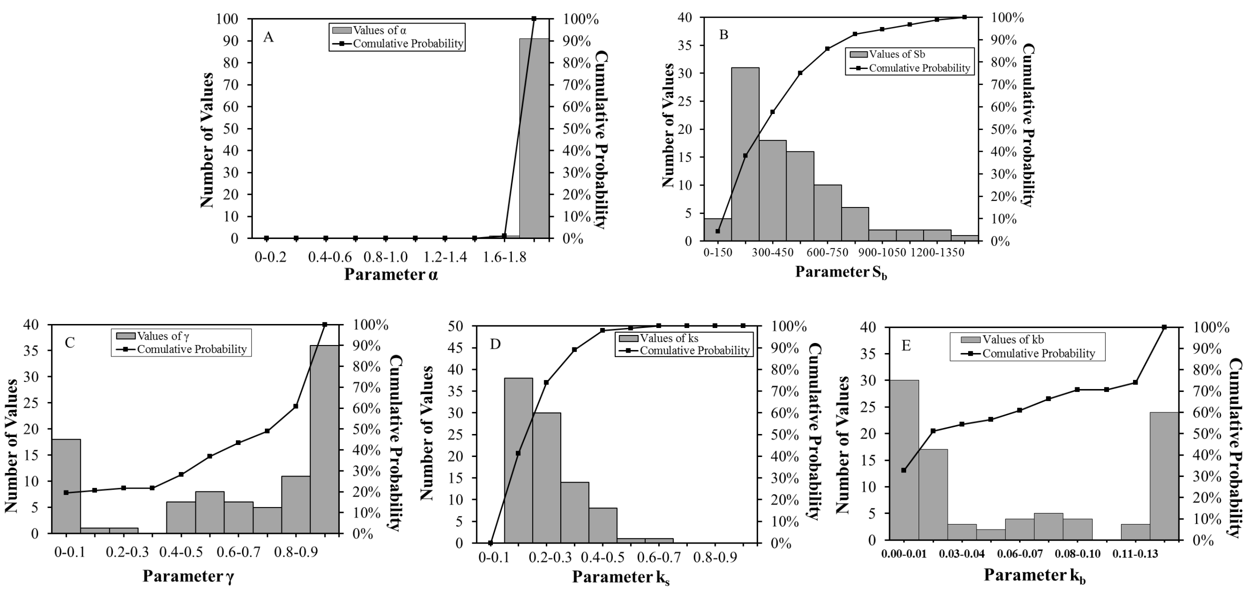

Figure 5: Histograms of the Unified daily model parameters.

2.2.3 Applied model on a selected catchment

In this part, we are considering one catchment located in Thurston County, Washington (USGS Site ID# 12027500) and drainage area of nearly 2318 km^2. The catchment mean daily

aridity index (P/E_p) equals to 2.64 and runoff coefficient (Q/P) equals to 0.73. The Unified model is implemented on this location. The Unified model calibration, and (validation) periods has 0.83 and (0.78) NSE values, respectively. The response of the model simulation and calibrated parameters shown in the results of comparison between the simulated runoff of each model and the observation of streamflow in mm/day. Figure 6 provides a detailed information about the behavior of this particular catchment based on the model output. In the Unified model, simulated runoff output is likely to underestimate high values particularly in the validation period as shown in Figure 7.

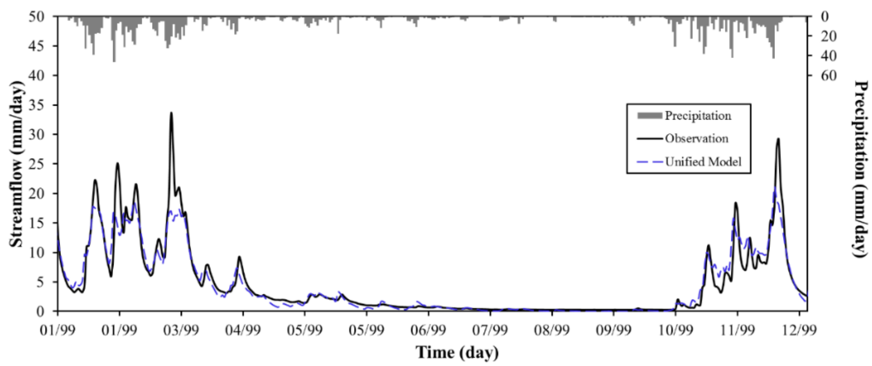

Figure 6: One-year hydrograph from the calibration period (01/01/1999 to 12/31/1999) to show the difference in streamflow among the studied models. The bold black line is the observed streamflow (Q_o). Precipitation is presented in the gray color bars. The blue (hyphened line) is the simulated streamflow of Unified model.

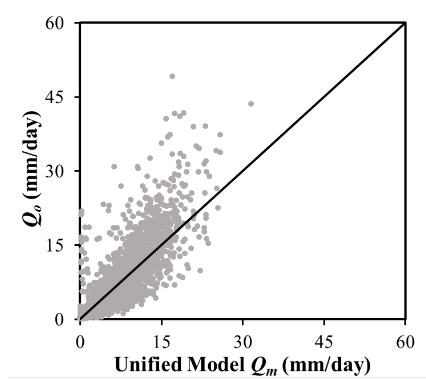

Figure 7: Comparison of studied and proposed models between simulated streamflow (Q_m) and observed streamflow (Q_o) at a daily time scale in the validation period.

CHAPTER 3 MONTHLY WATER BALANCE MODEL USING SCS-CN METHOD

The new proposed monthly Unified model has further extended into monthly time scale. This model is based on *Wang* [2018] probability distribution function of the soil storage capacity.

3.1 Methodology

3.1.1 The monthly Unified model

The developed daily water balance model (Unified model) has further extended into monthly time scale. The Unified monthly model has a similar model structure but the main difference between daily and monthly time scale is the direct runoff generation in equation (3.1) while the evaporation computation is similar to the daily model. The direct runoff is computed as R_d=P-W, while W is computed by following equation (2.3) and (2.4) for soil wetting which leads to the SCS-CN method is obtained by *Wang* [2018], as it is shown in Figure (8). However, the direct runoff (R_d) is directly fed to the streamflow (Q) with no surface runoff storage (S_d) as in equation (3.1).

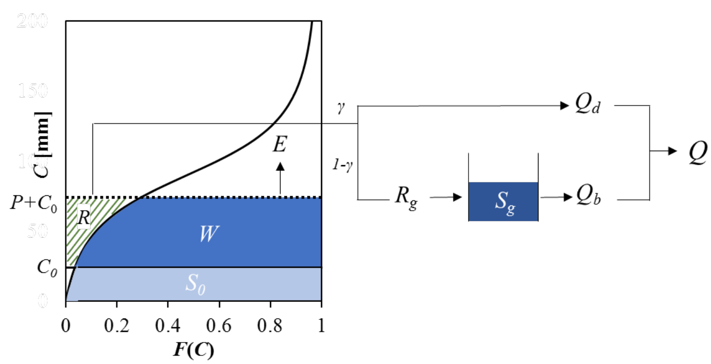

Figure 8: Monthly water balance model scheme for the Unified model.

$$Q_d=R_d \tag{3.1}$$

The evaporation is treated similarly to equation (2.8) in Chapter (2) and the groundwater recharge (R_g) is computed by $W+S_0-S_1-E$. The ending storage of the groundwater storage (S_{g1}) is computed

$$S_{g1}=(1-k_b)\left(R_g+S_{g0}\right) \tag{3.2}$$

where S_{g0} is the initial storage in the slow storage tank and k_b is coefficient of storage-discharge relation. The base flow from the slow storage tank is computed by assuming a linear storage-discharge relationship:

$$Q_b=k_b\left(R_g+S_{g0}\right) \tag{3.3}$$

The total runoff is computed by:

$$Q=Q_d+Q_b \tag{3.4}$$

3.1.2 State variables and parameters

The monthly Unified model uses two state variables (S, S_g) and four parameters (a, S_b, γ, and k_b) bounded by upper and lower values in Table (2).

Table 2. Monthly water balance model parameter ranges.

Unified Model		
Parameters	**Ranges**	**Units**
a	$0.01-2$	-
S_b	$50-1500$	mm
γ	$0.01-1$	-
k_b	$0.01-1$	$month^{-1}$

3.2 Results and discussion

The proposed monthly Unified is applied to the study catchment areas. The parameters values are estimated during the calibration period (1954-1973). To evaluate the estimated parameter values the NSE was computed as an indication of the best performance of the model. The set of parameters are estimated by maximizing the NSE values during the calibration period. Also, NSE is computed during the validation period between the years of 1974 – 2003.

3.2.1 Model performance

The monthly Unified model is comprised of four parameters (a, S_b, γ, and k_b), with no surface soil moisture storage and associated direct flow allocation parameter. The model parameters associated with the model are estimated based on the monthly precipitation, potential evaporation, and compared with observed runoff. The Unified model is applied over the selected 93 catchment areas across the United States in Figure 1.

The evaluation using the frequency distribution of NSE over 93 catchment locations across the United States is presented in Figure 9. In (Figure 9A), it shows the calibration values with 98% are higher than 0.5 at a 38 peak frequency of values between 0.8 and 0.9. In (Figure 9B), it shows the validation values with 97% of values are higher than 0.5 at a 34 peak frequency of values between 0.7 and 0.8.

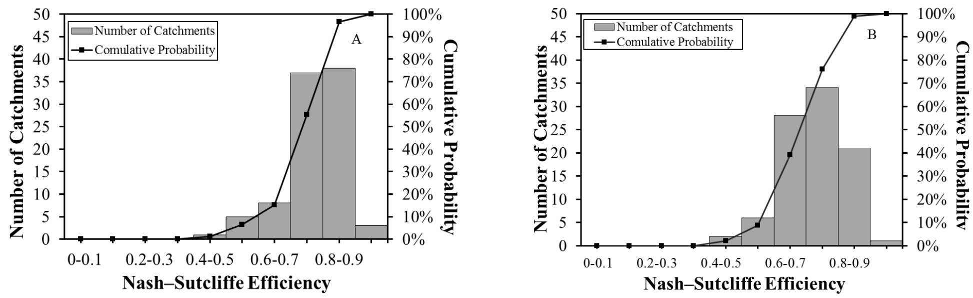

Figure 9: Histogram of Nash-Sutcliffe efficiency (NSE) for the monthly Unified model for the calibration period (A) and validation period (B).

3.2.2 Estimated model parameters

The Unified monthly model contains four parameters which facilitates the runoff generation. The reduction in the number of parameters is due to no surface soil moisture storage (S_d). It not needed because of all of the direct runoff flow is fed directly to the streamflow e.g. having the surface runoff parameter would make the model always reaching upper boundary. Therefore, it does not have any significant impact on the model. In the monthly Unified model, still have the shape parameter a which controls the soil moisture capacity distribution, weather the shape is concave up or down shape. The feasible region of solutions of the estimated parameters range is shown in Table 2.

The distribution of each parameter over the 92 catchments is found in Figure 10. In Figure (10A) the parameters a is skewed to the left having most of the values between 1.9 and 2.0 with a peak frequency value of 86. However, in parameters S_b and k_d are skewed to right having most of parameters between 150 and 300 (mm) for S_b with a peak of 41 frequency values as shown in Figure (10B). On the other hand, parameters k_d and γ have a u shape frequency distribution, having a peak of 49 frequency values between 0.0 and 1.0 for γ as it is presented in Figures (10C).

The parameter k_b have a three peak frequency distribution with a maximum value of 16 frequency values ranging between 0.5 and 0.6 (mm/month) in Figure (10D).

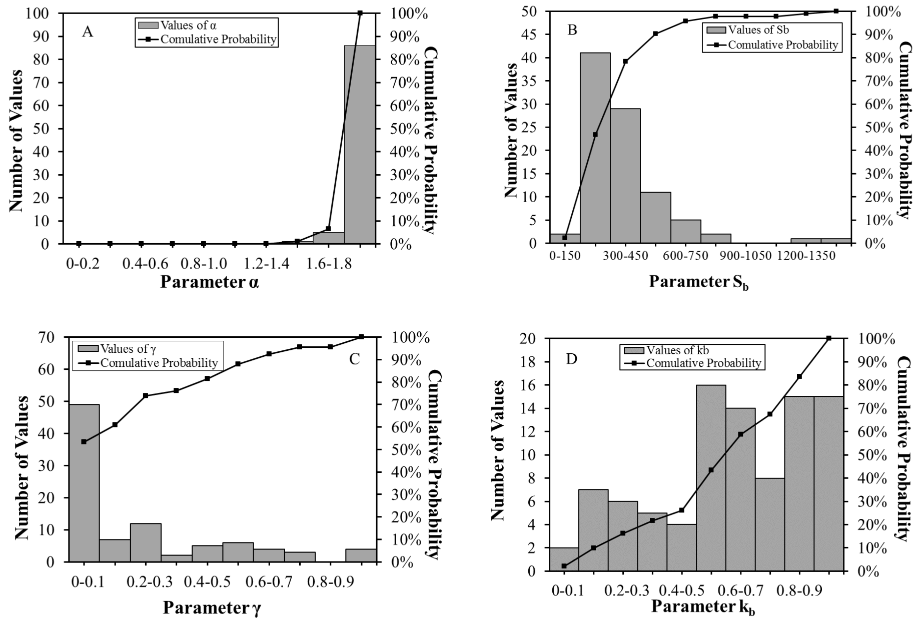

Figure 10: Histograms of the Unified monthly model parameters.

3.2.3 Applied model on a selected catchment

The Unified monthly model has been applied on Thurston County, Washington (USGS Site ID# 12027500). The model calibration, and (validation) periods have 0.94 and (0.90) NSE values, respectively. The response of the model simulation and calibrated parameters shown in the results of comparison between the simulated runoff of each model and the observation of streamflow in mm/month. Figure 11 provides a detailed information about the behavior of this particular catchment based on the model output. In the Unified model, simulated runoff output is likely to underestimate high values particularly in the validation period as shown in Figure 12.

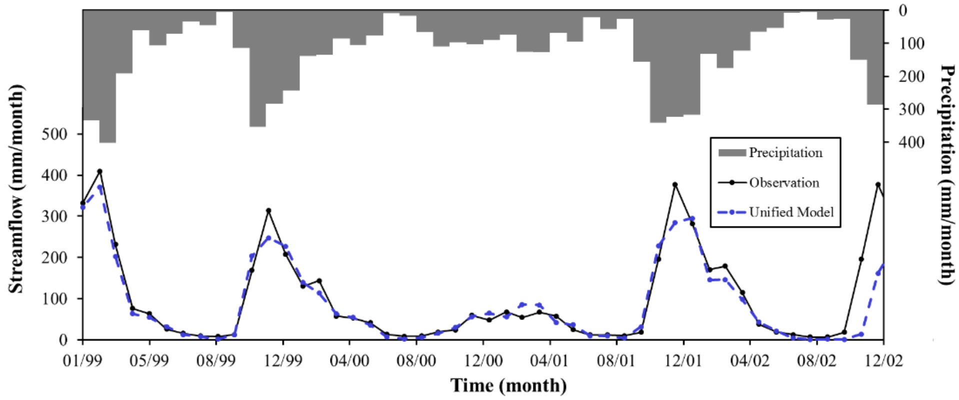

Figure 11: Three-year hydrograph from the validation period (01/1999 to 12/2002) to show the difference in streamflow among the studied models. The bold black dotted line is the observed streamflow (Q_o). Precipitation is presented in the gray color bars. The blue (hyphened dotted line) is the simulated streamflow of monthly Unified model.

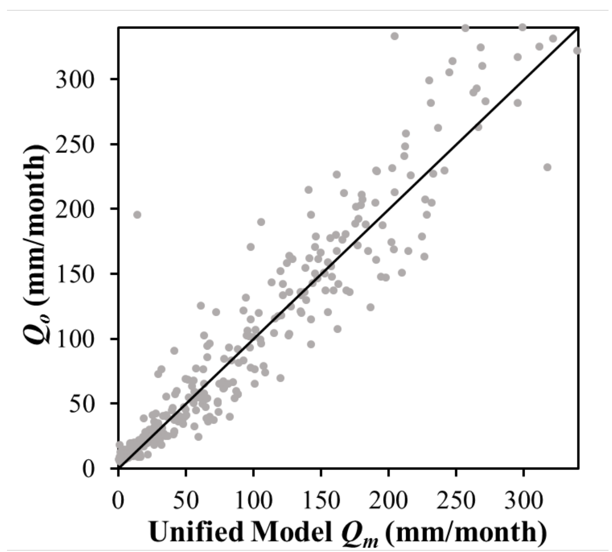

Figure 12: Comparison of studied and proposed models between simulated streamflow (Q_m) and observed streamflow (Q_o) at a monthly time scale in the validation period.

CHAPTER 4 INTER-ANNUAL and MEAN ANNUAL WATER BALANCE MODEL USING SCS-CN METHOD

The Inter-annual and mean annual Unified model is inspired by *Wang* [2018] probability distribution function of the soil moisture storage capacity.

4.1 Methodology

4.1.1 The Inter-Annual Unified model

The annual Unified model is the continuation of the daily, and monthly Unified models. The annual Unified model is comprised of one soil moisture storage (S) and two controlling parameters (a, and S_b). The two parameters have the same description as described in Section 2.1. The main difference between this model and previous discussed model (Chapter 2, and Chapter 3) is the streamflow (Q) generation. The annual Unified model is treated as one storage component. The soil wetting (i.e. infiltration) W is computed by following equation 2.3 in Chapter 2. Once W is computed, the sum of soil wetting and initial soil water storage (S_0), denoted by Y, which is obtained in equation 2.5. Then, the evaporation (E) is computed using equation 2.9. Finally, the streamflow is computed by:

$$Q = P - W \tag{4.1}$$

The annual Unified model scheme is presented in detail in Figure 13.

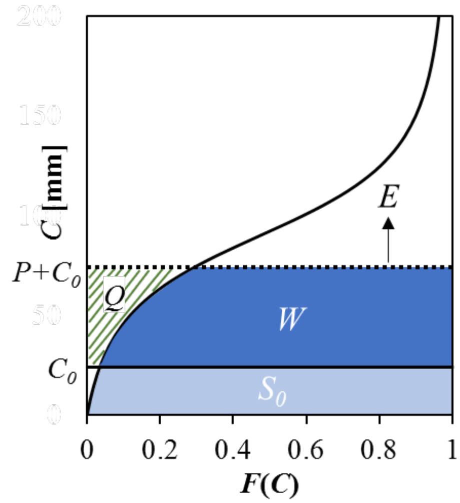

Figure 13: Annual water balance model scheme for the Unified model.

4.1.2 The Mean annual Unified model

In equations (2.3) and (2.9) the application of those two equations will lead to mean annual water balance directly. P and E_P are mean annual precipitation and mean annual potential evaporation, respectively. For mean annual water balance, the impact of initial water storage is negligible. Therefore, S_0 is set to 0. Substituting W from equation (2.3) into equation (2.9), the following equation is obtained:

$$\frac{E}{P} = \frac{1+\varphi^{-1}-\sqrt{(1+\varphi^{-1})^2-2a\varphi^{-1}}}{a^2}\left[\frac{E_P}{P}+\varphi-\sqrt{\left(\frac{E_P}{P}+\varphi\right)^2-2a\varphi\frac{E_P}{P}}\right] \quad (4.1)$$

Where,

$$\varphi = \frac{S_b}{P} \quad (4.2)$$

Equation (4.1) shows that long-term evaporation ratio, i.e., $\frac{E}{P}$, can be written as a function of climate aridity index $\left(\frac{E_P}{P}\right)$, the ratio of soil water storage capacity and mean annual precipitation (φ), and the shape parameter of the distribution of soil water storage capacity (a). The mean annual unified model scheme is presented in Figure 14.

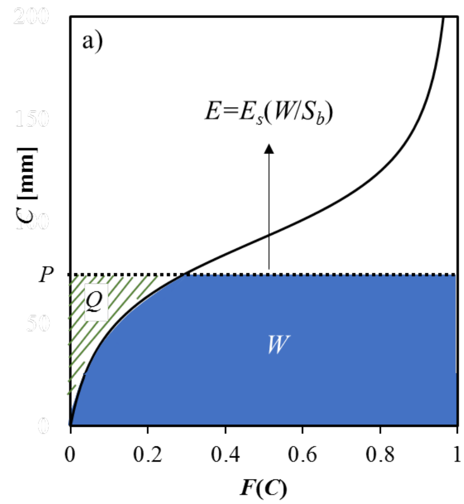

Figure 14: Mean annual water balance model scheme for the Unified model.

4.1.3 State variables and parameter estimated

The Inter-annual and mean annual Unified models have one state variable (S), and two parameters (a, and S_b). The parameters ranges are mentioned in Table 3.

Table 3. Inter-annual and mean annual water balance model parameter ranges.

Unified Model		
Parameters	**Ranges**	**Units**
a	$0.01 - 2$	-
S_b	$50 - 9000$	mm

4.2 Results and discussion

The annual Unified model has been calibrated and validated using the NSE goodness of fit. The estimated parameters are based on the calibration period (1954 -1973), and the validation period (1974-2003).

4.2.1 Model performance

The annual Unified model is comprised of two parameters (a, and S_b), with no surface or groundwater soil moisture storage and associated direct flow or recharge flow allocation parameters. The model parameters associated with the model are estimated based on the annual precipitation, potential evaporation, and compared with observed runoff. The Unified model is applied over the selected 93 catchment areas across the United States in Figure 1.

The evaluation using the frequency distribution of NSE over 93 catchment locations across the United States is presented in Figure 15. In (Figure 15A), it shows the calibration values with 97% are higher than 0.5 at a 47 peak frequency of values between 0.8 and 0.9. In (Figure 15B), it shows the validation values with 99% of values are higher than 0.5 at a 38 peak frequency of values between 0.7 and 0.8.

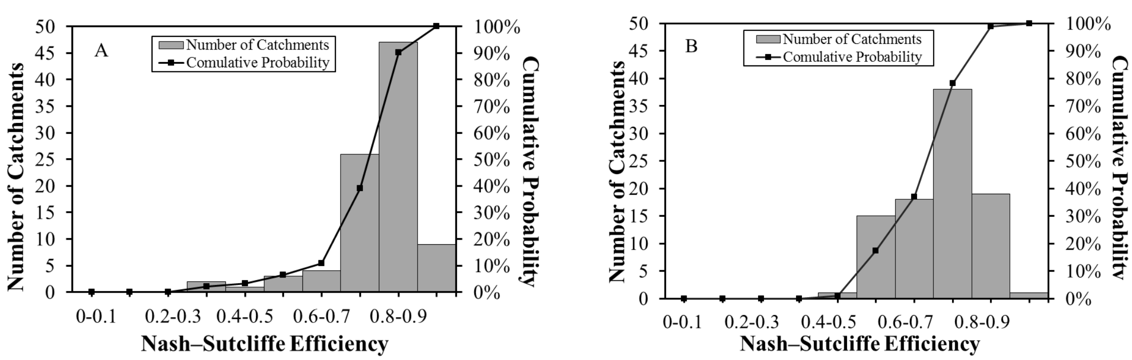

Figure 15: Histogram of Nash-Sutcliffe efficiency (NSE) for the annual Unified model for the calibration period (A) and validation period (B).

4.2.2 Estimated model parameters

The distribution of each parameter over the 92 catchments is found in Figure 16. In Figure (16A) the parameters a is skewed to the left having most of the values between 1.9 and 2.0 with a

peak frequency value of 79. However, in parameters S_b are skewed to right having most of parameters between 900 and 1800 (mm) for S_b with a peak of 30 frequency values as shown in Figure (16B).

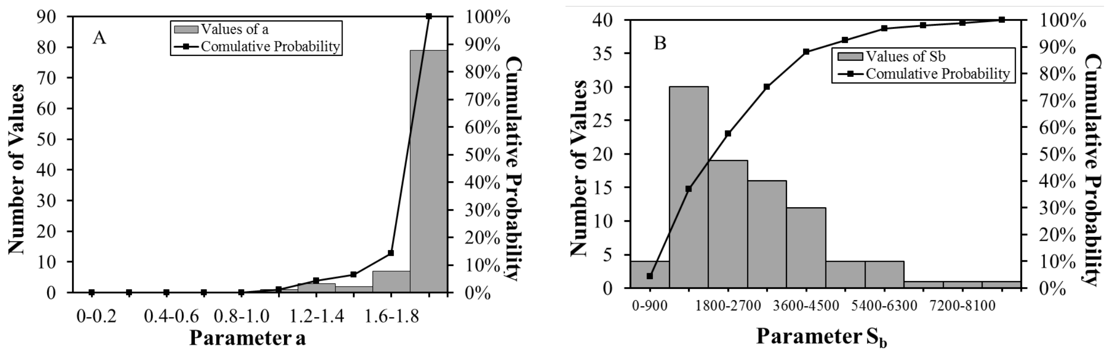

Figure 16: Histograms of the annual Unified model parameters.

4.2.3 Applied model on a selected catchment

The annual Unified model has been applied on Thurston County, Washington (USGS Site ID# 12027500). The model calibration, and (validation) periods have 0.89 and (0.78) NSE values, respectively. The response of the model simulation and calibrated parameters shown in the results of comparison between the simulated runoff of each model and the observation of streamflow in mm/year. Figure 17 provides a detailed information about the behavior of this catchment based on the model output. In the annual Unified model, simulated runoff output is likely to underestimate or overestimate high values particularly in the validation period as shown in Figure 18.

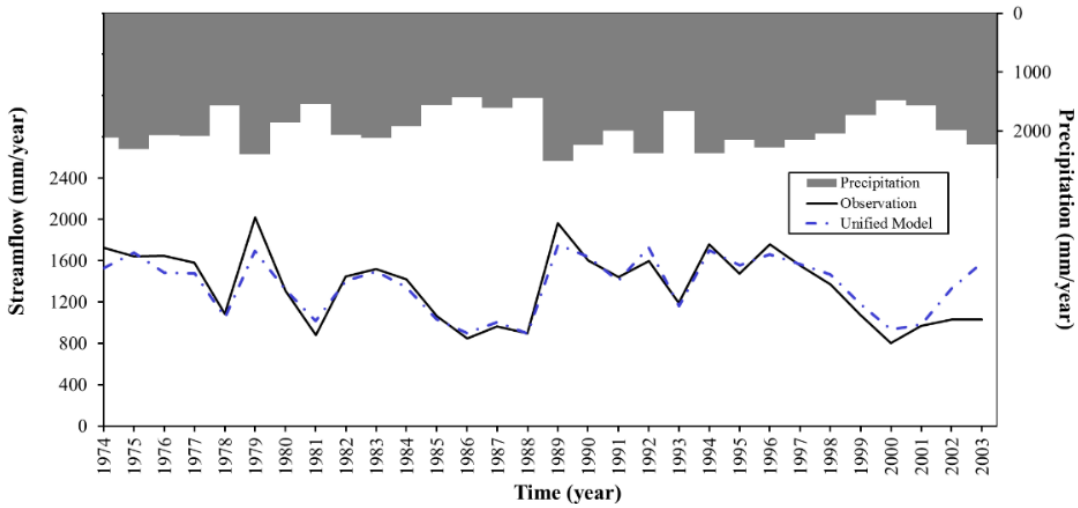

Figure 17: 30-year hydrograph from the validation period (1974 to 2003) to show the difference in streamflow among the studied models. The bold black dotted line is the observed streamflow (Q_o). Precipitation is presented in the gray color bars. The blue (hyphened dotted line) is the simulated streamflow of monthly Unified model.

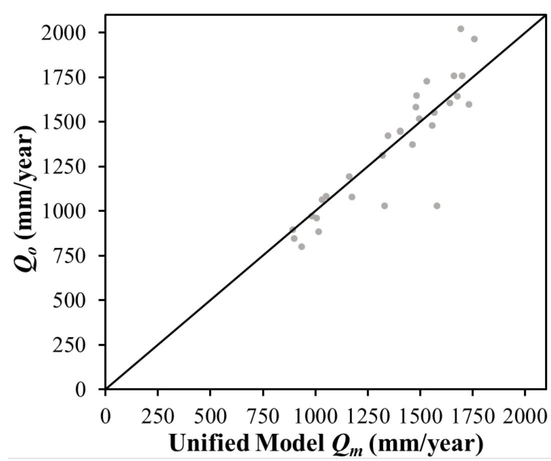

Figure 18: Comparison of studied and proposed models between simulated streamflow (Q_m) and observed streamflow (Q_o) at annual time scale in the validation period.

In Figure 19, plots equation (4.1) for three values of $\frac{S_b}{P}$ with a=1.98. Evaporation ratio increases with $\frac{S_b}{P}$ for given climate aridity index. Equation (4.1) captures the control of $\frac{E_P}{P}$ and $\frac{S_b}{P}$ (i.e.,

climate and soil water storage capacity) on long-term water balance. This equation can be interpreted as a two-parameter Budyko equation.

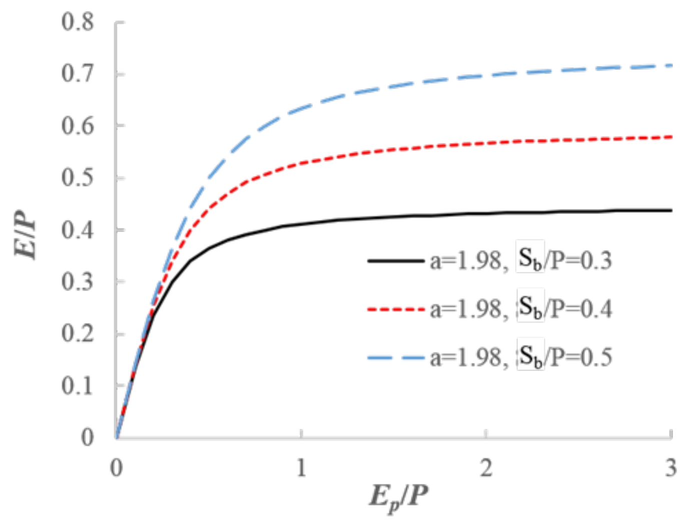

Figure 19: The obtained long-term water balance equation from the developed daily model.

CHAPTER 5 DIFFERENT TIME SCALE COMPARSION OF MODELS

Hydrologic models at the daily scale need to simulate the processes of runoff generation and routing, while taking into consideration the significant of soil water storage change and how it is controlled by the infiltration and evaporation processes. The daily time scale water balance models require more attention to the details due to its focus on soil moisture water storage change through hydrological processes. This applies a complexity to model daily water balance due to collecting a large number of data and the additional processes that are necessary to simulate with a greater degree of variability [*Xu & Singh*, 1998].

Numerous number of models have been developed at a daily time scale by describing the spatial variability of soil moisture storage capacity using the cumulative probability distribution function such as: Xinanjiang model [*Zhao*, 1977; *Zhao*, 1992], ARNO [*Todini*, 1996], and Variable Infiltration Capacity (VIC) model [*Wood et al*., 1992; *Liang et al*., 1994], or the distribution of the topographic index as in TOPMODEL [*Baven* and *Kirkby*, 1979; *Baven* et al., 1984], which is a part of the low number of parameters and physically meaningful. The advantage of the distribution function approach is that the signature of runoff generation process nonlinearities can be reflected in the distribution function but without introducing the large number of parameter values [*Baven*, 2012].

Therefore, in this chapter a comparison review of the proposed Unified daily model and the HyMOD model has been done to showcase the advantages and disadvantages of the Unified model over a well-known daily model that shares the same structure of modeling.

5.1 The Unified model compared with HyMOD, and abcd models

The water balance models in review have similarities and differences in the structural formulation. First, HyMOD (*Moore*, 1985, 1999; Boyle, 2001) used the probability of the power density function which has been widely used (*Boyle*, 2001; *Kollat* et. al, 2012; *Vrugt* et.al, 2003; *Wang* et.al, 2009). Second, the Unified model was used with two main considerations. 1) To replace the distribution of the soil moisture capacity using *Wang* (2018) soil moisture capacity distribution method. 2) The computation of evaporation when the soil partially saturated ($W + S_0$) and fully saturated (E_s) is proportional to the soil moisture capacity (S_b).

On the other hand, the abcd model is a non-linear model that was originally proposed by *Thomas* (1981) as an implementation of national assessment. The abcd model is a well-known monthly water balance model.

5.2 Methodology

5.2.1 HyMOD model

The HyMOD lumped conceptual model is based on the probability distribution model introduced by (*Moore*, 1985) with no snow component as it is shown in Figure (18). The soil moisture uses the storage capacity probability distribution function (PDF) in equation (10) for the storage defined by the maximum soil moisture storage (S_b) in equation (13) and the distribution of soil storage. The maximum soil moisture capacity within the watershed is denoted as C_{max} representing the maximum capacity of the soil moisture storage. C is average point-scale soil water storage capacity represented in equation (12). Parameter β defines the degree of spatial variability of storage capacity. The two storage reservoirs are controlled by direct runoff residence time (k_d)

and groundwater flow residence time (k_b). Streamflow is the addition of total outflow from both direct and groundwater reservoirs in equation (5.13).

$$F(c)=1-\left(1-\left(\frac{C}{C_{max}}\right)^{\beta}\right) \quad (5.1)$$

$$S_b=\int_0^1 C.df=\int_0^{C_{\max}} C\,.\,f(C)dc \quad (5.2)$$

$$C=C_{max}\left(1-\left(1-\frac{S(\beta+1)}{C_{max}}\right)^{\frac{1}{\beta+1}}\right) \quad (5.3)$$

By taking the inverse of equation (5.1) we will get C as in equation (5.3), and by substituting into equation (5.2) we have:

$$S_b=\frac{C_{max}}{\beta+1} \quad (5.4)$$

The runoff is computed as $R=P-W$ and $W=C-S_0$.The evaporation of the soil moisture storage occurs at the rate of the potential evaporation, and the remaining of rainfall are used to fill the soil moisture storage (S_1) as shown in equations (5.5 and 5.6). Otherwise, it equals the available soil moisture storage.

$$E=min(E_p,C) \quad (5.5)$$

$$S_1=C-E \quad (5.6)$$

The rainfall excess is sent to the direct runoff storage (S_{d1}) using a split ratio α which separates surface runoff and groundwater flow. The direct runoff (R_d), surface runoff (Q_d), groundwater recharge (R_g), and baseflow (Q_b) are computed by equations 5.7, 5.8, 5.9 and 5.10, respectively.

$$R_d=\alpha R \quad (5.7)$$

$$Q_d=k_d(R_d+S_{d0}) \quad (5.8)$$

Moreover, the surface storage (S_{d1}) is computed by equation (5.7) and the groundwater storage (S_{g1}) is computed by equation (5.10).

$$S_{d1}=(1-k_d)\,(R_d+S_{d0}) \tag{5.9}$$

$$R_g=(1-\alpha)R \tag{5.10}$$

$$S_{g1}=(1-k_b)\left(R_g+S_{g0}\right) \tag{5.11}$$

$$Q_b=k_b\left(R_g+S_{g0}\right) \tag{5.12}$$

The two flow reservoirs are controlled by direct runoff residence time (k_d) and groundwater flow residence time (k_b). Streamflow is the summation of outflows from the quick and slow reservoirs:

$$Q = Q_d+Q_b \tag{5.13}$$

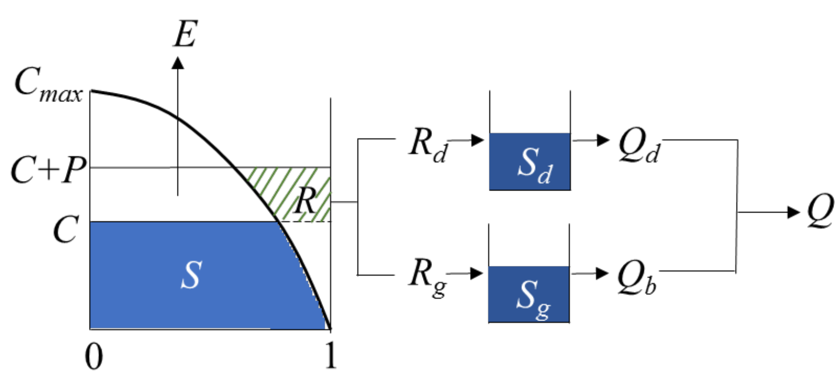

Figure 20: Daily water balance model scheme for HyMOD model.

5.2.2 HyMOD state variables and estimated parameters:

The model uses three state variables (S, S_d, and S_g) and four parameters (α, β, C_{max}, k_{b2}, and k_{d2}) bounded by upper and lower values in Table (4).

Table 4. Daily HyMOD water balance model parameter ranges.

HyMOD		
Parameters	**Ranges**	**Units**
β	$0.01 - 7$	-
C_{max}	$50 - 12000$	mm
α	$0.01 - 1$	-
k_{d2}	$0.14 - 1$	day^{-1}
k_{b2}	$0.01 - 0.14$	day^{-1}

5.2.3 abcd model

The model is applied for predicting the runoff (*R*) by utilizing the total precipitation for the month (*P*) and potential evapotranspiration (E_p) as inputs. The available water is defined as $A=P+S_0$ and evaporation opportunity as $Y=E+S_1$, where *E* is the evapotranspiration, S_1 is the ending soil moisture storage at the current step, and S_0 is the initial soil moisture storage at the current step. The model scheme is described in Figure 19. The ratio between *Y* and *A* is computed by:

$$\frac{Y}{A}=\frac{1+\frac{b}{A}-\sqrt{\left(1+\frac{b}{A}\right)^2-4a\frac{b}{A}}}{2a} \tag{5.14}$$

a ($0\leq a \leq 1$) is a parameter controlling the shape of the relationship, and *b* is a parameter controlling the soil moisture storage capacity. Once *Y* is computed by equation (5.14), *R* is computed by *A*-*Y*, and *E* is computed by equation (5.15):

$$E=Y\cdot\left[1-exp^{-\frac{E_p}{b}}\right] \tag{5.15}$$

The evaporation opportunity Y is further partitioned into evapotranspiration E and residual soil moisture storage. The relationship that governs the rate of soil moisture loss to potential evapotranspiration leads to equation (5.15), and S_1 is computed by Y-E. The available water for runoff is further partitioned to surface runoff (R_d) computed by equation (5.16) and groundwater recharge (R_g) computed by equation (5.17).

$$R_d=(1-c)\cdot R \qquad (5.16)$$

where the parameter c is the baseflow index, i.e., the ratio between long-term baseflow and total streamflow. The groundwater recharge is computed by:

$$R_g=c\cdot R \qquad (5.16)$$

According to the linear storage-discharge relation of the groundwater storage (S_{g1}), the baseflow from the groundwater storage is computed by:

$$Q_b=d\cdot S_{g1} \qquad (5.17)$$

where d is the parameter for groundwater residence time, and S_{g1} is the ending storage from the groundwater tank. By water balance the groundwater storage (S_{g1}) is computed by:

$$S_{g1}=(1-d)\left(R_g+S_{g0}\right) \qquad (5.18)$$

The direct runoff is computed in equation (5.18), having no surface runoff tank.

$$Q_d=(1-c)\cdot R \qquad (5.19)$$

where c is the baseflow index parameter, i.e., the ratio between long-term baseflow and total streamflow. The groundwater recharge (R_g) is computed by:

$$R_g=c\cdot R \qquad (5.20)$$

assuming a linear storage-discharge relation for groundwater storage, the baseflow from the groundwater storage is computed by:

$$Q_b = d \cdot S_{g1} \quad (5.21)$$

where d is the groundwater residence time parameter, and S_{g1} is the ending storage in the groundwater tank. By water balance the groundwater storage, S_{g1} is computed by:

$$S_{g1} = (1-d)\left(R_g + S_{g0}\right) \quad (5.22)$$

where $S_{g0}$the initial storage in the groundwater tank and the total runoff is is computed by:

$$Q = Q_d + Q_b \quad (5.23)$$

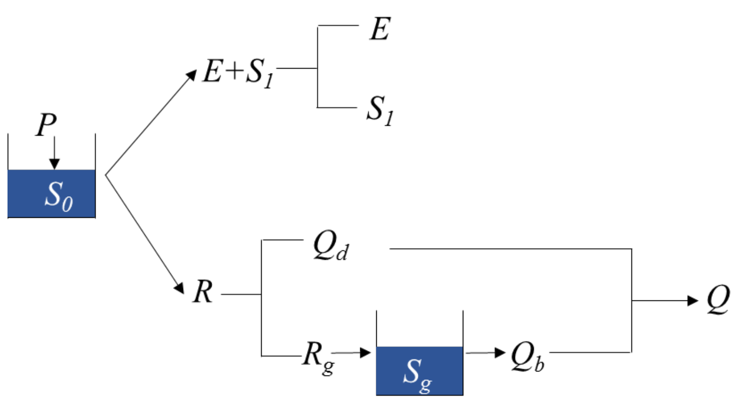

Figure 21: Monthly water balance model scheme for abcd model

5.2.4 abcd state variables and estimated parameters

The model uses two state variables S, S_d, and S_g and four parameters a, b, c, d bounded by upper and lower values in Table (5).

Table 5. Monthly abcd water balance model parameter ranges.

abcd		
Parameters	**Ranges**	**Units**
a	$0.01 - 1$	-
b	$50 - 1500$	-
c	$0.01 - 1$	-
d	$0.01 - 1$	-

5.3 Results and discussion

The temporal lumping of hydrologic data can cause loss of valuable information regarding the timing of precipitation and evapotranspiration. This can appear on small time scales such as daily and monthly, and dramatically increases at the annual scale where seasonality does not affect anymore. The variability in streamflow, precipitation, and evapotranspiration decreases, which tends to lower the direct runoff simulated and a higher portion of baseflow occurring. To deal with such a problem, buffering is usually performed. However, each buffer zone requires an additional parameter. Also, a significant note that should be taking into consideration that in larger catchments, buffering is responsible for dealing with the runoff response while accounting for the temporal scale and lumping in input data. Similarly, in a low variation of streamflow "slow runoff" it more likely to be associated with baseflow while high variability "fast flow" is a result of direct runoff (*Eckhardt*, 2005). However, in the groundwater flow through the unsaturated zone, this has a fast and slow component, and fast flow is considered direct runoff and the slow flow will be lumped with baseflow (*Xu & Singh*, 1998). The described concept of the model is performed is these two models (HyMOD, and Unified model). Even though the two models have their similar model structure but internally they vary in the runoff generation process.

5.3.1 Model performance

Initially, the evaluation of the model calibration results is based on the NSE examination using the exceedance of probability and categories. The NSE has been commonly used as an objective function in many studies (*Ahmad et.al*, 2010, *Collischonn et.al*, 2008, and *Gupta et.al*, 2011).

5.3.1.1 Daily Unified and HyMOD Performance

In the validated models period, Unified model outperformed the HyMOD model in most of the catchments regions as shown in Figure (20a). The change in the performance is not significant however it appears to be correlated as shown in Figure (20b). However, in Figure 21 it shows the correlation between the Unified model and HyMOD in the calibration period Figure (21a) and in the validation period Figure (21b).

The combination of evaporation and soil moisture distribution introduced earlier in Chapter 3, played a major role in the model performance. The difference between HyMOD and Unified model is that in Unified model the soil wetting ratio approaches to 1 when soil moisture storage index approaches to infinity. However, the soil wetting ratio in HyMOD equals soil moisture storage, while it is lower than C_{max} due to the finite bound of the distribution function of the storage capacity. Also, the computation of evaporation in HyMOD is based on the soil moisture storage which occurs at the rate of the potential evaporation, and the remaining of rainfall is used to fill the soil moisture storage. On other hand, the Unified model evaporation is computed using based on the ratio of partially or fully saturated concept as it is described in detail in Chapter

3. Therefore, the model performance based on the exceedance probability of NSE are relativity close with a superiority of Unified model over the HyMOD.

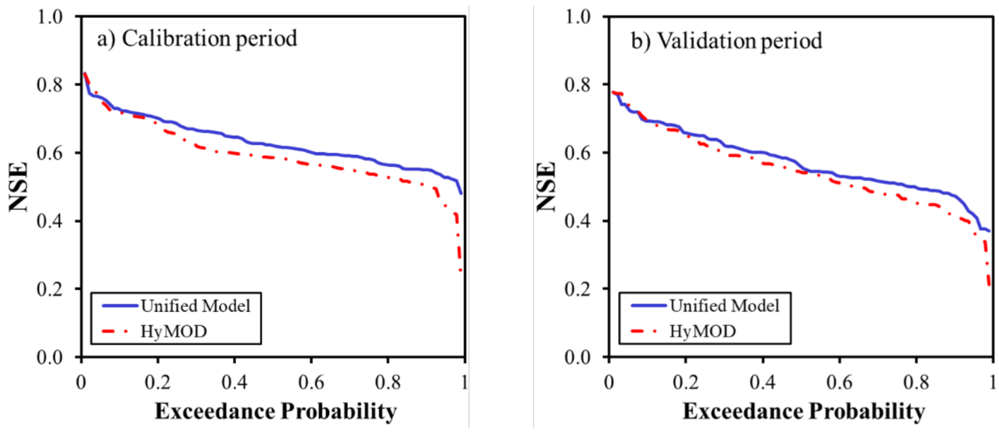

Figure 22: Performance comparison between the daily Unified model presented in the solid blue line and HyMOD model presented with the hyphened red line.

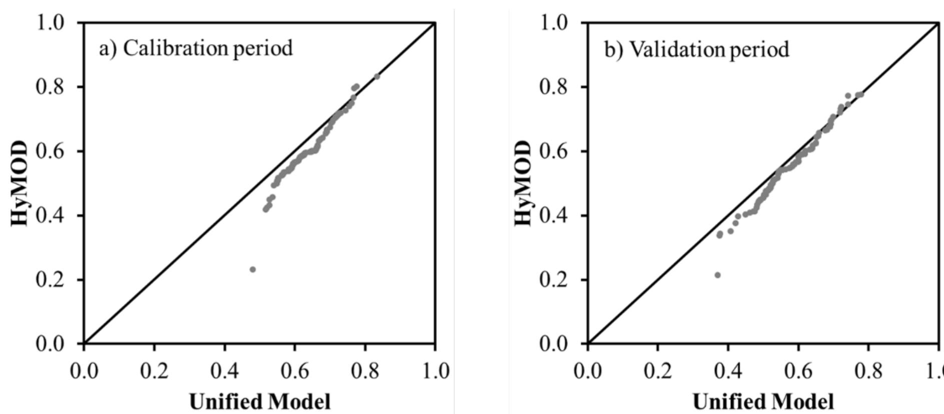

Figure 23: Correlation comparison between the daily Unified model and HyMOD in the calibration and validation periods.

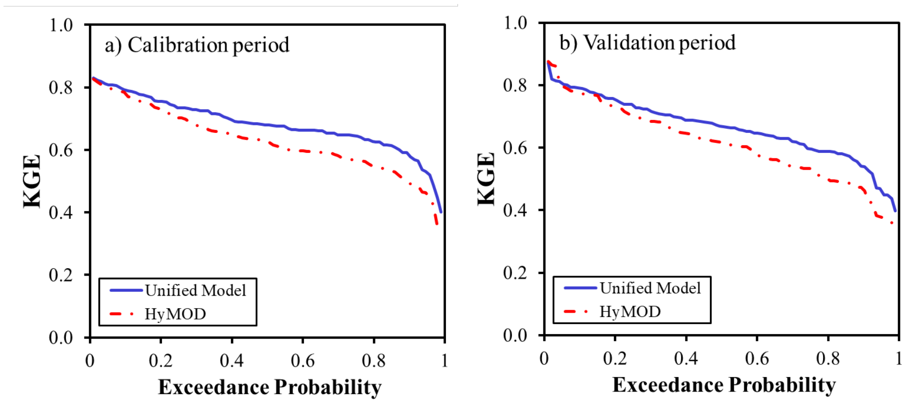

Figure 24: KGE comparison between daily Unified model and HyMOD in the calibration and validation periods.

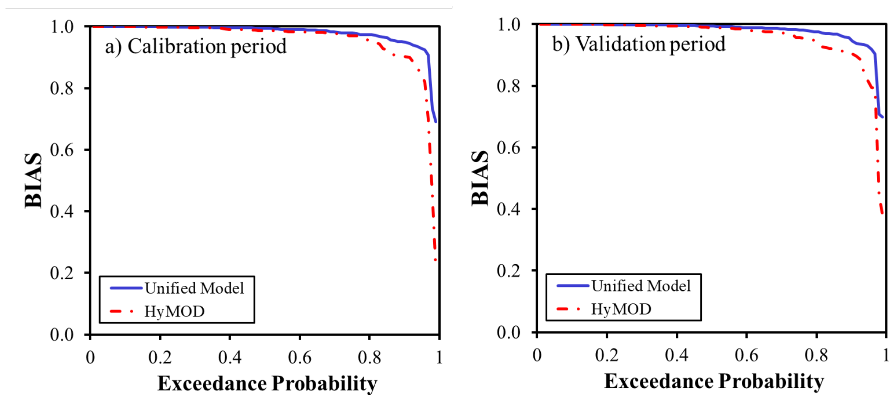

Figure 25: BIAS comparison between daily Unified model and HyMOD in the calibration and validation periods.

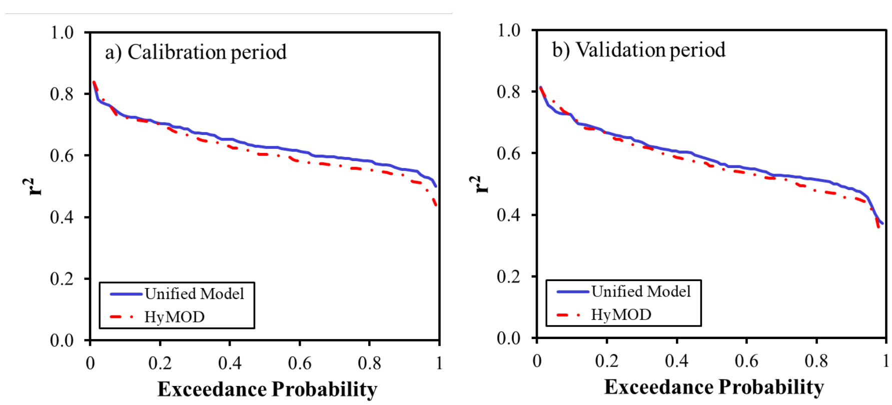

Figure 26: The coefficient of determination comparison between daily Unified model and HyMOD in the calibration and validation periods.

The NSE values in a categorical order is examined to show the distinction closely shown in Figure (21). The categories that have been used are: strong, moderate, weak, and very weak. The group performance thresholds values are 0.75, 0.67, and 0.59, respectively. The categories that have been used as follows: strong (1.0 - 0.75), moderate (0.75 - 0.67), weak (0.67 - 0.59), and very weak (<0.59). Consequently, in Table (6) shows the catchment performance based on the selected category and model NSE values of the calibration and validation periods. Accordingly, the Unified model showed catchments classified from strong to moderate with a percentage of 24%, and 18%, respectively. The percentage is divided to 7% strong, and 22% moderate in the calibration period and 2% strong, and 16% moderate in the validation period. Similarly, the HyMOD shows the percentage of 24 % and 16% strong to moderate in the calibration and validation periods, respectively. However, the NSE was split into 7% strong, and 17% moderate in the calibration period and 2% strong, and 14% moderate in the validation period. The HyMOD has more percentage of very weak NSE catchments values compared with Unified model with 51% and 63% in the calibration and validation periods, respectively. The KGE evaluation performance has been implemented in Figure (23). During the calibration and validation periods the KGE values of the Unified Model higher than HyMOD. On the other hand, the BIAS in Figure (24) performance values that Unified model is less accurate during the both calibration and validation periods. However, the coefficient of determination (r^2) in Figure (25) follows a similar and consistent behavior of the NSE values.

Table 6. NSE values based on categorical order for the calibration and validation periods.

NSE (Catchments)	HyMOD	Unified Model

	Cal	Val	Cal	Val
Strong (1-0.75)	6	2	4	3
Moderate (0.67-0.75)	20	15	15	10
Weak (0.59-0.67)	39	23	24	18
Very weak (<0.59)	27	52	49	61

5.3.1.2 Monthly Unified and abcd

The Monthly Unified model versus the abcd model has been compared using the exceedance probability of catchments NSE performance values. The comparison resulted into a better performance of the Unified model over the abcd model. However, the Unified model showed an advancement in the performance, the abcd model has some parts that show a slight significance over the Unified model as shown in Figure (22). However, in Figure (23), both the monthly Unified model and abcd models showed a high value of correlation as in Figure (23a) in calibration period and Figure (23b) in the validation period.

The difference in the resulted values are from the computation of the Evaporation opportunity by equation (5.14) due to the partitioning of precipitation and initial soil moisture into evaporation and ending soil moisture storage and runoff, which is different from the Unified model where the difference between soil wetting and initial storage from the soil moisture capacity is partitioned into direct runoff and groundwater. Also, the evaporation in the abcd model is computed by the loss of soil moisture to the potential evaporation at an exponential rate as in equation (5.15).

The categorical distinction from the NSE values has been tested over the monthly Unified and abcd models. According to Table (7), the catchment performance has been divided into four

categories which is similar to Section 5.3.1.2. The Unified model showed catchments classified from strong to moderate with a percentage of 89%, and 66% for the calibration and validation periods, respectively. The percentage is divided to 70% strong, and 21% moderate in the calibration period and in the validation period 37% strong, and 29% moderate. Similarly, the abcd shows the percentage of 85 % and 65% strong to moderate in the calibration and validation periods, respectively. However, the NSE was split into 67% strong, and 18% moderate in the calibration period and 38% strong, and 29% moderate in the validation period. The HyMOD has more percentage of very weak NSE catchments values compared with Unified model with 11% and 34% in the calibration and validation periods, respectively. In Figure (26, 28, and 30), it shows a similar pattern of accuracy in the calibration and validation periods. However, in the BIAS values the validation period shows that some of the values were more accurate at some of the catchments while other are less accurate in Figure (29).

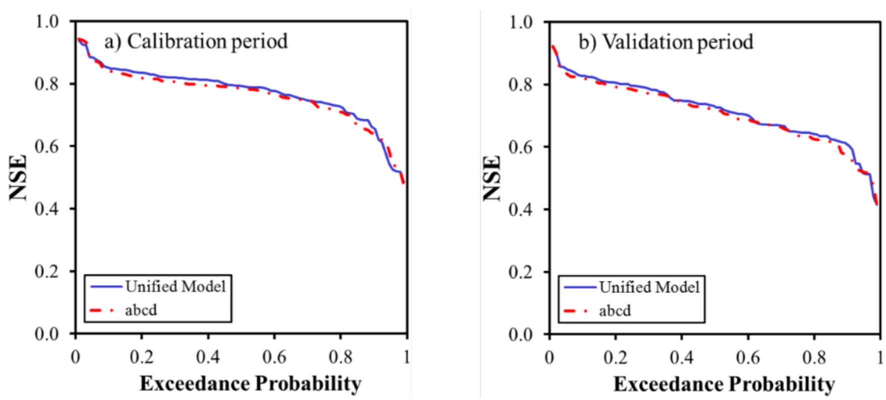

Figure 27: Performance comparison between the monthly Unified model presented in the solid blue line and abcd model presented with the hyphened red line.

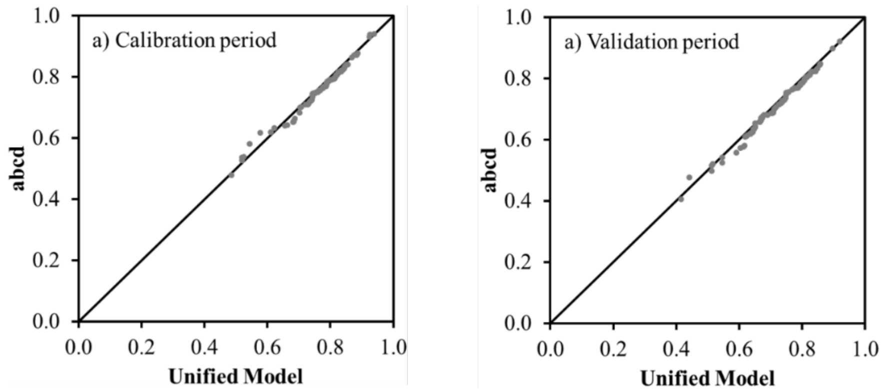

Figure 28: Correlation comparison between the monthly Unified model and abcd in the calibration and validation periods

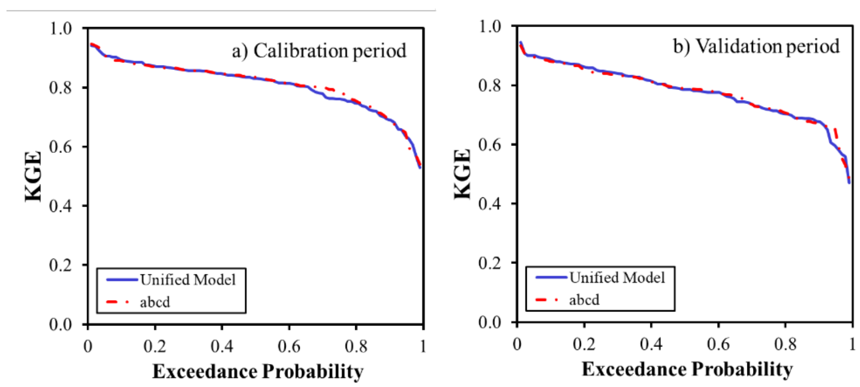

Figure 29: KGE values comparison between monthly Unified model and abcd in the calibration and validation periods.

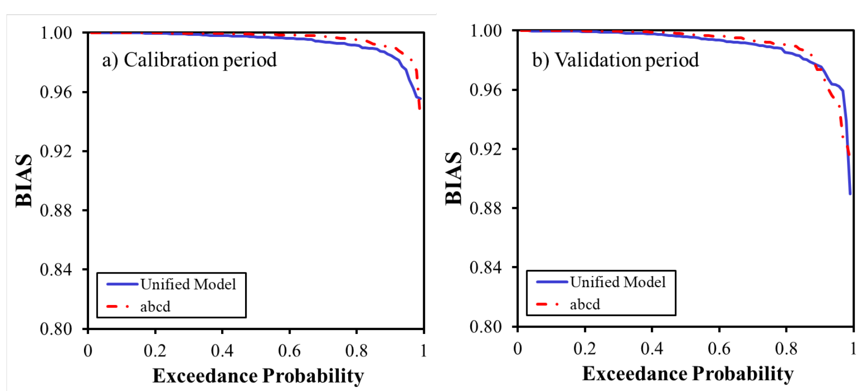

Figure 30: BIAS comparison between monthly Unified model and abcd in the calibration and validation periods.

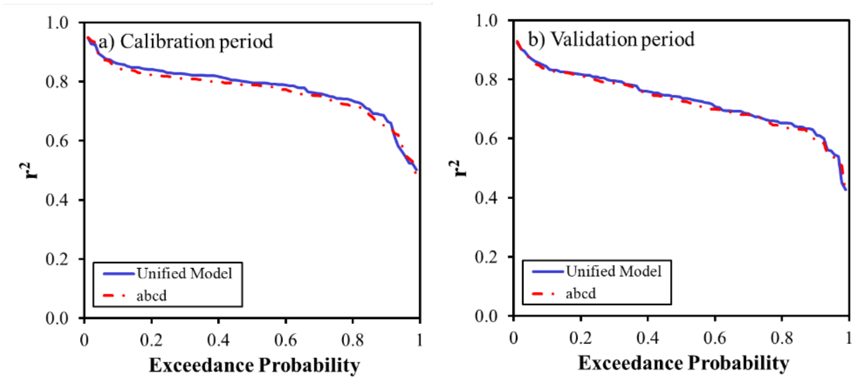

Figure 31: The coefficient of determination comparison between daily Unified model and abcd in the calibration and validation periods.

Table 7. NSE values based on categorical order for the calibration and validation periods.

NSE (Catchments)	**abcd**		**Unified Model**	
	Cal	Val	Cal	Val
Strong (1-0.75)	62	35	64	34
Moderate (0.67-0.75)	16	27	18	27
Weak (0.59-0.67)	9	19	4	24
Very weak (<0.59)	5	11	6	7

5.3.2 Estimated parameters

The estimated parameters involved in each tame scale model have the same physical attributes. However, the difference comes out from the partitioning of precipitation and soil moisture capacity.

5.3.2.1 Daily Unified and HyMOD

The HyMOD model involves five parameters (α, β, $C_{\max}$, k_{b2}, and k_{d2}) and three state variables (S, S_d, and S_g). Also, the Unified model shares the same number of parameters (α, S_b, γ,

k_d and k_b) and have the similar controlling attributes on the runoff generation process. Parameter α and a are the shape factor that describe the soil moisture capacity distribution. Parameter S_b, and $C_{\max}$ describes the maximum soil moisture capacity. Parameters β, and γ are allocation parameters that divide the runoff into surface runoff and groundwater. k_d, and k_{d2} are the residence time of direct runoff while k_b, and k_{b2} are the residence time of groundwater storage. Therefore, in this section we compare the effective relationship of the parameters involved that shares the same controlling factor on the runoff model.

In Figure 31, all catchment optimal parameters were compared against each model similar physical attribute parameter. The soil moisture capacity represented in Figure (31a) shows that the daily Unified model overestimate the values while HyMOD values are low, except for one catchment. The ratio of surface to groundwater parameter appears to be relatively correlate among the two model's comparison, while having parameters reaching the upper bounds of the parameter range in Figure (31b). However, in Figure (31c) the storage to surface runoff parameters (k_d and k_{d2}) both models are highly correlated and apparently the combination of both models' parameters are affecting the excess of the soil to the surface runoff. The groundwater residence time parameter did not show good relationship with the HyMOD mdoel as in Figure (31d).

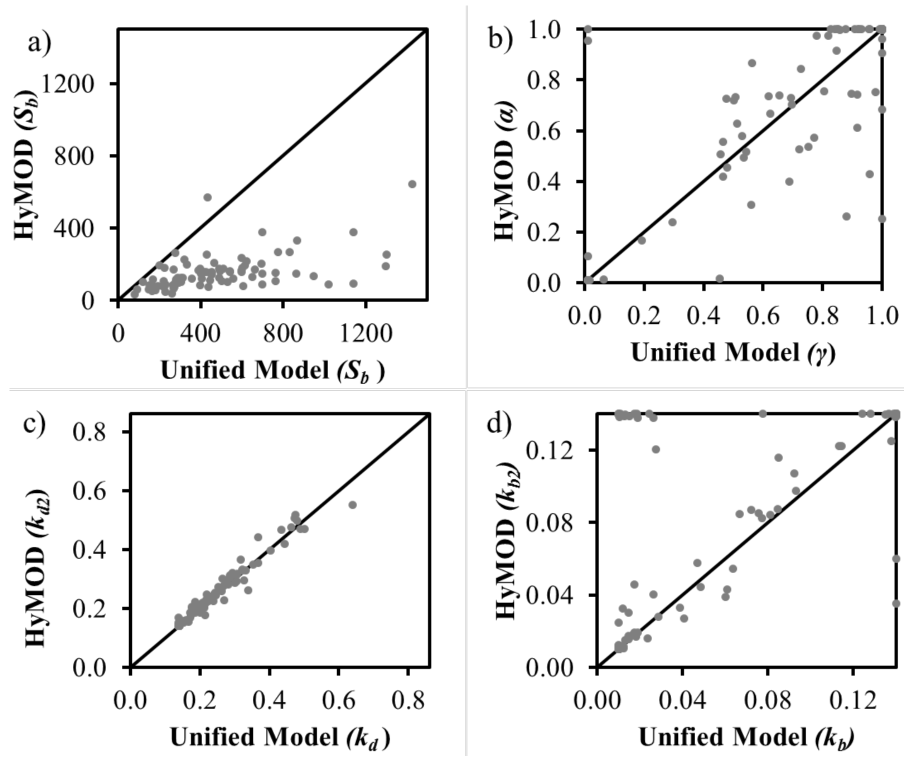

Figure 32: Comparison of the daily Unified model parameters against the HyMOD.

5.3.2.2 Daily Unified Model Sensitivity Analysis

For a slected study area located in Thurston County, Washington (USGS Site ID# 12027500) and drainage area of nearly 2318 km^2. The catchment mean daily aridity index ($\frac{P}{E_p}$) equals to 2.64 and runoff coefficient ($\frac{Q}{P}$) equals to 0.73. , a 1000 simulation have been done using the Unified model to look at each parameter behavior and how the GA varies to converge to the optimal solution. In this application, we use a population size of 50 when the number of variables is 5. Mainly three parameters seem to be more sensitive (a, S_b, and k_d) as shown in Figure (32), and one number might not be useful to represent the optimal solution. However, 88%, and (97 %) of the NSE calibration, and (validation) values, respectively, appears to be consistent with the optimal

value of this location. Consequently, this shows the degree of the robustness of the method used to generate the optimal values of this location.

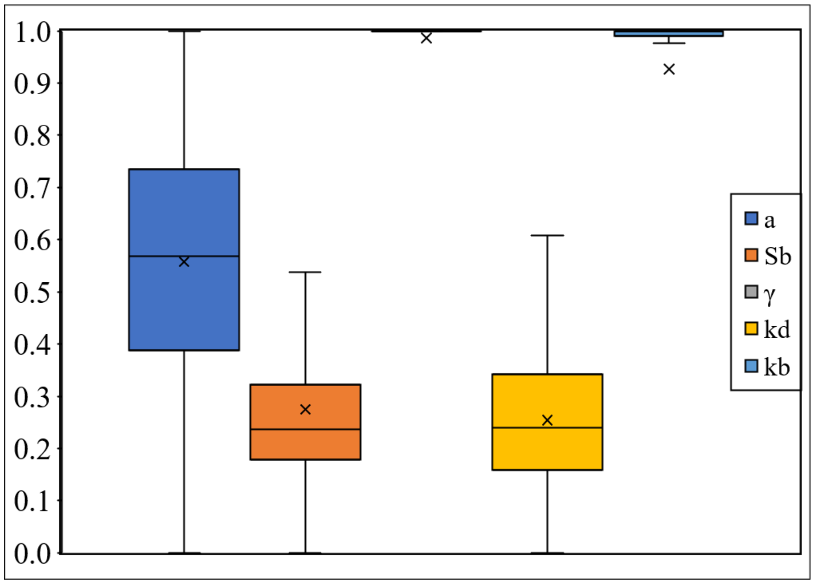

Figure 33: comparison of the normalized calibrated parameters (a, S_b, γ,k_d, and k_b) for the Unified model in one catchment based on 1000 simulations. the box-plot: the inside middle lines are the median values, the x sign are mean values, the outer boarder of the box lines represents the quartile range, the top side of the box is the 3rd quartile and lower bottom side represents the 1st quartile.

5.3.2.3 Daily Unified Model uncertainty analysis

To better understand the catchment behavior and responses, it has better to have the best accuracy and precision of the model predictions to help decision makers push to better quantification. Different approaches for uncertainty estimation can be used to which includes state-space filtering, model averaging, and Bayesian approaches. Particularly, we use a Bayesian approach a recently developed deferential evaluation adaptive metropolis (DREAM) Markov Chain Monte Carlo (MCMC) scheme (Vurgt et al., 2003).

The DREAM function uses more than twenty other functions to implement its various steps and functionalities and generate samples from posterior distribution. Here in this selected watershed, we are using the vector of simulated values to evaluate the extent of the uncertainty. The Unified model closely tracks the observed streamflow as it is shown in Figure (33) with a 95% prediction uncertainty is indicated with dark grey region, where as the remaining predictions error is represented in light grey region. About 95% of the observations lies within the grey region, an indication that simulation uncertainty ranges are statistically adequate. The possibilities of the marginal distribution of the subset of random variables are shown in Figure (34) to show the different variables defining the interested variables needed in Figure (35). The convergence of the samples chains of the variables are shown in Figure (36).

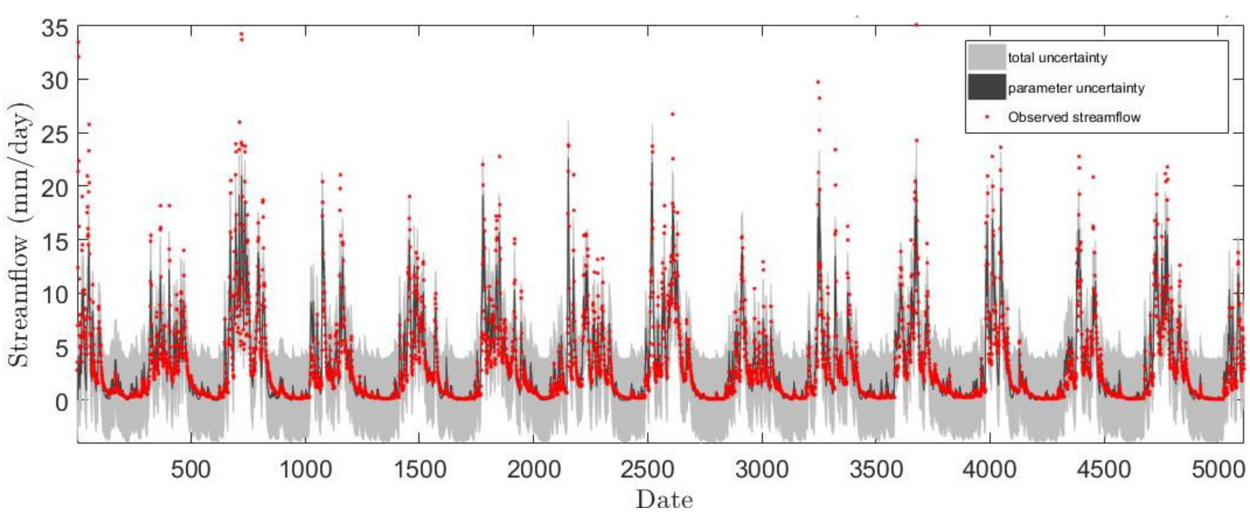

Figure 34: Streamflow prediction uncertainty ranges derived with DREAM for a representative portion of the calibration period.

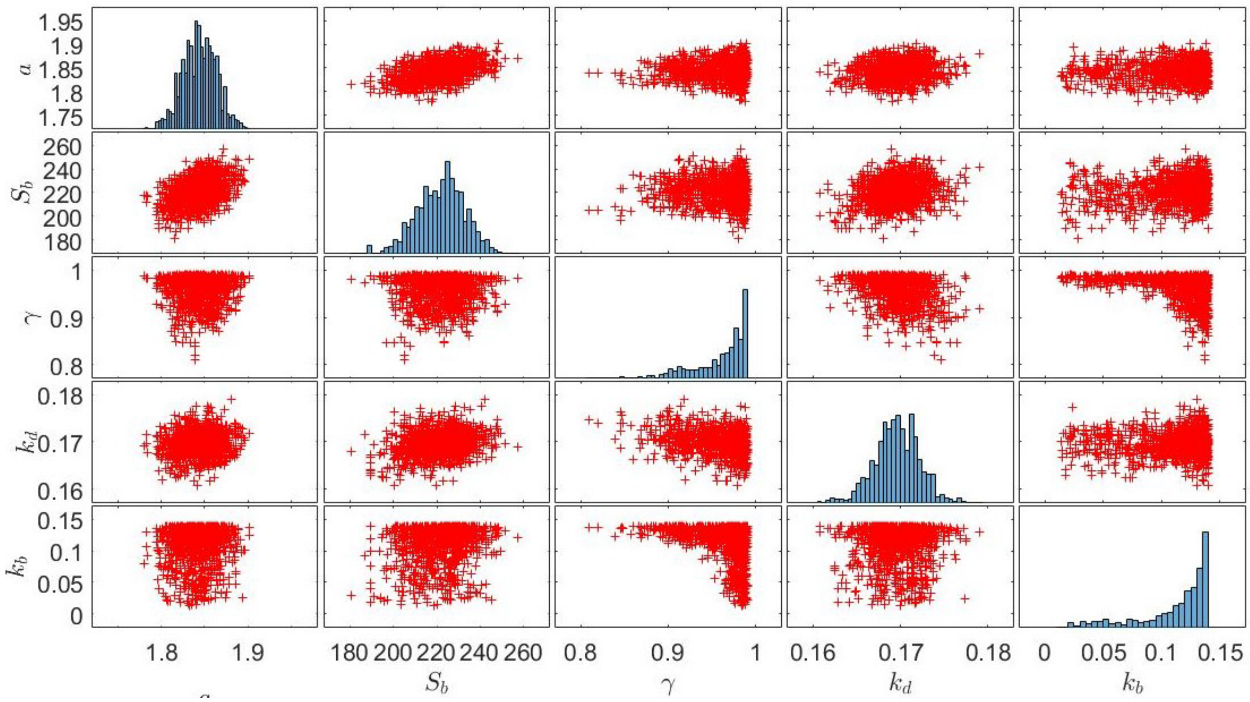

Figure 35: The marginal distribution and bivariate scatter plots posterior samples by DREAM.

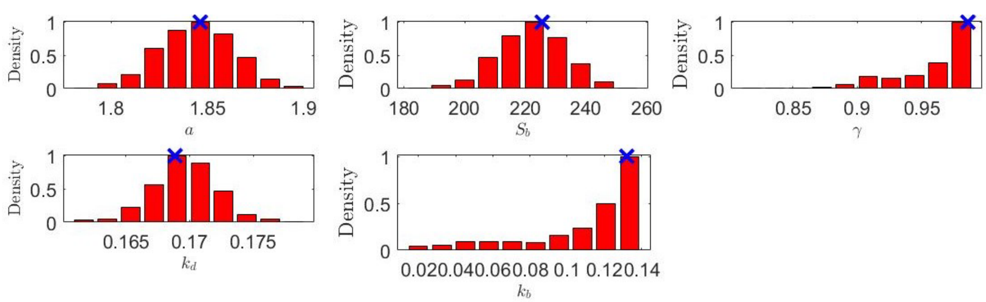

Figure 36: Marginal distribution of sampled parameters by DREAM.

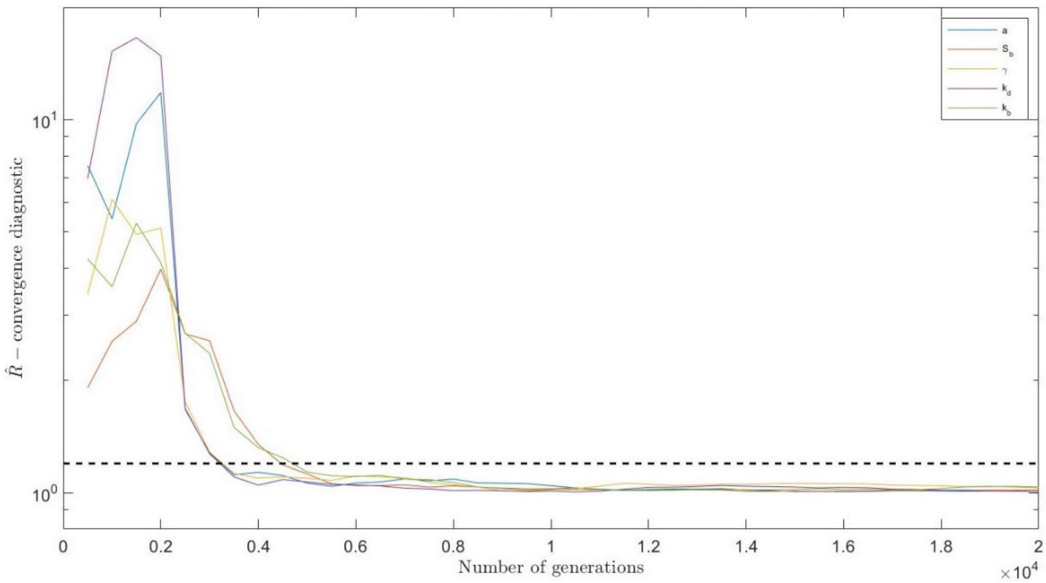

Figure 37: Convergence of sampled chains of parameters using univariate diagnostic (DREAM).

5.3.2.3 Monthly Unified and abcd

The Monthly Unified model involves four parameters and two state variables as described in section 3.1.1. Also, the abcd model shares the same numbering of parameter and state variables. Each model parameter have in common relationship, the parameters b and S_b which are the optimal estimated values of the soil moisture capacity, it is noticeable that the abcd model has overestimated the values while the monthly unified values are underestimated as presented in figure (38a). On the other hand, the Unified (1-γ) values showed an overestimation of the optimal values, which means that abcd model allocates less runoff than the Unified model as it appears in Figure (38b). The d ,and k_d values of the residence time of the groundwater storage have a good correlation with some minor over estimated values on the monthly Unified model as shown in Figure (38c).

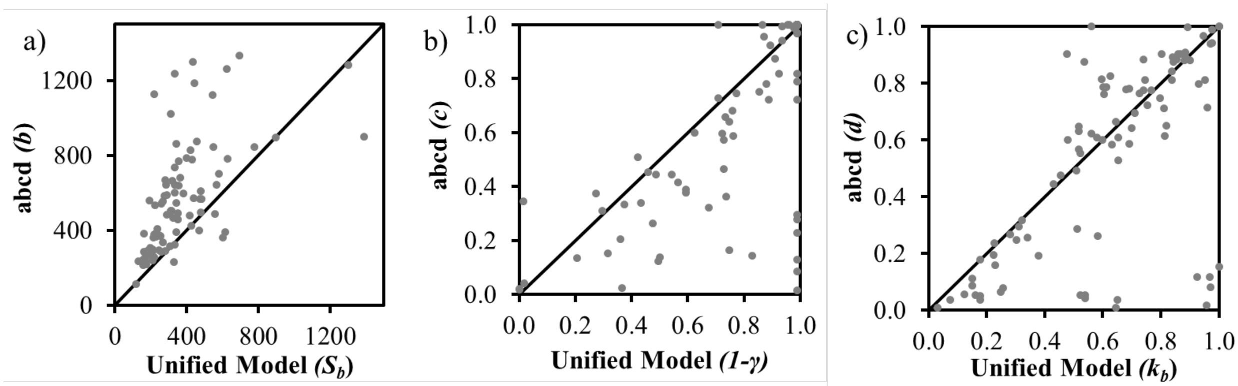

Figure 38: Comparison of the monthly Unified model parameters against the abcd model.

5.3.3 Applied models on selected catchments

All time scales of the Unified model have been applied on a selected number of catchments based on the mean monthly precipitation mode and potential evaporation as shown in Figure 39. The selected locations climate, and locations are shown in Table 8. Also, the evaluation values of NSE and RMSE of those selected location in Table 9.The comparison of models will be based on the cumulative distribution of the daily soil moisture capacity and the exceedance probability of soil moisture storage, evaporation and streamflow for simulated and observed values. On the monthly model comparison, it is based on the soil moisture storage, evaporation, and streamflow. Lastly in the annual Unified model, the comparison is based on the streamflow.

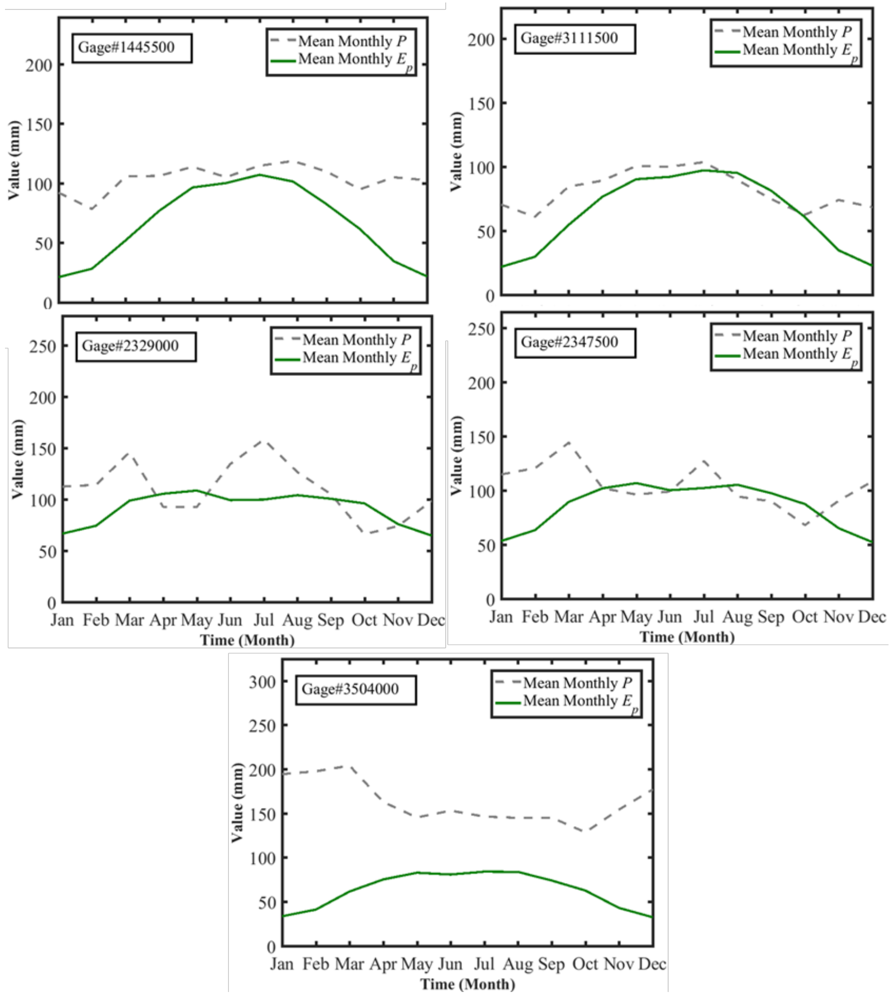

Figure 39: Mean monthly precipitation (green solid line) and potential evaporation (dashed gray line).

Table 8. Spatial and climate characteristics of the selected catchments

No.	**Gage ID (USGS)**	**Location**	**Drainage Area (km^2)**	***E/P***	***E_p/P***	***Q/P***	***P/E_p***
1	01445500	Pequest River at Pequest NJ	274	0.58	0.63	0.42	1.59
2	03111500	Short C N. Dillonvale, OH	319	0.63	0.77	0.37	1.29
3	02329000	Ochlockonee River N. Havana, FL.	2953	0.75	0.83	0.25	1.21
4	02347500	Flint River Near Culloden, GA.	4791	0.67	0.82	0.33	1.22
5	03504000	Nantahala River Near Rainbow Springs, NC.	134	0.30	0.39	0.70	2.57

Table 9. Calibration and validation evaluation values of NSE and RMSE for the Unified model

No.	Gage ID (USGS)	***NSE Cal***	***NSE Val***	***RMSE Cal***	***RMSE Val***
1	01445500	0.71	0.68	0.65	0.85
2	03111500	0.63	0.52	0.73	0.88
3	02329000	0.62	0.56	0.88	0.99
4	02347500	0.69	0.68	0.966	0.96
5	03504000	0.77	0.74	1.47	1.57

5.3.3.1 Daily Unified and HyMOD

According to the mean monthly precipitation and potential evaporation signature, it is noticed that precipitation have one, two, and three modes based on the selected catchments. Also, mean monthly potential evaporation could bypass the precipitation in several months which have an impact on the streamflow generation and its attributes. The soil moisture capacity (S_b) and the shape parameter (a, and β) can affect the runoff generation among the selected catchments.

The one mean monthly precipitation mode, selected catchment (Gage ID: 03111500) showed a similar pattern of modeled streamflow even though there is a huge gap between the soil moisture capacity (Figure 40). The reason behind this obvious observation is the method used in computing the evaporation and soil moisture capacity, showing this observation is to confirm the computation can play a major role even after getting a similar NSE values between the HyMOD and Unified models as in Figure 41. The low value of NSE in the calibration period (HyMOD [0.63], and Unified [0.64]) shows a scattering behavior along the 1:1 correlation line in Figure 41. On the other hand, the modeled Unified versus HyMOD modeled streamflow showed an underestimation (Figure 42).

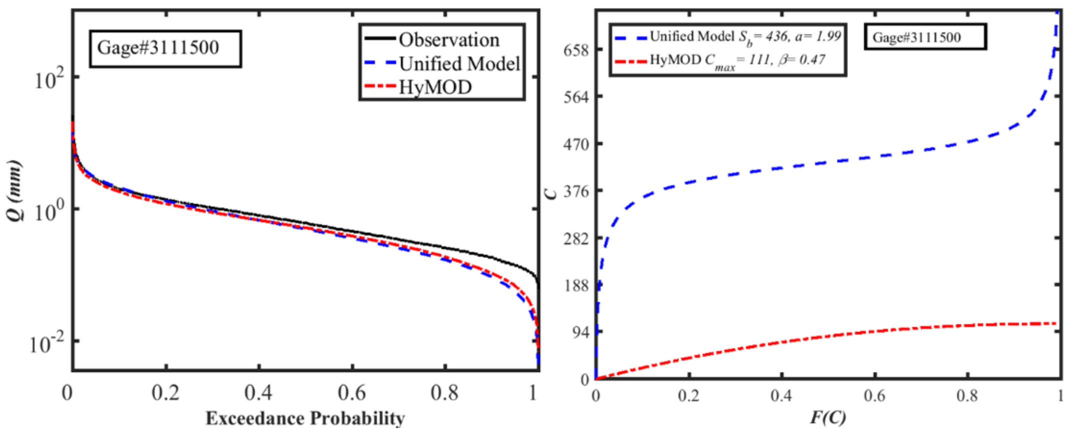

Figure 40: Streamflow exceedance probability (a, c, and e), and soil moisture capacity (b, d, and d) of the daily Unified (blue) and HyMOD (red) of catchment (Gage ID: 03111500).

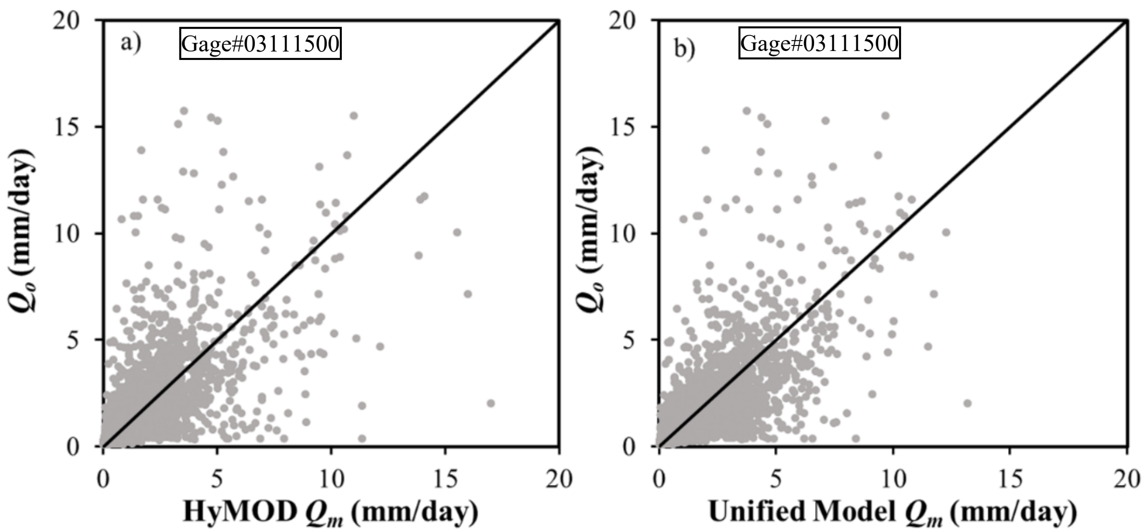

Figure 41: Comparison of modeled streamflow daily a) HyMOD, and b) Unified models against the observed streamflow of catchment (Gage ID: 03111500).

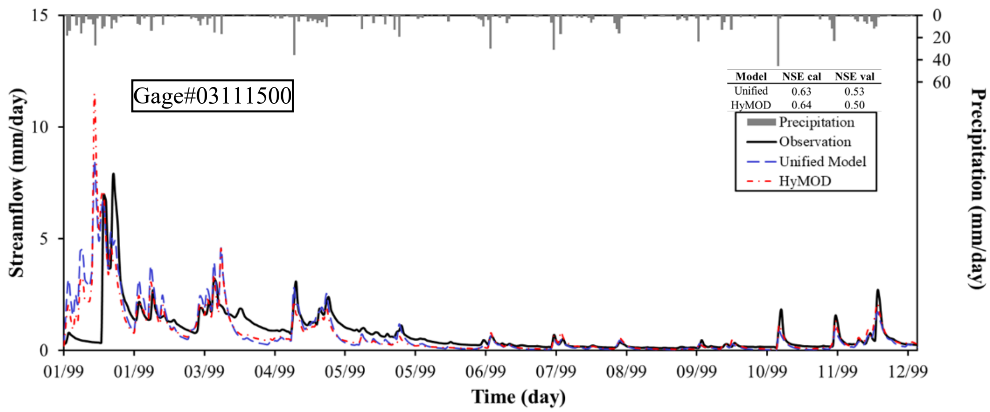

Figure 42: Comparison of observed (black), daily Unified (blue), and HyMOD (red) streamflow of catchment (Gage ID: 03111500).

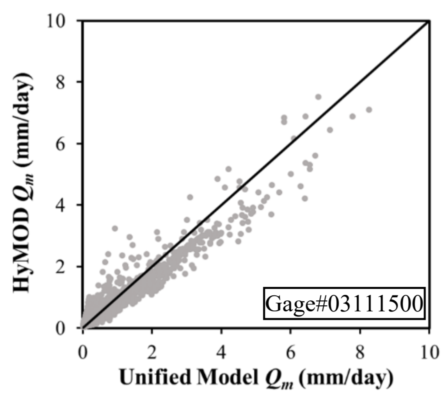

Figure 43: Modeled values of the Unified model and HyMOD of catchment (Gage ID: 03111500)

The two mode precipitation in the summer and spring seasons (Gage ID: 02347500, 2329000) or spring and winter (Gage ID: 03504000) showed a low NSE values in the calibration Unified (0.69, 0.62, and 0.78) and HyMOD (0.67, 0.61, and 0.77), the validation Unified (0.68, 0.56, and 0.74) and HyMOD (0.67, 0.57, and 0.74) as it appears in Figure 44. However, the comparison has low NSE values but still the simulated runoff values shows a good correlation as shown in Figure 45. However, it did not show similar behavior in the soil moisture capacity (Figure 45). The modeled HyMOD and Unified underestimate the streamflow and have similar streamflow

pattern (Figure 45). In Figure 46 low values of streamflow are underestimated in both models (Unified and HyMOD), while high values are overestimated due to low NSE value. The NSE value in Gage ID: 03404000 is higher than Gage ID: 02347500, and 02329000 which affect the accuracy of the modeled values of streamflow (Figure 47).

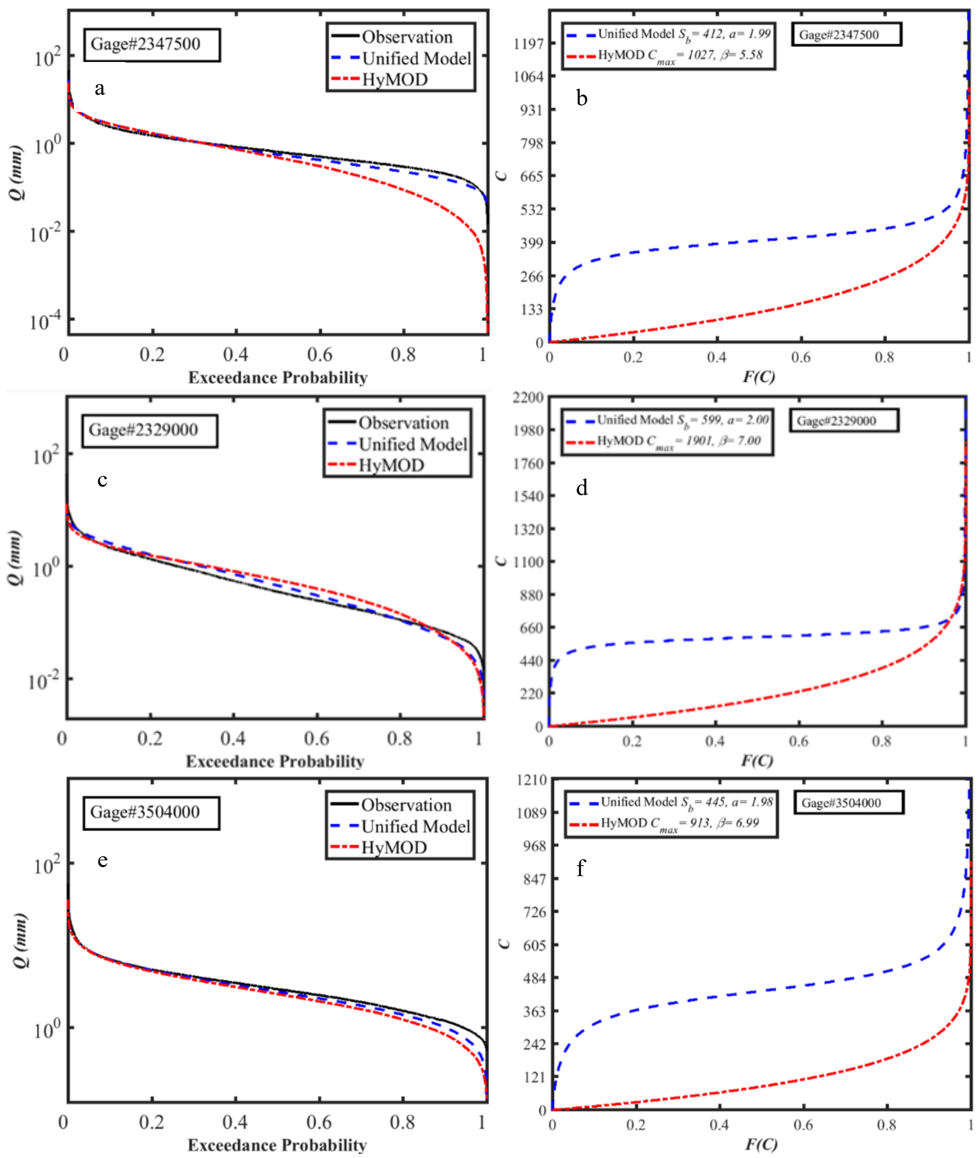

Figure 44: Streamflow exceedance probability (a, c, and e), and soil moisture capacity (b, d, and d) of the daily Unified (blue) and HyMOD (red) of catchment (Gage ID: 02347500, 02329000, and 03504000).

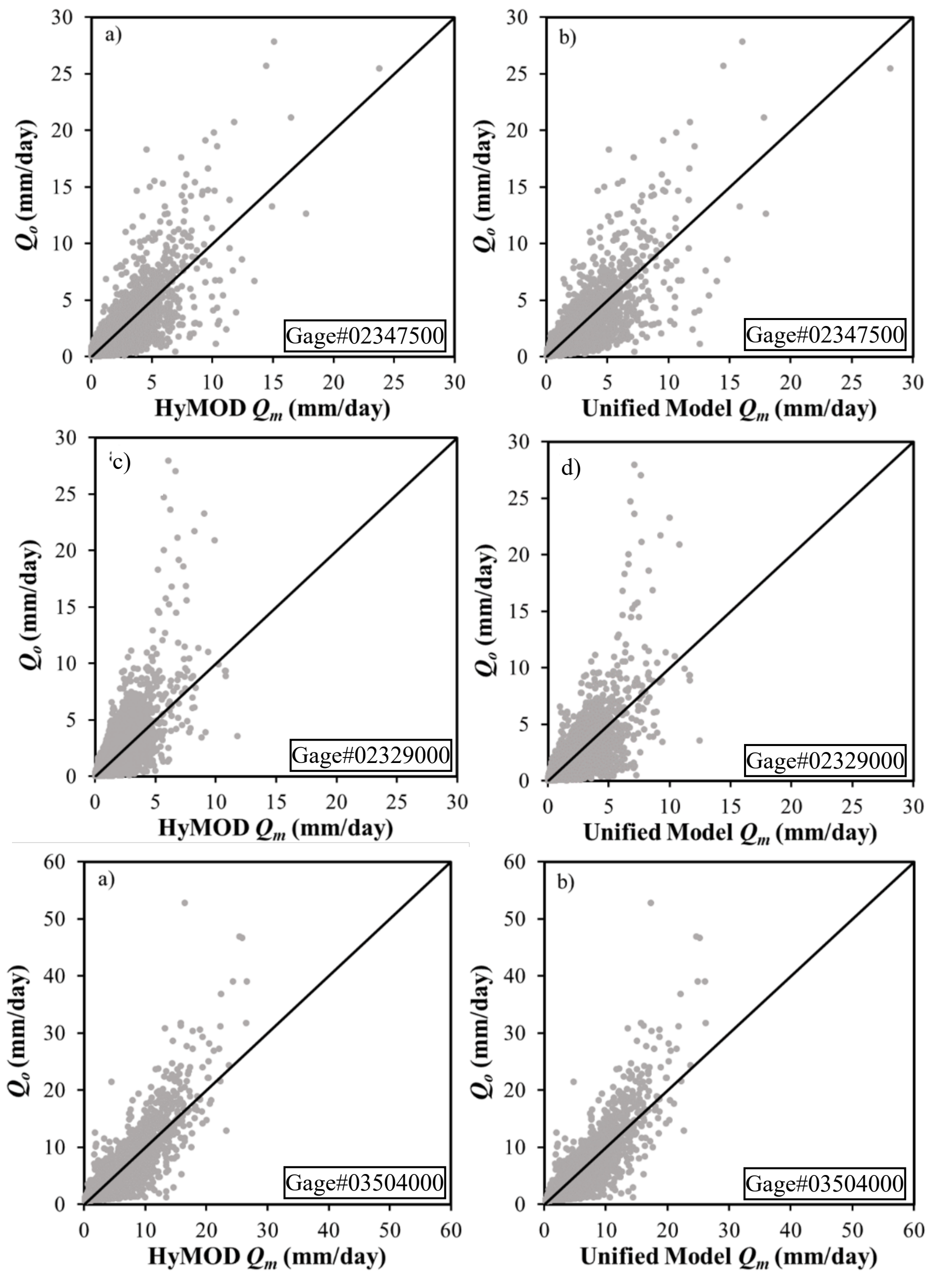

Figure 45: Comparison of modeled streamflow daily a) HyMOD, and b) Unified models against the observed streamflow of catchment (Gage ID: 023475000, 02329000, and 03504000).

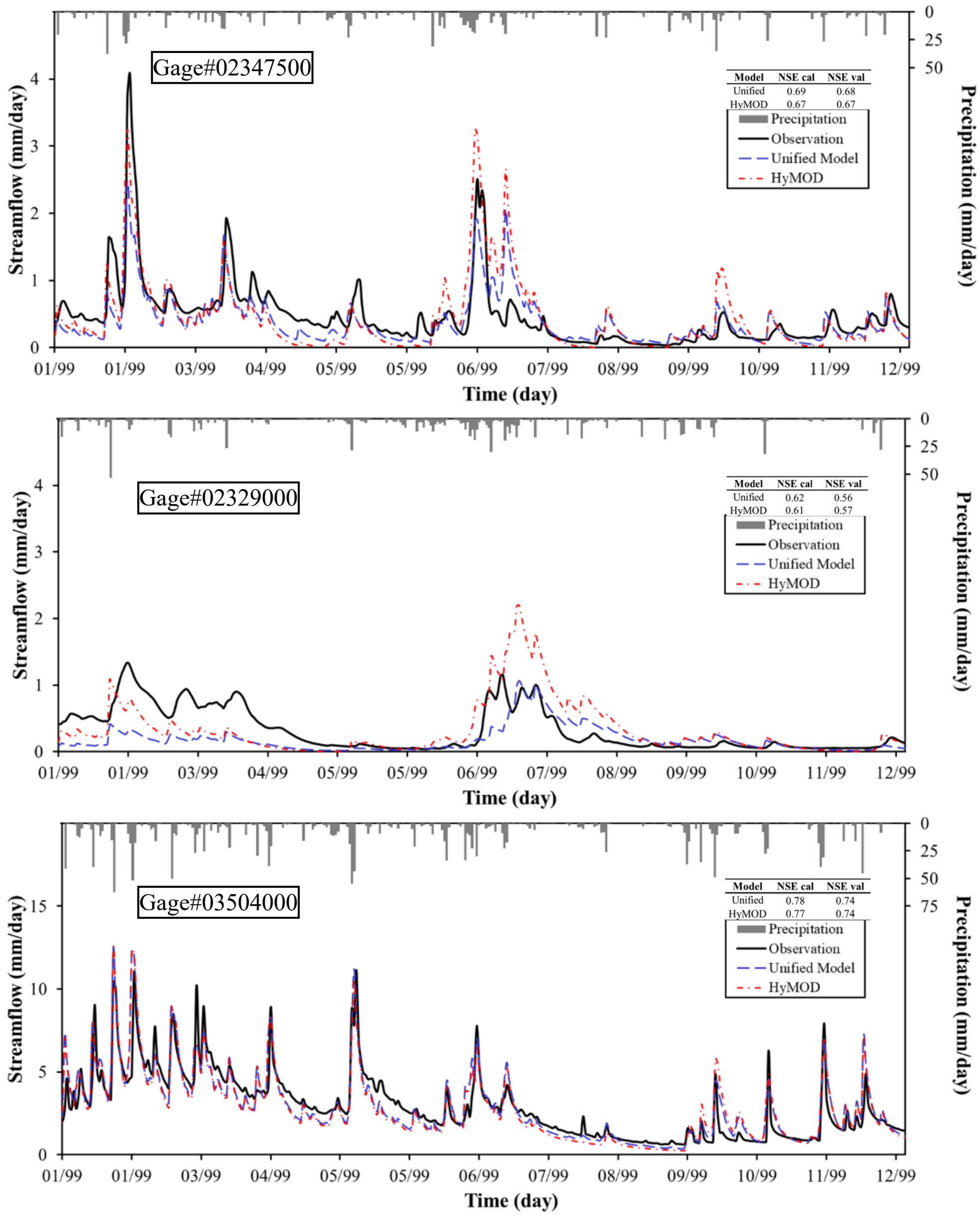

Figure 46: Comparison of observed (black), daily Unified (blue), and HyMOD (red) streamflow of catchment (Gage ID: 02347500, 02329000, and 03504000).

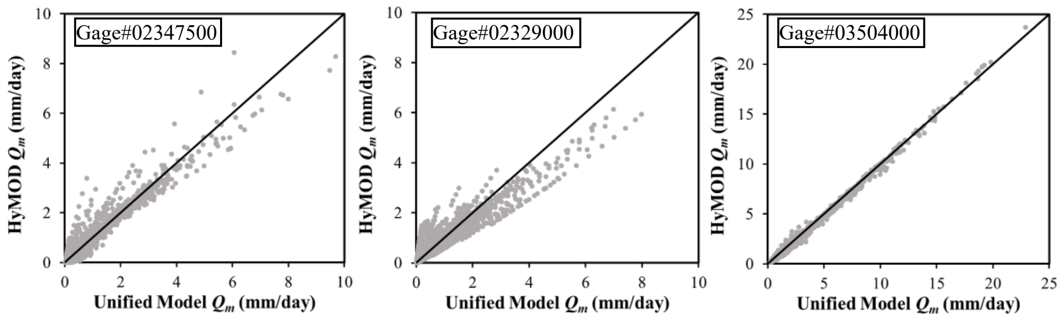

Figure 47: Modeled values of the Unified model and HyMOD of catchment (Gage ID: 023475000, 02329000, and 03504000).

The three-mean monthly precipitation mode in spring, fall, and summer seasons (Gage ID 1445500) showed a huge gap between the soil moisture capacity (S_b , and C_{max}) as in Figure (48b). However, the low and high values of streamflow showed a difference (Figure 49a, and 49b). The streamflow is underestimated over both models (Unified, and HyMOD) as shown in Figure 50, and 51.

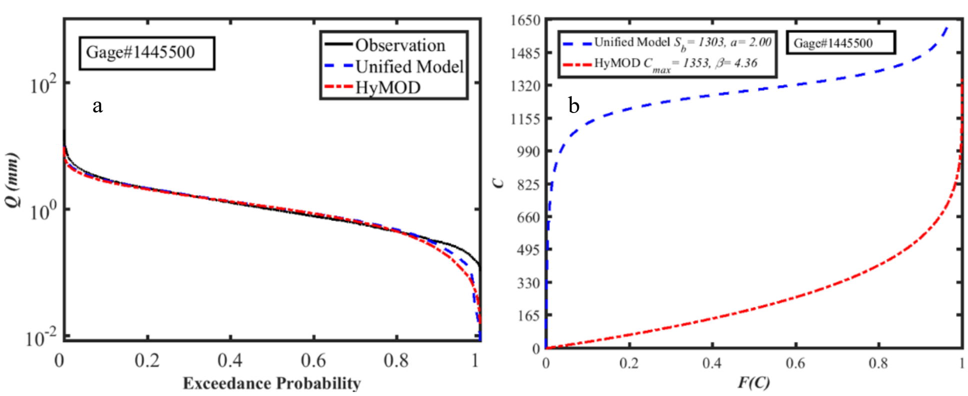

Figure 48: Streamflow exceedance probability, and b) soil moisture capacity of the daily Unified (blue) and HyMOD (red) of catchment (Gage ID: 01445500).

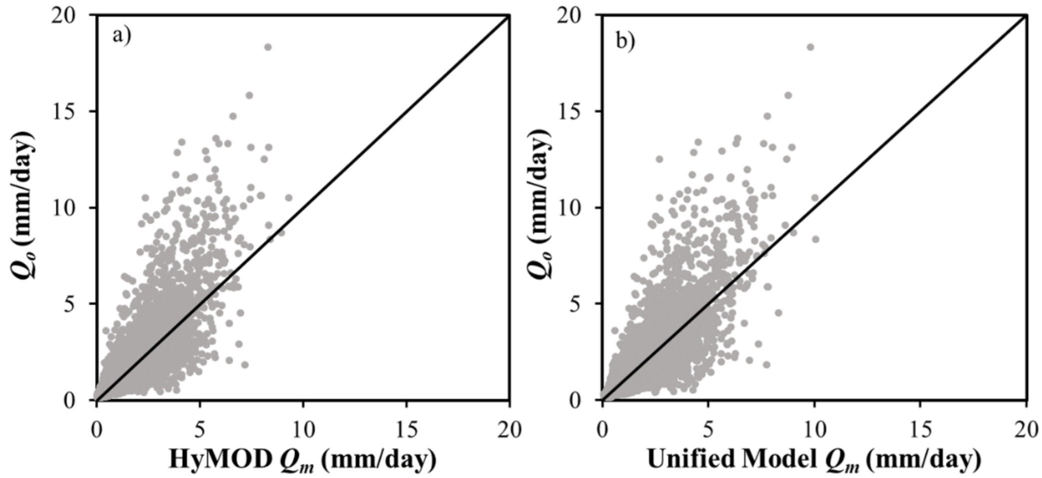

Figure 49: Comparison of modeled streamflow daily a) HyMOD, and b) Unified model against the observed of catchment (Gage ID: 01445500).

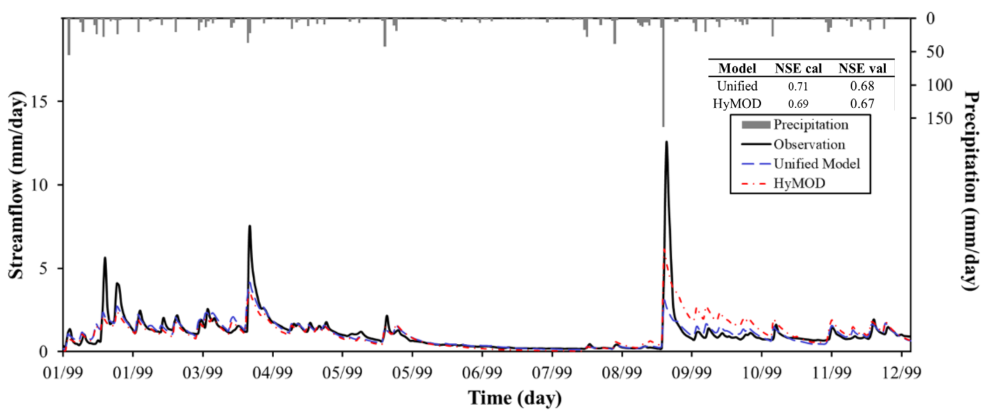

Figure 50: Comparison of observed (black), daily Unified (blue), and HyMOD (red) streamflow of catchment (Gage ID: 01445500).

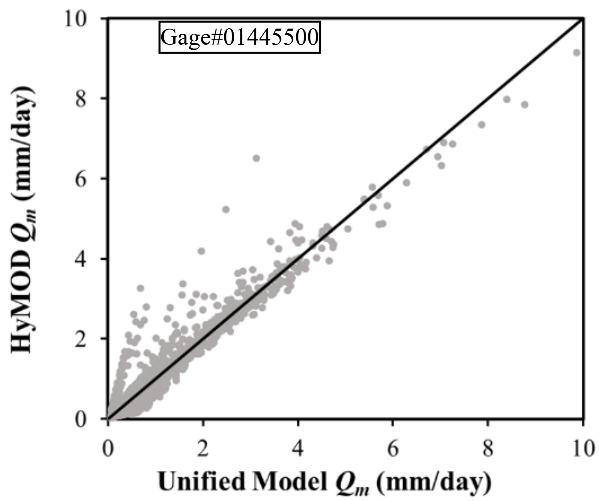

Figure 51: Modeled values of the Unified model and HyMOD of catchment (Gage ID: 01445500).

5.3.3.2 Monthly Unified and abcd

Similar to the daily model comparison, the Unified model and abcd models are compared based on the selected catchment from Table 8, mean monthly precipitation and potential evaporation mode as in Figure 39. The difference in results in NSE has shown better values for the selected catchments. However, the climatic attributes from precipitation and potential evaporation are the driven forces that play a major role in changing the streamflow condition.

The one mode precipitation (Gage ID: 03111500), showed better performance in monthly than daily as shown in Figure 39. The comparison showed good correlation between abcd and Unified models with a less scattering in Figure 52. The Unified model verses the abcd model are very close to each other streamflow values (Figure 53). The soil moisture storage is low while the evaporation values are high (Figure 54). Therefore, the Unified model computation are high in values of evaporation and low in soil moisture storage. This allow more evaporation to be released to the atmosphere and more soil moisture to be stored.

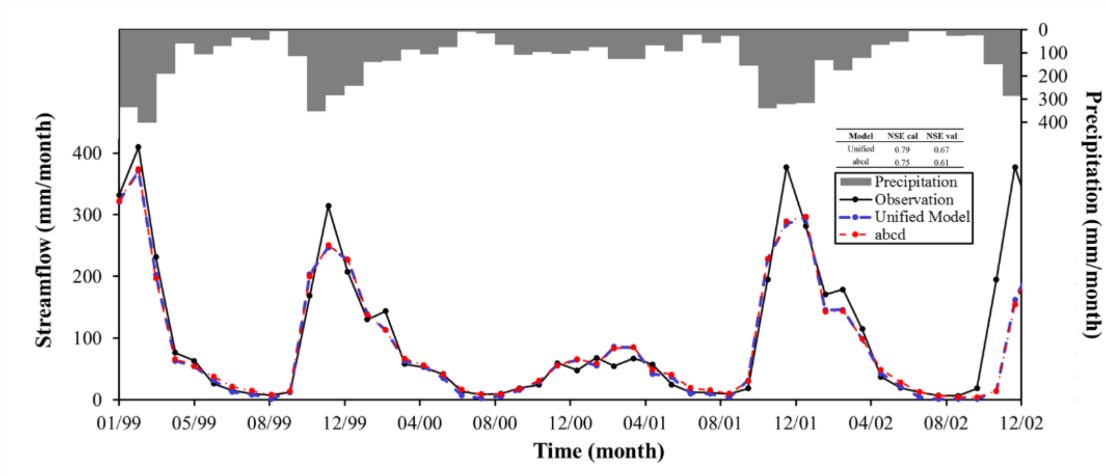

Figure 52: Comparison of modeled streamflow monthly a) abcd (red line), and b) Unified models (blue line) against the observed (black line) streamflow of catchment (Gage ID: 03111500).

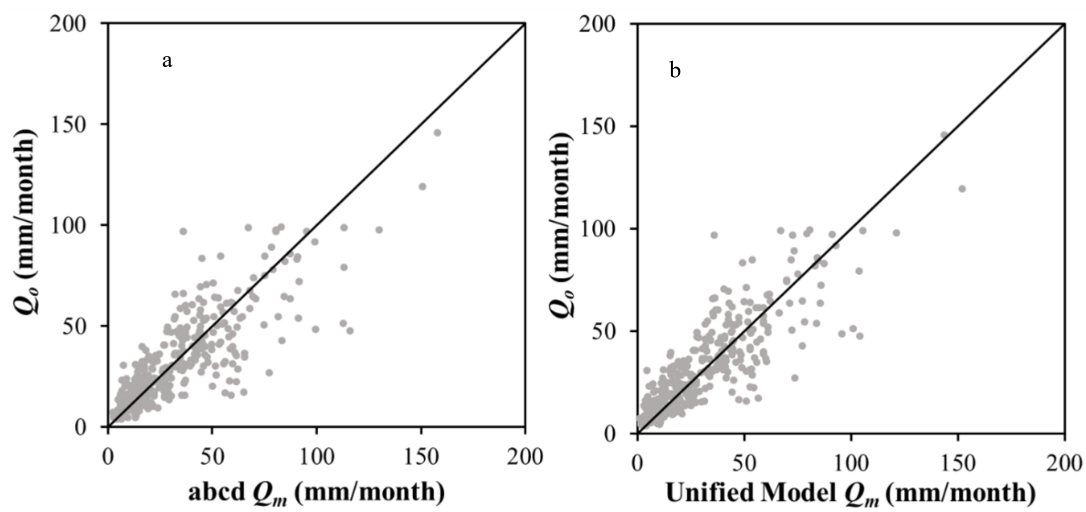

Figure 53: Comparison of modeled streamflow monthly a) abcd, and b) Unified models against the observed streamflow of catchment (Gage ID: 03111500).

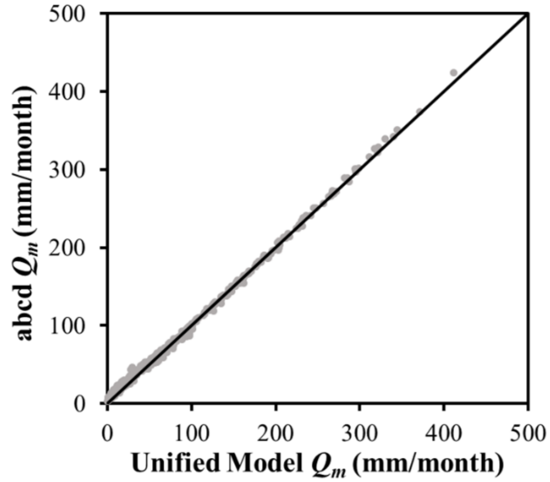

Figure 54: Modeled values of the Unified and abcd models of catchment (Gage ID: 03111500).

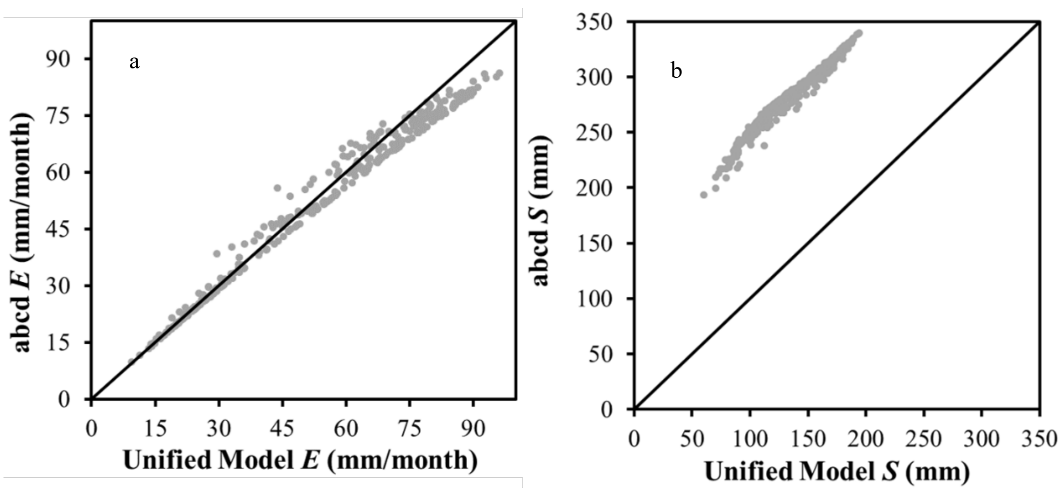

Figure 55: modeled a) evaporation and b) soil moisture storage of abcd and Unified models.

The two-mode precipitation in the spring and summer seasons (Gage ID: 02347500, 02329000) or spring and winter (Gage ID: 03504000). Seasonal variability plays a major role in water balance models (abcd and Unified). The two mode spring and summer seasons selected catchment have different effect on streamflow generation. In Gage ID: 02347500, the NSE values in calibration and validation are higher than Gage ID: 02329000 (Figure 55). Therefore, peak flow and low flow are not captured with accuracy. In Figure 56, there is an underestimation in peak

flow in Gage ID: 03504000 while an overestimation Gage ID: 02347500, and 02329000 as shown in Figure (57).

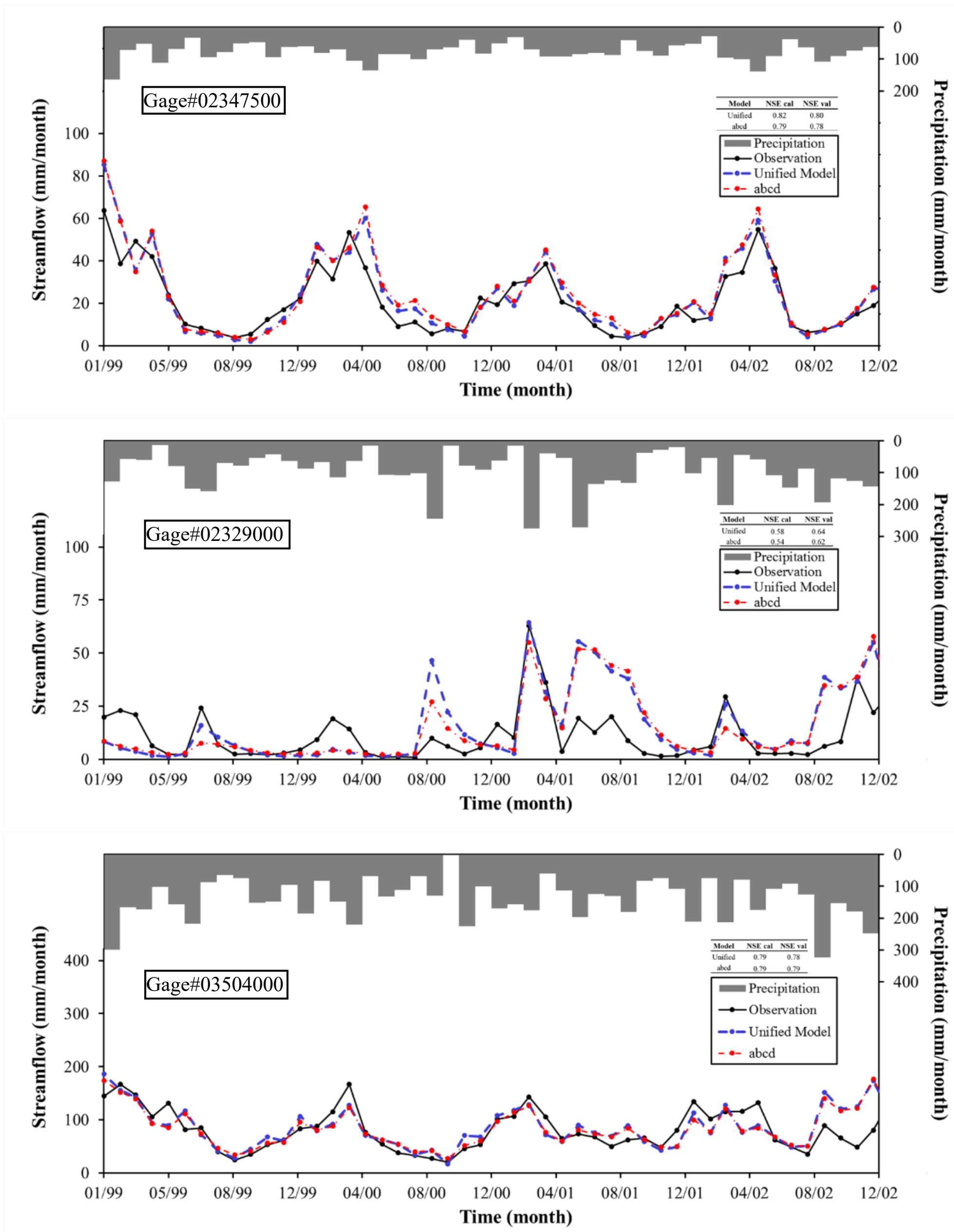

Figure 56: Comparison of observed (black), daily Unified (blue), and abcd (red) streamflow of catchment (Gage ID: 02347500, 02329000, and 03504000).

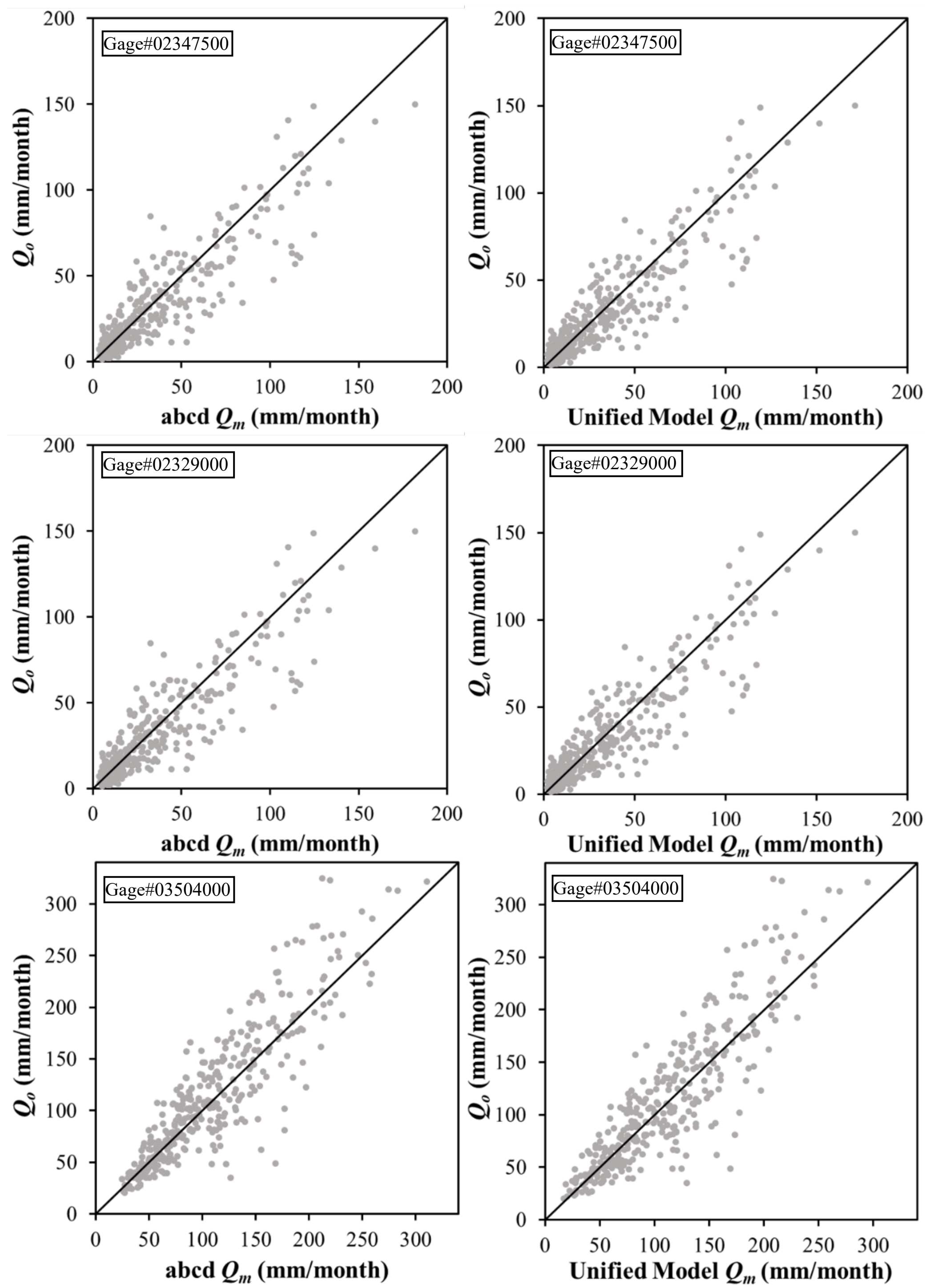

Figure 57: Comparison of modeled streamflow monthly Unified models against the observed streamflow of catchment (Gage ID: 023475000, 02329000, and 03504000).

The soil moisture storage and evaporation play major role in the water balance model (abcd and Unified). The soil moisture storage is overestimated from the modeled values of abcd and underestimated in Unified model, regardless of the seasonal effect. However, the modeled evaporation values are overestimated in Unified model in Figure (58). In Figure (58e), the modeled evaporation values are overestimated by abcd while underestimated by Unified.

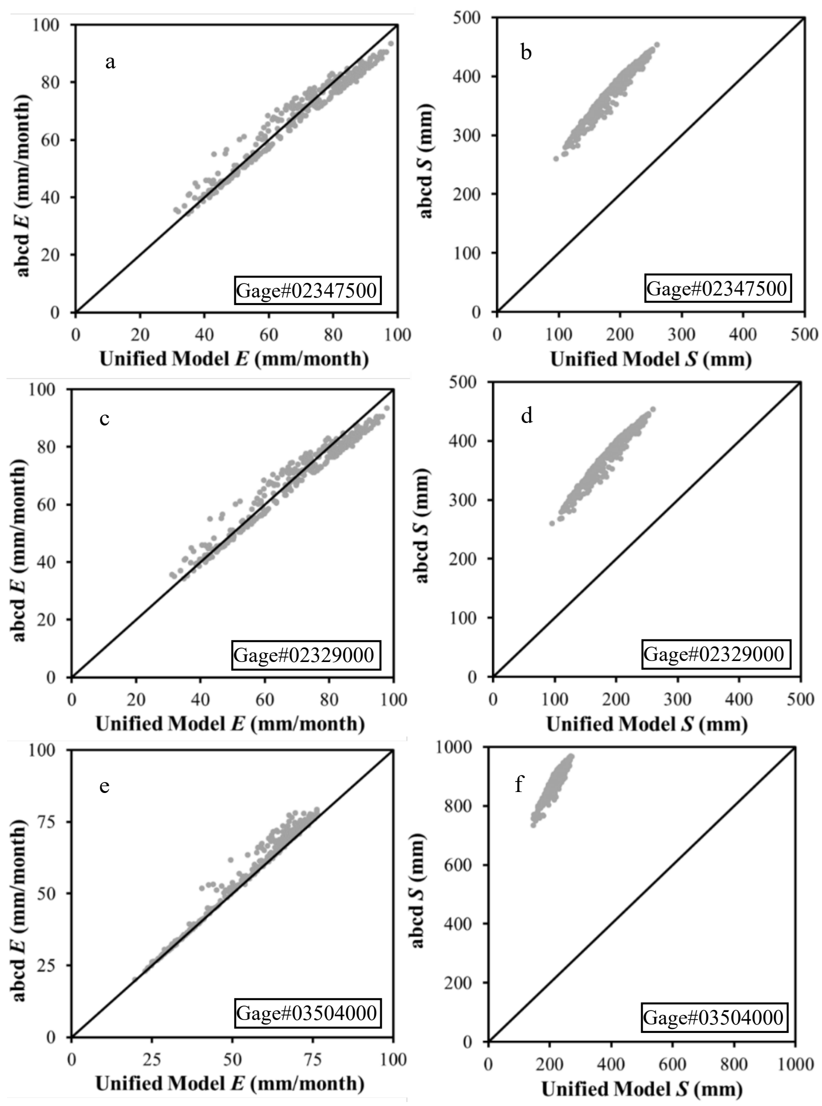

Figure 58: Modeled evaporation (a, c, and e), and soil moisture storage (b, d, and f) of abcd and Unified models.

The modeled values of stream flow in Figure 59, shows a good correlation between abcd and Unified models with an overestimation in peak flow by abcd model. The soil storage moisture modeled values are overestimated therefore the peak flow values are over estimated.

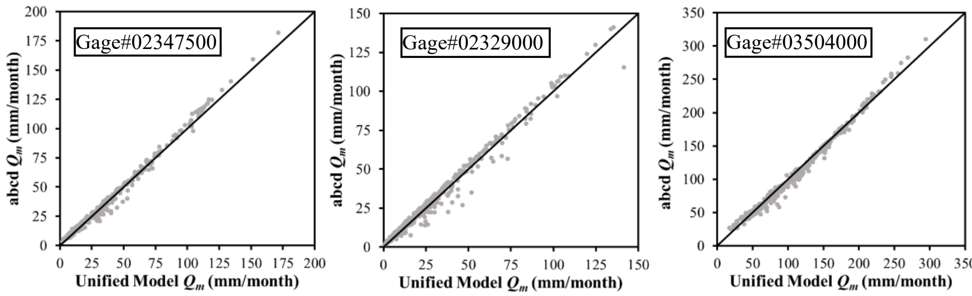

Figure 59: Modeled values of the Unified model and abcd of catchment (Gage ID: 023475000, 02329000, and 03504000).

The three-mode precipitation (Gage ID 1445500), showed a good NSE values with an underestimation of peak flows as shown in Figure 60 and Figure 61. The overestimation in the modeled flow values are presented in Figure 62, especially peak flow. The reason that makes peak flows high in values is the modeled soil moisture storage and evaporation values. The Unified model overestimate the evaporation and underestimate the soil moisture storage in Figure 63.

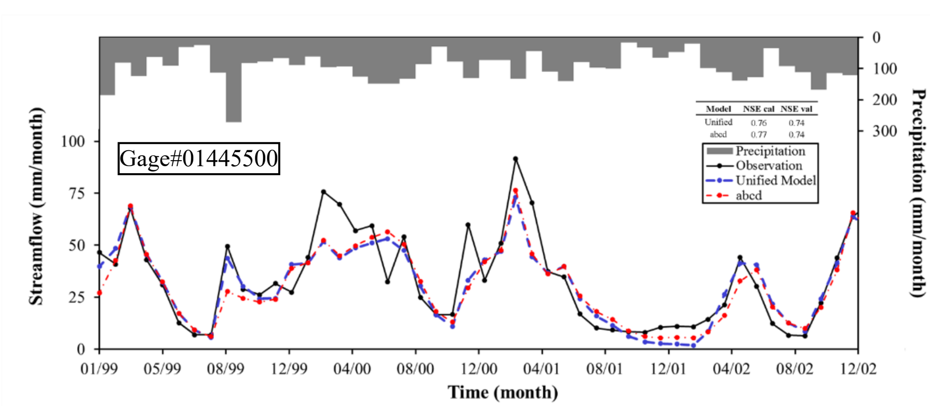

Figure 60: Comparison of observed (black), monthly Unified (blue), and abcd (red) streamflow of catchment (Gage ID: 1445500).

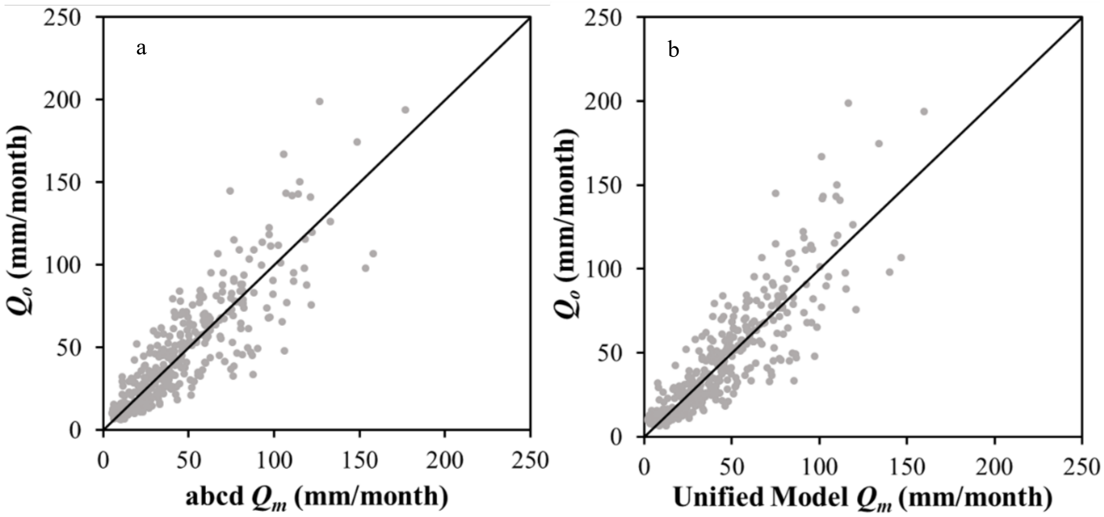

Figure 61: Comparison of modeled streamflow monthly a) abcd, and b) Unified model against the observed of catchment (Gage ID: 01445500).

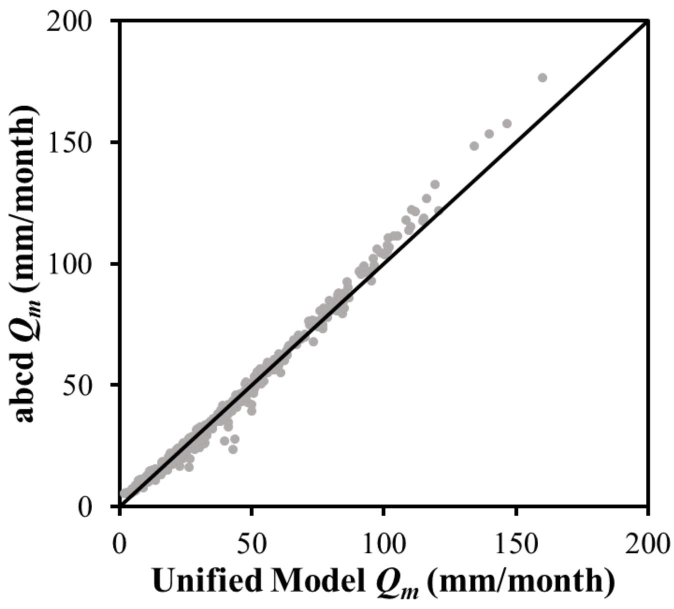

Figure 62: Modeled values of the Unified model and abcd of catchment (Gage ID: 01445500)

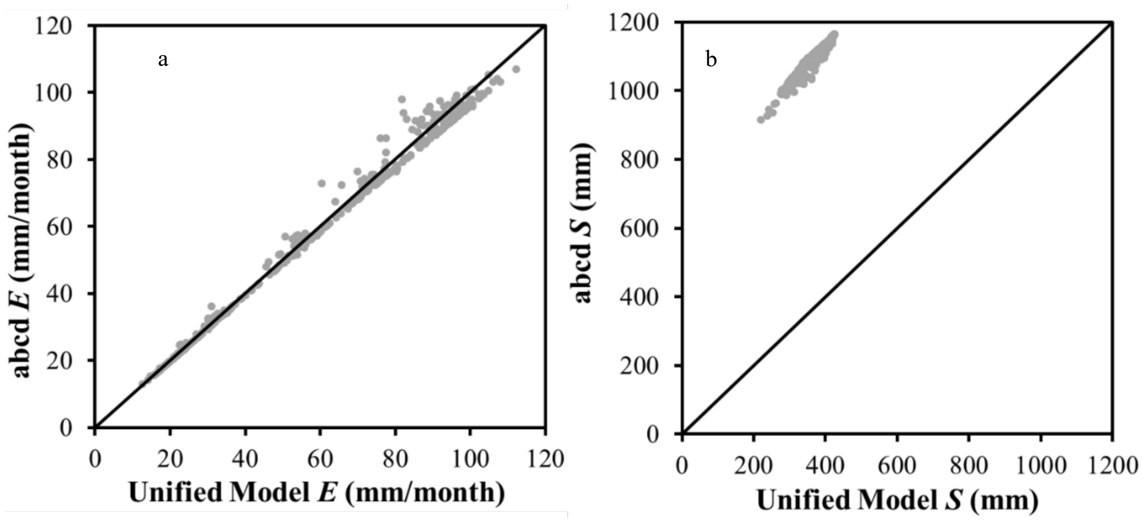

Figure 63: Modeled a) evaporation, and b) soil moisture storage of abcd and Unified models.

5.3.3.3 Inter-annual Unified

The annual scale is not affected by the soil moisture storage and runoff routing is not necessary. Precipitation is partitioned into runoff and evaporation.

The one mode precipitation (Gage ID: 03111500) showed a good correlation regarding the streamflow comparison in Figure 64. The annual model is very sensitive duo to the compressing of the precipitation and potential evaporation values. The modeled annual streamflow has a good correlation as it appears in Figure 65.

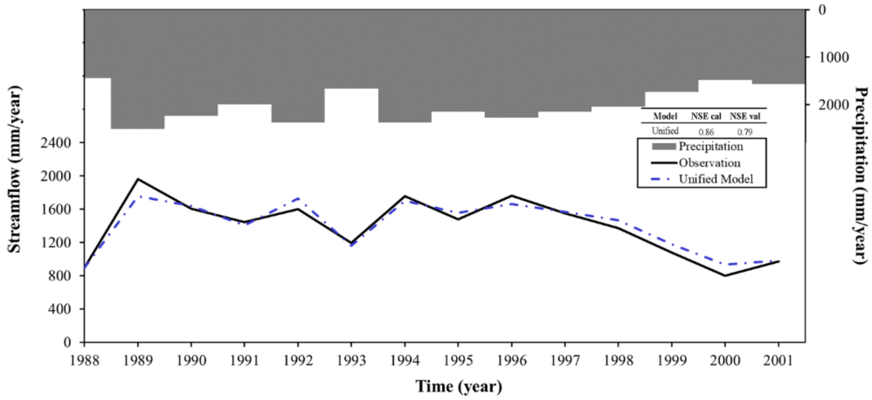

Figure 64: Comparison of observed (black), and annual Unified (blue) streamflow of catchment (Gage ID: 03111500).

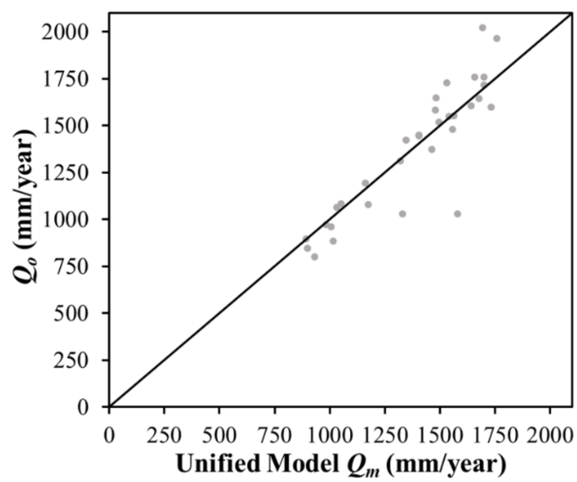

Figure 65: Comparison of modeled streamflow annual Unified models against the observed streamflow of catchment (Gage ID: 03111500).

The two-mode precipitation, spring and summer seasons (Gage ID: 02347500, 02329000) or spring and winter (Gage ID: 03504000). The NSE values in Gage ID: 02347500, and 02329000 is high (0.9) in calibration period however it is low in the validation period (0.75). Therefore, the modeled streamflow has a huge variability between the observed values and Unified modeled in Figure 66. On the other hand, it is more consistent in Gage ID: 03504000 and follows the observed streamflow values with high correlation in Figure 67. The validated modeled period is compared

with observed values of streamflow showed a high correlation in Gage ID: 02347500, and 03504000. On the other hand, Gage ID: 02329000 has a low correlation with more scatter values.

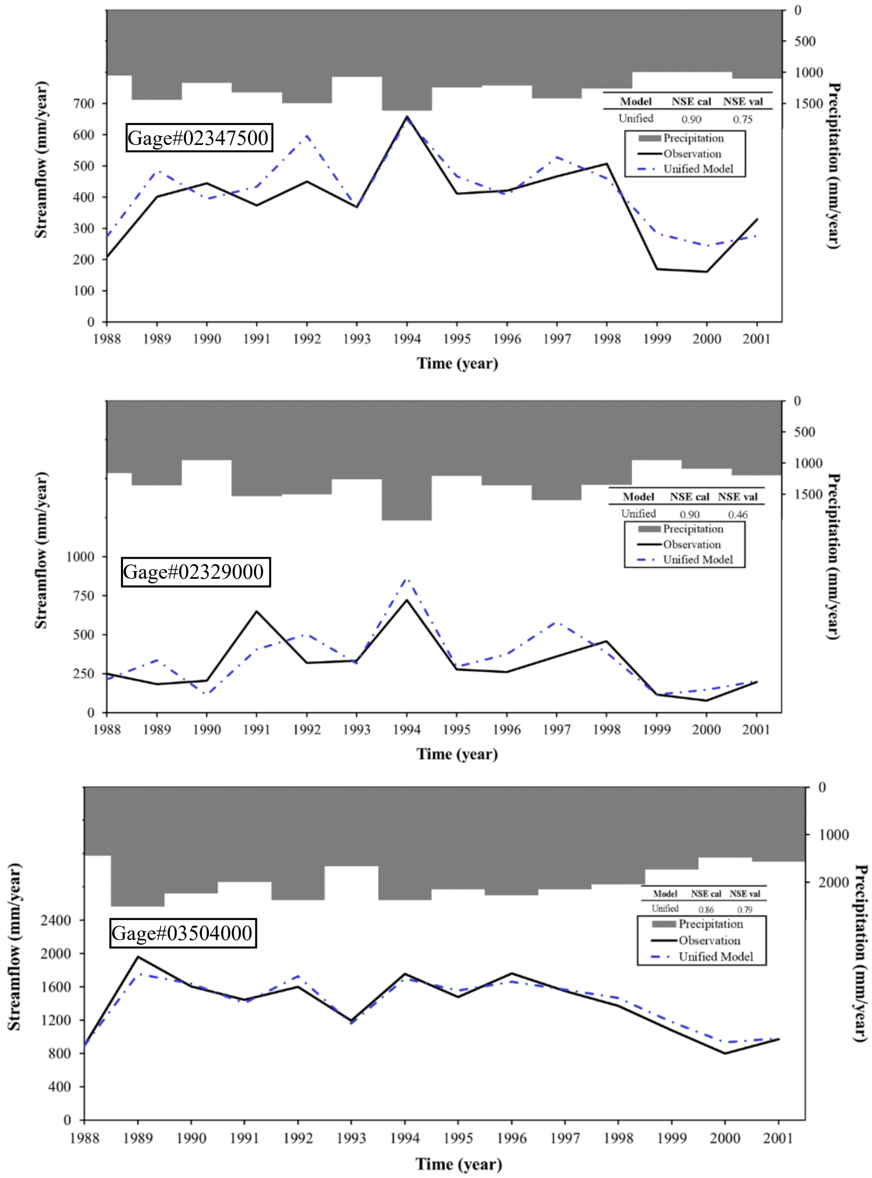

Figure 66: Comparison of observed (black), and annual Unified (blue) streamflow of catchment (Gage ID: 02347500, 02329000, and 03504000).

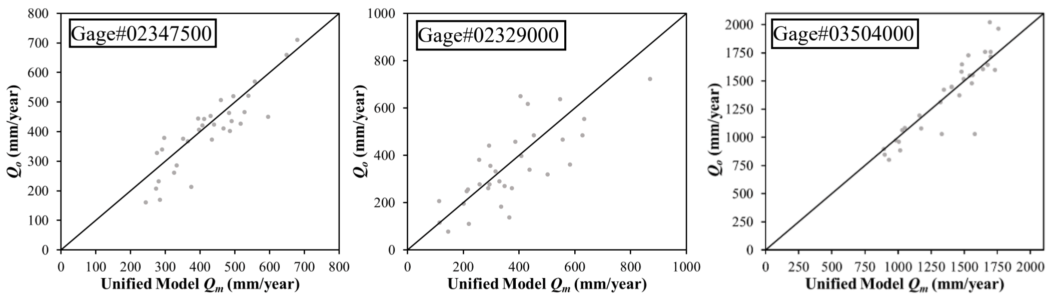

Figure 67: Comparison of modeled streamflow annual Unified models against the observed streamflow of catchment (Gage ID: 023475000, 02329000, and 03504000).

The three-mode precipitation (Gage ID 01445500), showed a high NSE values in the calibration (0.86) and validation (0.82) periods. In Figure (68), low values of streamflow are overestimated, and peak flow is accurately captured. This trend is conspicuously shown in Figure 69, where peaks are captured adequately by Unified model and low flow is overestimated.

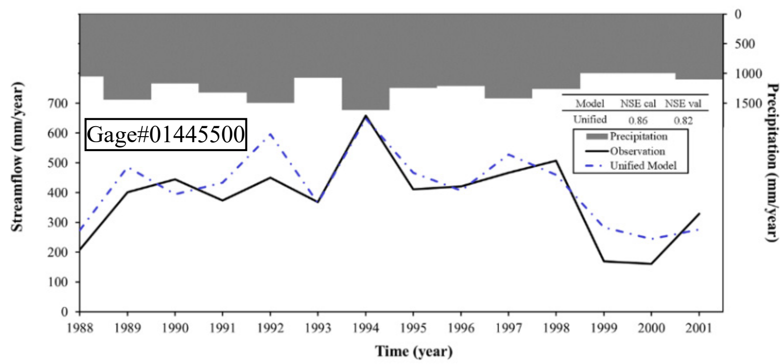

Figure 68: Comparison of observed (black), and annual Unified (blue) streamflow of catchment (Gage ID: 01445500).

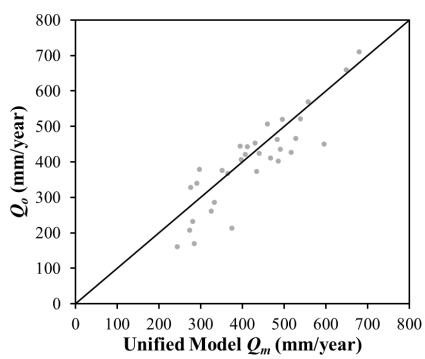

Figure 69: Comparison of modeled streamflow annual Unified models against the observed streamflow of catchment (Gage ID: 01445500).

CHAPTER 6 SUMMARY

The understanding of effect of climate and catchments characteristics at different time scales remains a challenging task due to the large spatial heterogeneity, and temporal variability. This work presents a hydrologic water balance model over various climate conditions by unifying the framework and applying it at daily, monthly, and annual time scale. The proposed Unified model structure adopted the SCS-CN method at daily scale using probability distribution function by *Wang* [2018] and evaporation method adopted from the proportionality of partially to fully saturated soil moisture capacity. This model was compared with HyMOD, and abcd models and applied on 92 catchment area across the United States at different time scales. The comparison of the validation NSE exceedance probability showed a slight superiority of the Unified model over the HyMOD, and abcd NSE values.

In each model optimized parameter, values were compared to show, even though if the models were relatively the same in the model structure, the output values can differ. However, in the surface runoff storage residence time (k_d) and groundwater storage residence time (k_b) appears to be relatively similar. On the other hand, the soil moisture capacity parameter (S_b) of the Unified model, it seems to have higher values than HyMOD and lower values than abcd. These parameters change slightly the response of the generated runoff; therefore, all models have a similar pattern in the validation runoff. The selected catchments show an underestimation of the runoff generation especially at the low to intermediate flow, and peak flow even though it has high NSE validation value.

The combination of the probability distribution function and the proportional evaporation method in the Unified model had the main effect on the model performance. The model shows that

it might be significant to apply it as a useful tool for decision-makers and researchers. The simplification of the model structures and lower number of parameters are maybe preferable to be the best model structure based on its characteristics for a given catchment [*Shine et al*., 2013]. Nonetheless, the generalized proportionality relationship of SCS-CN implicates that runoff generation at different time scales is modeled and have a better performance among the current well-known models (HyMOD, and abcd).

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