THESIS

COMPARISON OF REGIONALIZATION METHODS FOR A PROCESS BASED HYDROLOGIC MODEL IN MAJOR RIVER BASINS OF COLORADO

Submitted by

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WE HEARBY RECOMMEND THAT THE THESIS PREPARED UNDER OUR SUPERVISION BY PRANAY SANADHYA ENTITLED COMPARISON OF REGIONALIZATION METHODS FOR A PROCESS BASED HYDROLOGIC MODEL IN MAJOR RIVER BASINS OF COLORADO BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE.

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ABSTRACT OF THESIS

COMPARISON OF REGIONALIZATION METHODS FOR A PROCESS BASED HYDROLOGIC MODEL IN MAJOR RIVER BASINS OF COLORADO

Distributed watershed models are increasingly used for management of scarce water resources around the world. However, the utility of these models in ungaged or poorly gaged basins is a major issue in the field of hydrological sciences. Performance of watershed models cannot be evaluated for regions with paucity or unavailability of observed streamflow records; thus, a challenge is posed for the effective management of water resources in a region. Regionalization methods that relate watershed characteristics to model parameters are considered as a potential approach to overcome this challenge. The aim of this research is to analyze different regionalization methods and categorize the ones performing efficiently for the regionalization of the Soil and water assessment tool (SWAT) in five major river basins of Colorado. These River basins include: the Arkansas River basin at Canon City, the Cache la Poudre River basin at mouth of canyon, the Gunnison River basin above Blue Mesa dam, the San Juan River basin near Archuleta, and the Yampa River basin near Maybell. SWAT models were prepared for the study watersheds and their performance was evaluated corresponding to naturalized monthly streamflow available for these watersheds.

Initially, these prepared models were reconciled with a global sensitivity analysis method known as Fourier Amplitude Sensitivity Test (FAST) to identify sensitive model

parameters and the corresponding hydrologic processes they represent. Sensitivity analysis was performed for the two objective functions: mean monthly streamflow and the corresponding root mean square error (RMSE). Results of the sensitivity analysis showed that the majority of sensitive parameters were similar between the watersheds, resulting in a common parameter set selection for Colorado watersheds. Interestingly, sensitivity of parameters was observed to be varying depending upon the objective function. Through this part of the study, the significance of association between snowmelt and sub-surface hydrologic processes for generation of streamflow in mountainous watersheds was realized.

Secondly, regionalization methods based on different approaches were used to compute the values of parameters identified as sensitive in the previous step. Later, performances of SWAT models developed for the study watersheds were evaluated by using the parameter values obtained from diverse regionalization methods. These methods included: arithmetic mean approach, approaches based on similarity indices (SI) related to watershed attributes, spatial proximity, Bayesian statistical analysis, and multi-site calibration. In order to perform regionalization, a watershed was considered as ungaged and the parameter values for the watershed were obtained by using regionalization methods. Performances of these methods were evaluated by using the jack-knife cross validation technique and computing a performance measure 'E'. The method based on the weighted arithmetic mean approach using SI and the multi-site calibration approach were observed as the most favorable regionalization methods for

Colorado watersheds. Likewise, regionalization methods with average and rather poor performances were also identified.

This research analyze the applicability of SWAT in mountainous regions and shows that the distributed hydrologic models like SWAT are capable of flow simulations and hydrologic modeling in mountainous regions like Colorado. Observed interactions between the SWAT parameters related to sub-surface processes and snow related processes helps in understanding the role of these hydrologic processes in magnitude and timing of streamflow generation in mountainous watersheds. This study shows that a great extent of similarity in terms of critical hydrologic processes exists between the major river basins of Colorado and thus helps in selecting a common SWAT parameter set for snow dominated mountainous regions. Performance of regionalization methods as analyzed in this study shows the importance of methods based on weighted arithmetic mean approach and the multi-site calibration approach for performing regionalization of SWAT in snow dominated mountainous regions.

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CHAPTER 1: INTRODUCTION

Management of water resources in the Western United States has become an increasingly important issue due to drastic climatic events, like the Dust Bowl years (1930s), and the severe draught periods, which have occurred over various scales of space and time (Ray et al., 2008). A clear understanding of the hydrologic processes critical to the generation of streamflow, in terms of magnitude and timing, is of the utmost importance for effective management of water resources in these areas. River basins in Colorado (South Platte, Arkansas, Rio Grande, Gunnison, Colorado, Yampa, and San Juan) are one of the major sources of water supply to many western states (Arizona, California, Colorado, Kansas, Nebraska, Nevada, New Mexico, Utah, and Wyoming) and also to states like Oklahoma, Arkansas, and Texas. These river basins receive the majority of precipitation in the form of snow and thus, snowmelt dominated hydrographs are observed in these areas (NRDC, 2008). In Colorado, around 85% of runoff and groundwater recharge is obtained from snowmelt (Snow, 2005). Identifying the interactions between snowmelt, groundwater, and streamflow is considered vital for the successful management of water resources in snow-dominated mountainous regions (Flerchinger et al., 1992).

Comprehensive hydrologic models, which can assist in identifying critical hydrologic processes along with their interactions in the hydrologic cycle, are important for efficient management of water resources in mountainous regions. Hydrologic modeling in such regions has historically been challenging due to scarcity of climatic data, especially in higher elevations or alpine locations (Smith and Berg, 1982). Extreme elevation gradients which lead to poor data resolution (Marks et al., 1992) and orographic effects that provide tremendous variation in amount of precipitation produced (Hartman et al., 1999), further complicates the modeling approach in mountainous regions. Thus, the traditional modeling approach as shown in Figure 1.1 becomes less important for mountainous watersheds. Hydrologic models have been increasingly used by hydrologists and water resource managers to address a variety of hydrological problems. However, the applicability of such models for ungaged watersheds, where the streamflow record is not available, is still questionable (Sivapalan et al., 2003). This questionability increases in mountainous regions like Colorado, because of the extent of the spatial and temporal variability present in the terrain. Realistic estimates of the hydrologic response of ungaged basins in mountainous region of Colorado is of foremost importance, as it will assist in efficient planning and management of the water resources that ultimately supply a majority of the Western United States.

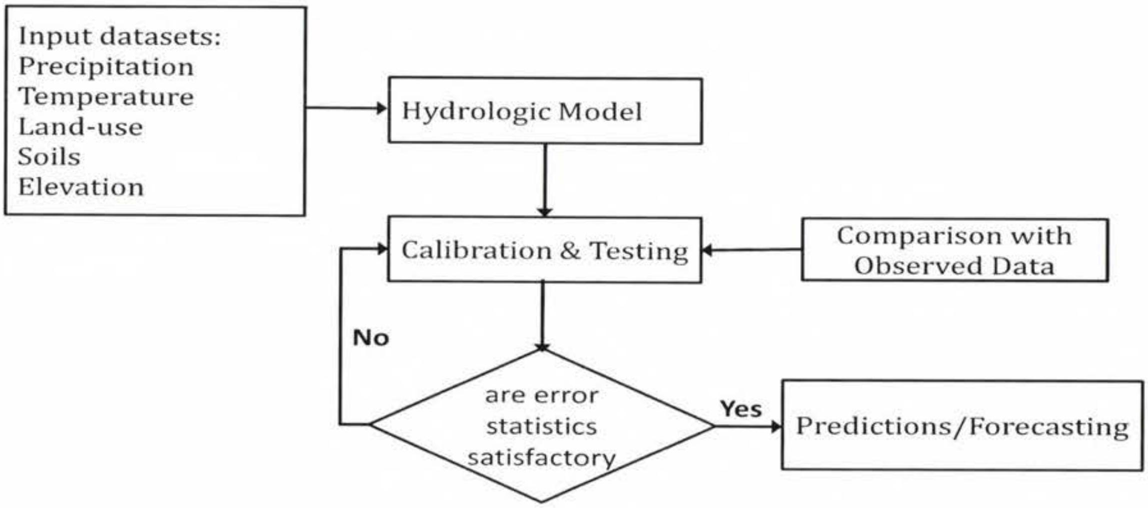

Figure 1.1. Schematic of traditional modeling approach

For this study, five major river basins in Colorado were analyzed, including the Arkansas River at Canon City, the Cache la Poudre River at the mouth of the canyon, the Gunnison River above Blue Mesa Dam, the San Juan River near Archuleta, and the Yampa River near Maybell. The Cache la Poudre and Arkansas River basins are located on the eastern side of the Continental Divide and therefore are tributaries of the Mississippi River. The remaining three watersheds are on the Western side of the Continental Divide and drain into the Colorado River, which later flows into the Gulf of California. These watersheds mainly receive precipitation in the form of snow, and thus, the observed streamflow in these watersheds displays seasonal variation dominated by spring and summer snowmelt (NRDC, 2008). Water flowing in these river basins is diversely used for irrigation, municipal, industrial, and recreational purposes. The flow regimes in many river basins in Colorado are considerably affected by man-made influences, such as dams and reservoirs, diversion of water, and irrigation return flows, in order to meet regional demands. The importance of hydrologic processes and interactions thereof affecting generation and timing of streamflows in these river basins are not fully realized (Ben, 2005), which could potentially lead to poor management of water resources in mountainous region of Colorado.

The overall goal of this study is to evaluate the efficiency/applicability of the Soil and Water Assessment Tool (SWAT) for representing hydrological processes in mountainous watersheds of Colorado. Thus, the SWAT model parameters will be used as surrogates for hydrologic processes they represent. Specifically the following objectives are defined:

1. Characterize the main and interaction effects of the SWAT model parameters and associated hydrologic processes in magnitude and timing of streamflow generation in five major river basins of Colorado.
2. Examine the extent of similarity/dissimilarity of critical hydrologic processes in five major river basins in Colorado.
3. Test the performance of the SWAT model for prediction of monthly streamflows in five major river basins of Colorado.
4. Evaluate the performance of regionalization methods and identify those performing efficiently for snow-dominated mountainous watersheds of Colorado.

Part of this thesis as shown in chapter 2 provides a computational framework for identifying the critical hydrologic processes and the corresponding SWAT parameters in major river basins of Colorado with respect to volume as well as timing of monthly flow generation. Later, the extent of similarity between these study watersheds based on critical hydrologic processes is also examined and a common SWAT parameter set is selected for snow dominated mountainous watersheds of Colorado. Chapter 3 evaluates the performance of SWAT as a hydrologic model for flow simulations in mountainous watersheds by performing a single-site calibration of study watersheds. This approach however becomes inefficient when there is scarcity or unavailability of observed data record and therefore is not applicable for hydrologic predictions and assessments in case of ungaged watersheds. Later part of chapter 3 addresses a variety of regionalization methods in order to analyze the usefulness of hydrologic models like SWAT for flow simulations in ungaged watersheds. Finally, performances of these diverse regionalization methods are evaluated and the best methods are identified. A schematic or framework showing major aims of this study is shown in Figure 1.2. The concluding chapter discusses the results and findings from this research.

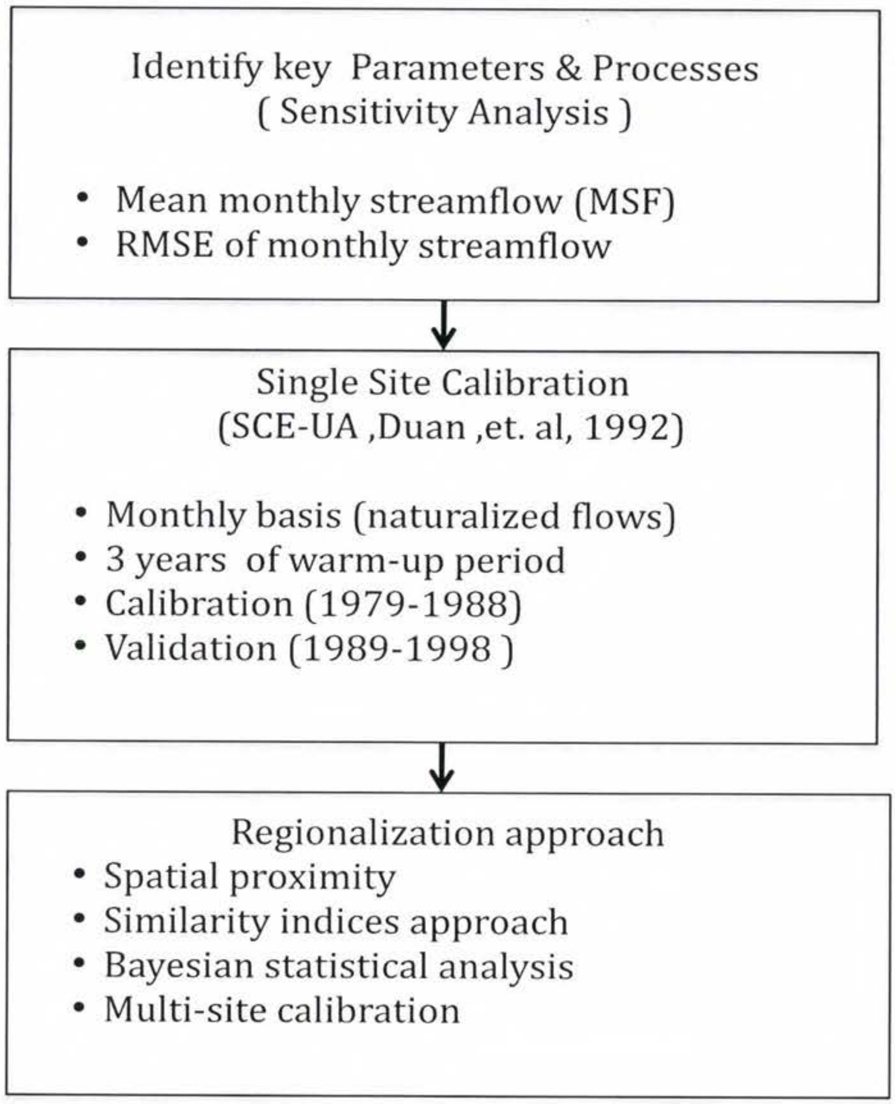

Figure 1.2. Schematic showing major aims of this study

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Chapter 2: Global Sensitivity Analysis of Hydrologic Processes in Major River Basins in Colorado

Abstract

Watershed models are often used to predict flow regimes under varying land use and climatic conditions. The credibility of such predictions, however, depends on adequate representation of important watershed processes in the system. In particular, the dynamic relationship between snow and flow processes in snow-dominated mountainous watersheds can alter the timing and distribution of streamflows. The present work investigates the importance of various watershed processes and interactions thereof in five snow-dominated mountainous river basins in Colorado, ranging between 2,735-8,943 square kilometers in size. The Soil and Water Assessment Tool (SWAT) was used to simulate hydrologic processes in the study watersheds, SWAT was reconciled with a global sensitivity analysis, namely the Fourier Amplitude Sensitivity Test (FAST), in order to identify its important parameters and critical watershed processes that they represent. Two different objective functions were used to evaluate the importance of model parameters: average monthly streamflow and the corresponding root mean square error (RMSE) over a 20-year period from January 1979 through December 1998. While the objective function formulation based on the average monthly streamflows aimed to capture the impact of parameters on the volume of flow, the sensitivity of RMSE of monthly streamflow predictions to various parameters revealed the influence of parameters on both volume and timing of flows.

Results indicated that streamflow volume in the study watersheds was mostly influenced by groundwater processes. However, the interactions between groundwater and snow processes were key in the timing of the monthly flow hydrographs. Finally, similarities in the results of sensitivity analysis in the study watersheds were exposed. The majority of important parameters were common amongst all study watersheds, underlining the possibility of regionalization of the SWAT model for Colorado's snow-dominated watersheds.

Keywords: watershed, mountainous, snow-dominated, modeling, SWAT, sensitivity analysis, FAST

2.1 Introduction

Sound management of water resources in the Western United States and other mountainous regions around the world requires a clear understanding of critical processes that control the magnitude and timing of streamflow. Snowmelt contributes to nearly 70% of the annual flow in river basins in this area where availability of water mainly depends on the snowfall and melt pattern (Mote, 2007; NRDC, 2008). Varying land use and climatic conditions can alter the accumulation and melting pattern of snow thereby affecting water yield and runoff generation (Bosch and Hewlett, 1982; Hamlet et al., 2005). This poses a challenge for effective management of water resources in high elevation watersheds. A key source of streamflow generation in mountainous and forested watersheds is recharge from snowmelt to groundwater systems (Dincer et al., 1970; Martinec, 1975; Rodhe, 1981; Flerchinger et al., 1994). Recognizing the interactions between snow accumulation, snowmelt, groundwater and streamflow is therefore vital for effective management of water resources in snow-dominated mountainous regions (Flerchinger et al., 1992).

Identification of critical natural processes and their dynamic interactions that are key in the generation and distribution of water in large river basins often involves the use of comprehensive watershed models (Perkins et al., 1999; Yongqin., 2004; Lay et al., 2008). Hydrologic modeling in mountainous regions has historically been challenging due to scarcity of climatic data, extreme elevation gradients, and orographic effects (Marks et al., 1992). The complex hydrologic processes of snowfall and snowmelt, dominant in mountainous watersheds, further complicate the modeling approach in these areas (Luce et al., 1999).

Adequate representation of snow cover and snowmelt at various scales in mountainous areas has inspired the development of various simulation models (Anderson, 1968; Rango and Martinec, 1979; Jordan, 1991). These models range in complexity from simple lumped to physically-based energy balance approaches. The list of commonly used snowmelt models includes: the snow accumulation and ablation model (SNOW-17) (Anderson, 1973), the snowmelt runoff model (SRM), the precipitation-runoff modeling system (PRMS), and the streamflow synthesis and reservoir regulation model (SSARR) (USACE, 1998).

The SNOW-17 model is a component of the national weather service river forecast system (NWSRFS). It is a conceptual model that only accounts for snow accumulation and ablation. SRM is one of the most popular and widely used single event models and was developed with the capacity to use remotely-sensed snow cover information when simulating snowmelt runoff. However, SRM does not account for soil moisture and frozen grounds. The continuous model PRMS is mainly used for watershed analysis with respect to streamflow generation from snowmelt. It is a comprehensive watershed model that is well suited only for short term forecasts of 3-5 days. Likewise, the SSARR model has a continuous simulation capacity and is suitable for streamflow and runoff forecasting along with river-reservoir system studies but is not efficient for permafrost conditions and uses a lumped snowmelt relationship. Snowmelt models typically do not account for the surface and sub-surface water balance in the analysis and therefore have limited reliability in applications for management of water resources, flood hazard assessment, and impacts of climate change.

The soil and water assessment tool (SWAT) developed by the USDA Agricultural Research Service (Arnold et al., 1998) is a comprehensive watershed model that can simulate various components of the hydrologic cycle at the field to watershed scales. It is a process-based, continuous model that operates on a daily time step. Simulation of hydrologic cycle by SWAT is always based on water balance (Neitsch et al., 2005).

The ability of SWAT to simulate the hydrology of mountainous watersheds under the effects of elevation and variable snowmelt conditions was supported by Fontaine et al. (2002) with their study on the Wind River basin in Wyoming. Later, this capability of SWAT was assessed by Wang and Melesse (2005), who performed their study on a Minnesota watershed that had very low topographic relief. Performance of SWAT in high elevation and mostly forested watersheds was evaluated by Ahl et al. (2008) with their study on a Rocky Mountain region watershed in Montana. However, SWAT has not been fully evaluated on a regional basis for a mountainous region comprising multiple watersheds.

Sensitivity analysis provides a means of identifying important model parameters and corresponding hydrologic processes that dominate the hydrology of an area. Various sensitivity analysis methods can be used to rank model parameters according to their influence on the model outputs in watersheds around the world. Researchers and scientists have used different sensitivity analysis methods with SWAT for various reasons, examples of which are presented below.

Arnold et al. (2000) performed a local sensitivity analysis of SWAT parameters in order to analyze the sensitivity of different hydrological processes to SWAT parameters for three different watersheds in the upper Mississippi River basin. Local sensitivity analysis was performed by Spruill et al. (2000) in order to recognize sensitive SWAT parameters for effective streamflow modeling in a karst-influenced Kentucky watershed. The Latin Hypercube One-factor-At-a-Time (LH-OAT) sensitivity analysis was performed by Holvoet et al. (2005) in order to spot dominant hydrological parameters and their influence on pesticide modeling in the Nil Basin in central Belgium. The LH-OAT method is based on random sampling technique similar to Monte-Carlo sampling and provides a robust analysis without too many model runs. Griensven et al. (2006) used the LH-OAT method for identifying sensitive SWAT parameters affecting flow, sediments, and nutrient modeling in the Bosque River catchment in Texas and the Sandusky River catchment in Ohio. Migliaccio and Chaubey (2008) performed a local sensitivity analysis in order to predict the influence of SWAT parameters on annual flow volume and sediment yield in the Illinois River watershed in Northwest Arkansas. The impact of management practices on water quality and quantity was examined by Ullrich and Volk (2009) in the Parthe watershed in central Germany by performing a local sensitivity analysis of SWAT parameters related to tillage and management operations. Coffey et al. (2010) performed an LH-OAT based sensitivity analysis in order to identify sensitive SWAT pathogen parameters and their influence on simulating transport of bacteria- like E. coli in Irish catchments.

Most of the studies presented above, dealt with identifying the sensitivity of SWAT parameters on streamflow, sediments, nutrients or pesticides in different study watersheds around the world. Sensitivity analysis performed in each of these studies was either based on a local method or a sampling-based method that only accounts for the individual importance of input parameters to an output variable. These methods, unlike the global sensitivity analysis methods, do not consider the association between different groups of input parameters and thus cannot address the impact of an input parameter as an interaction term on the output variable.

To date, only one study, Francos et al. (2003), has used a global sensitivity analysis method, Fourier Amplitude Sensitivity Test (FAST), with SWAT. They identified the sensitivity of SWAT parameters with respect to the flow and water quality in a Northern England watershed. This analysis involved a two-step sensitivity analysis procedure using the Morris screening method and FAST. However, in this study some key input parameters with respect to output variables were not included during the analysis because of a lack of computational efficiency. Including a sufficient number of input parameters in a global sensitivity analysis method requires high computational efficiency as well as a stability test in order to identify the ideal number of model evaluations required for stable sensitivity analysis results.

Previous studies related to sensitivity analysis of SWAT flow parameters mainly dealt with identifying parameters with respect to volume and/or peak flows (White and Chaubey 2005; Ndomba et al 2008; Setegn et al., 2009). None of the studies have addressed the sensitivity of parameters relating to the timing and pattern of flow hydrograph in a watershed. This sort of sensitivity analysis is especially important in the case of snow-dominated mountainous watersheds, where the interactions between different hydrologic processes play an important role in generation of streamflow. Few studies have performed sensitivity analysis of SWAT parameters in mountainous watersheds. These studies used either a local sensitivity analysis or a screening method for the analysis (Wang et al., 2005; Lemonds et al., 2007; Ahl et al., 2008). Global sensitivity analysis techniques such as FAST and method of Sobol' that can identify sensitivities with respect to interactions between different groups of input parameters have not been used in the studies on mountainous watersheds. These methods are considered indispensable in snow-dominated mountainous regions, where the interactions between sub-surface hydrology and snow processes are key to generation of streamflow (Dincer et al., 1970).

The overall goal of this study is to identify key SWAT parameters and their corresponding hydrologic processes that control the magnitude and timing of streamflow in major Colorado watersheds. To this end, the following objectives are defined: (1) examine the computational requirements for stability of FAST sensitivity analysis results, (2) characterize the main and interaction effects of SWAT model parameters and associated hydrologic processes in magnitude and timing of streamflow generation, and (3) examine the similarity/dissimilarity of critical hydrologic processes in the snow-dominated watersheds of Colorado.

2.2. Methods and Material

The computational framework in this study consisted of the SWAT hydrologic model and the FAST global sensitivity analysis. The framework was applied in the following five major river basins in Colorado: the Arkansas River at Canon City, the Cache la Poudre River at mouth of canyon, the Gunnison River above Blue Mesa Dam, the San Juan River near Archuleta, and the Yampa River near Maybell. Multiple watersheds were selected in order to reinforce the findings for snow-dominated and mountainous watersheds. Inclusion of multiple watersheds in the analysis accounted for the diversity in land use, soil, and elevation along with varying climatic conditions. The study watersheds are located on both sides of the Continental Divide.

All SWAT simulations were performed over a 20-year period from January 1979 through December 1998. A 3-year warm up period was used to adjust the initial conditions for hydrologic simulations. Streamflow in most of Colorado River basins are considerably affected by man-made influences such as dams and reservoirs, diversion of water to nearby streams, and irrigation return flows. Therefore, naturalized flows were used for comparison of observed and simulated streamflow. Naturalized flows are only available on a monthly basis for the study watersheds, and thus, the objective functions used for the sensitivity analysis were evaluated on a monthly time step.

Two separate objective functions were used in the study to capture the influence of SWAT parameters and their corresponding processes on the magnitude as well as the timing of monthly streamflows. Prior to application of the integrated SWAT/FAST analysis in all study watersheds, the computational requirements in terms of minimum number of model evaluations for obtaining stable (i.e., consistent) results was investigated in the Cache la Poudre River basin.

2.2.1. Study Area

The present study encompasses five major river basins located primarily in Colorado. The Cache la Poudre and San Juan River basins include small areas in the neighboring states of Wyoming and New Mexico, respectively. Figure 2.1 shows the location of the watersheds. The Cache la Poudre and Arkansas River basins are located on the eastern side of the Continental Divide and therefore drain into the Mississippi River. The remaining three watersheds are on the Western side of the Continental Divide and drain into the Colorado River, which later flows into the Gulf of California. All the watersheds have a typical characteristic of high relief, with an elevation range of 1,500 meters to 4,400 meters as shown in Figures 2.2-2.6.

Diversity in elevation leads to significant variability in the amount and form of precipitation within these watersheds. Average precipitation in the Rocky Mountains at an elevation of 3230 meters is almost six times more than the western slope, which has an elevation of 1,520 meters (Hjermstad, 1970). Climate of Colorado is greatly influenced by topography. For example, average annual precipitation recorded at Wolf Creek Pass (elevation 3,307 m) located in the San Juan Mountains is 10 times more then Manassa (elevation 2,344 m) situated at a short distance to east of Wolf Creek Pass (Doesken et al., 2003). Similarly, a variation of 19 (°C) is observed between the mean annual temperature of Pikes Peak and Las Animas located within a distance of 145 km. These watersheds mainly receive precipitation in the form of snow, and thus, the observed streamflow in these watersheds displays seasonal variation dominated by spring and summer snowmelt (NRDC, 2008). Snow cover in these areas can start as early as mid-October and persist well into mid-June (NRCS, 2007). Around May, the snowpack begins releasing meltwater to surface and sub-surface hydrologic systems. Runoff generated from snow acts much differently than runoff generated from rainfall since snowmelt is a slow and gradual process and therefore takes time to become a part of the water balance.

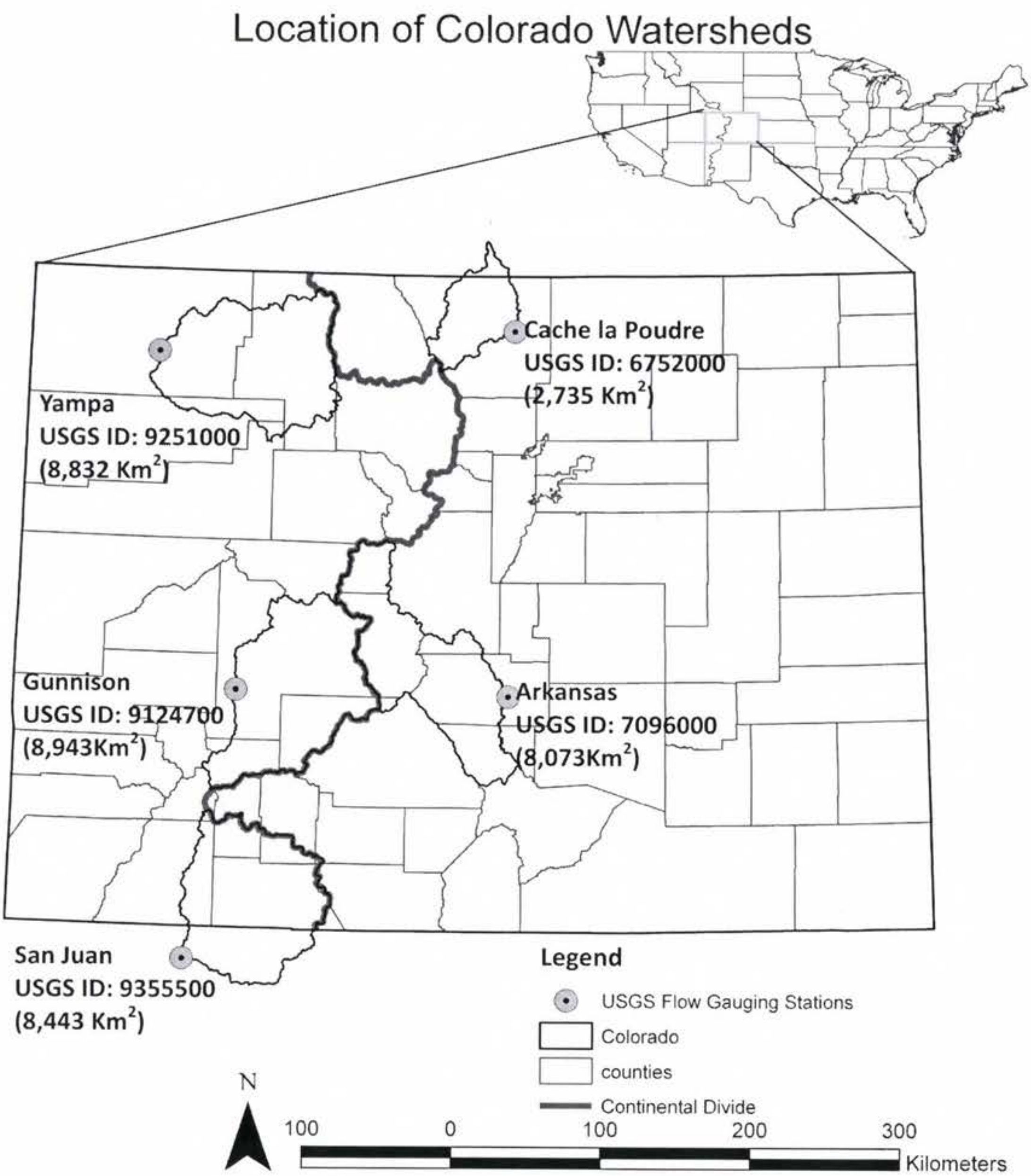


Figure 2.1. Location of study watersheds and corresponding USGS streamflow gauging stations.

Table 2.1. Land use, soil, and topographic attributes of study watersheds

Watershed	Land use*[1]		Hydrologic Soils*[2]		Elevation Range (meters)
	Description	%	Group	%	
Arkansas River 8,073 (km^2)	Forest-Evergreen	48.7	A	8.45	1632-4396
	Range-Brush	9.16	B	40.5	
	Range-Grasses	37.1	C	9.15	
	Southwestern range land	5.05	D	42.0	
Cache la Poudre River 2,735 (km^2)	Forest-Evergreen	64	A	0.0	1593-4131
	Range-Brush	18.4	B	11.0	
	Range-Grasses	15.3	C	41.6	
	Water	2.36	D	47.4	
Gunnison River 8,943 (km^2)	Forest-Evergreen	44	A	10.3	2183-4351
	Forest-Deciduous	9.52	B	32.5	
	Range-Brush	25.9	C	50.0	
	Range-Grasses	17.8	D	7.19	
	Southwestern range land	2.88			
San Juan River 8,443 (km^2)	Forest-Evergreen	50.1	A	0.0	1724-4279
	Forest-Deciduous	9.76	B	20.2	
	Range-Brush	29.6	C	36.7	
	Range-Grasses	7.58	D	43.1	
	Hay	2.98			
Yampa River 8,832 (km^2)	Forest-Deciduous	32.7	A	4.9	1804-3763
	Forest-Evergreen	17.8	B	69.1	
	Range-Brush	47.0	C	17.2	
	Range-Grasses	2.56	D	8.82	

*[1]Land use classification was obtained using National Land Cover Dataset, 2001

*[2]Hydrologic soil group classification was obtained from State Soil Geographic (STATSGO) database. Group A and D refer to soil having high and very low infiltration rate respectively, while Group B and C refer to soil with moderate and slow infiltration rate.

Land use in the state of Colorado is mainly comprised of evergreen and deciduous forests at high elevation, while lowlands are mostly covered by shrubs and grasslands. Soils in the area have very low to moderate infiltration rates. Details related to land use, soils, and other information are provided in Table 2.1.

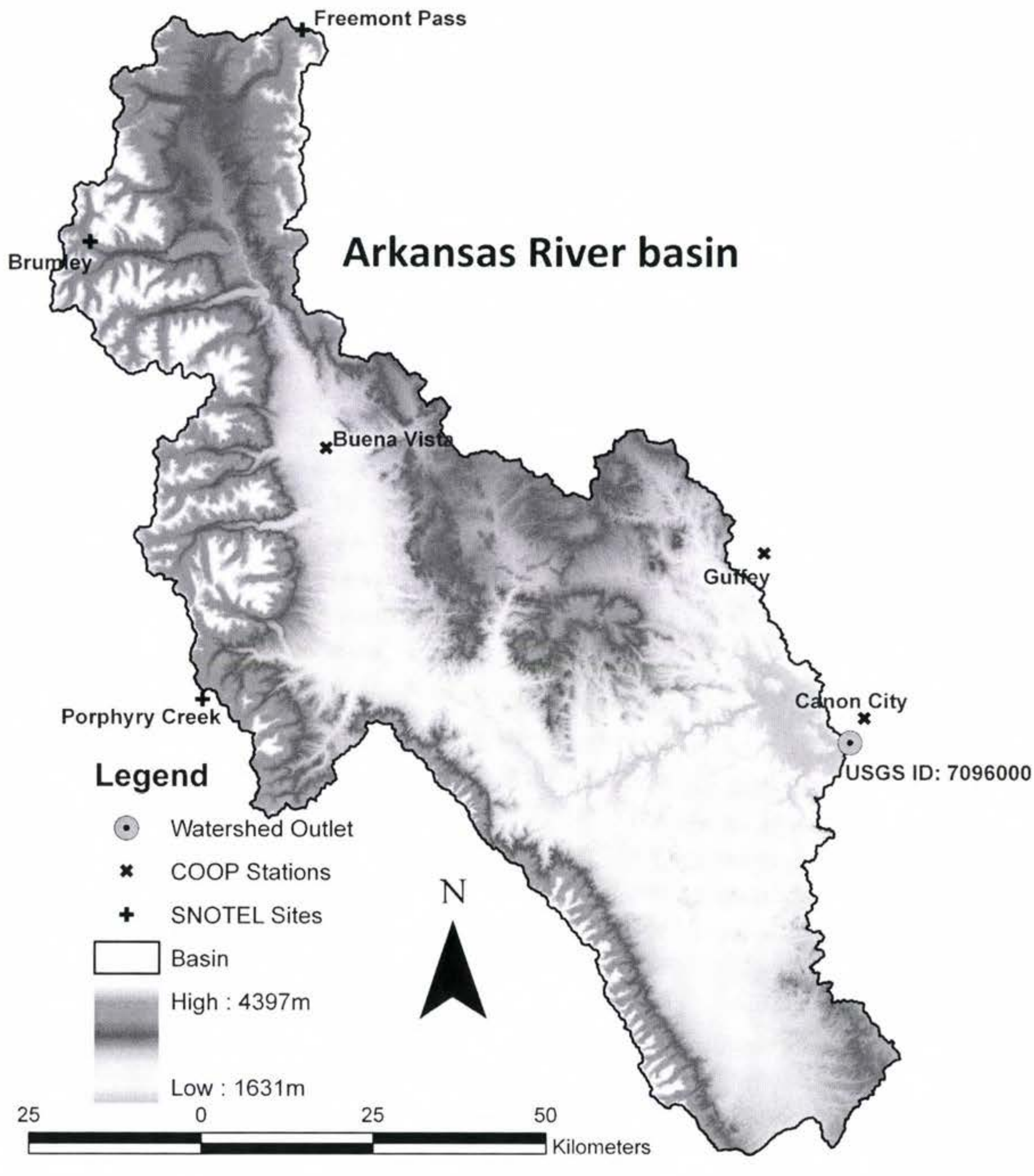


Figure 2.2. Elevation diversity in Arkansas River basin along with the location of climatic stations used in the analysis.

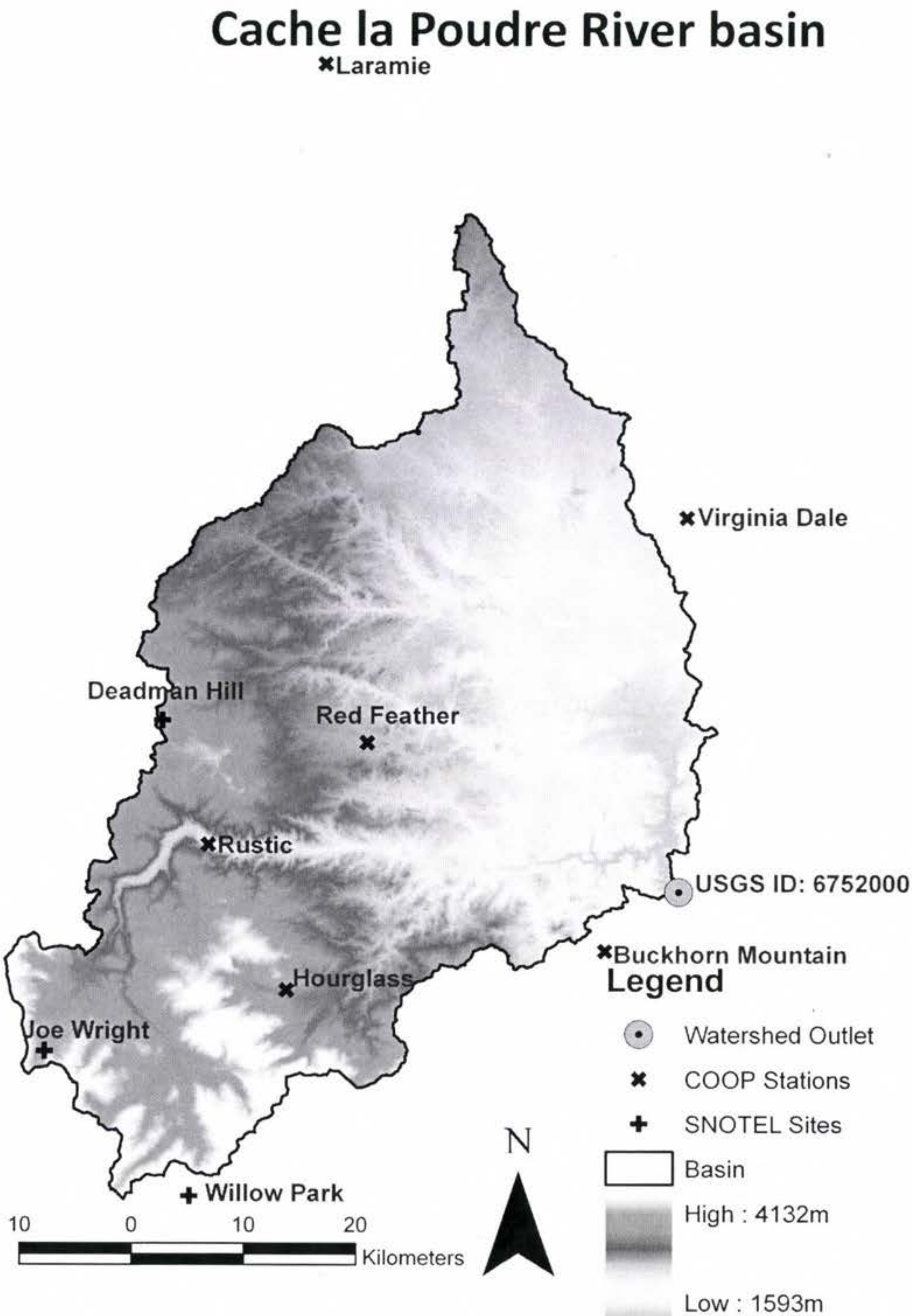


Figure 2.3. Elevation diversity in Cache la Poudre River basin along with the location of climatic stations used in the analysis.

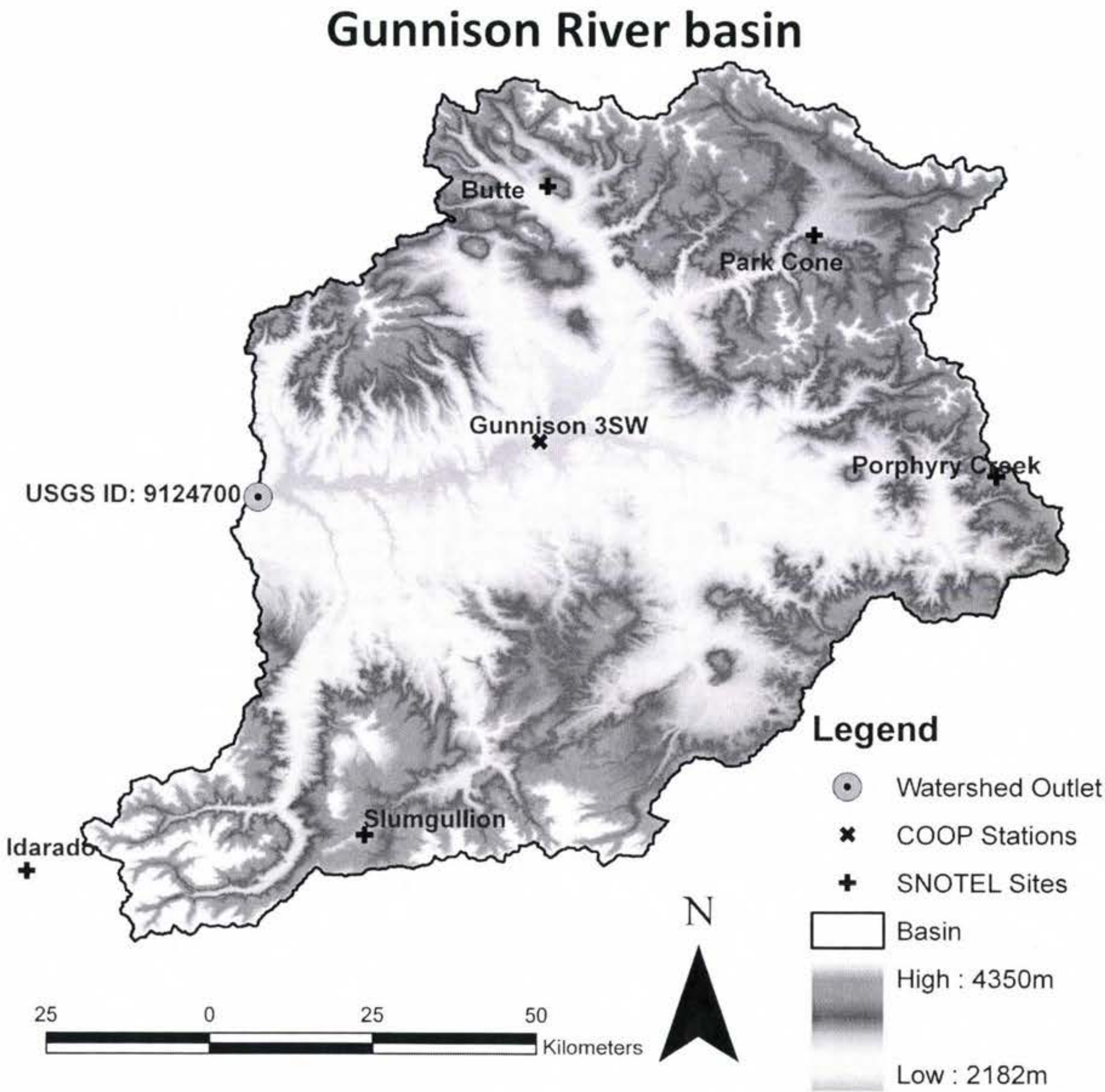


Figure 2.4. Elevation diversity in Gunnison River basin along with the location of climatic stations used in the analysis.

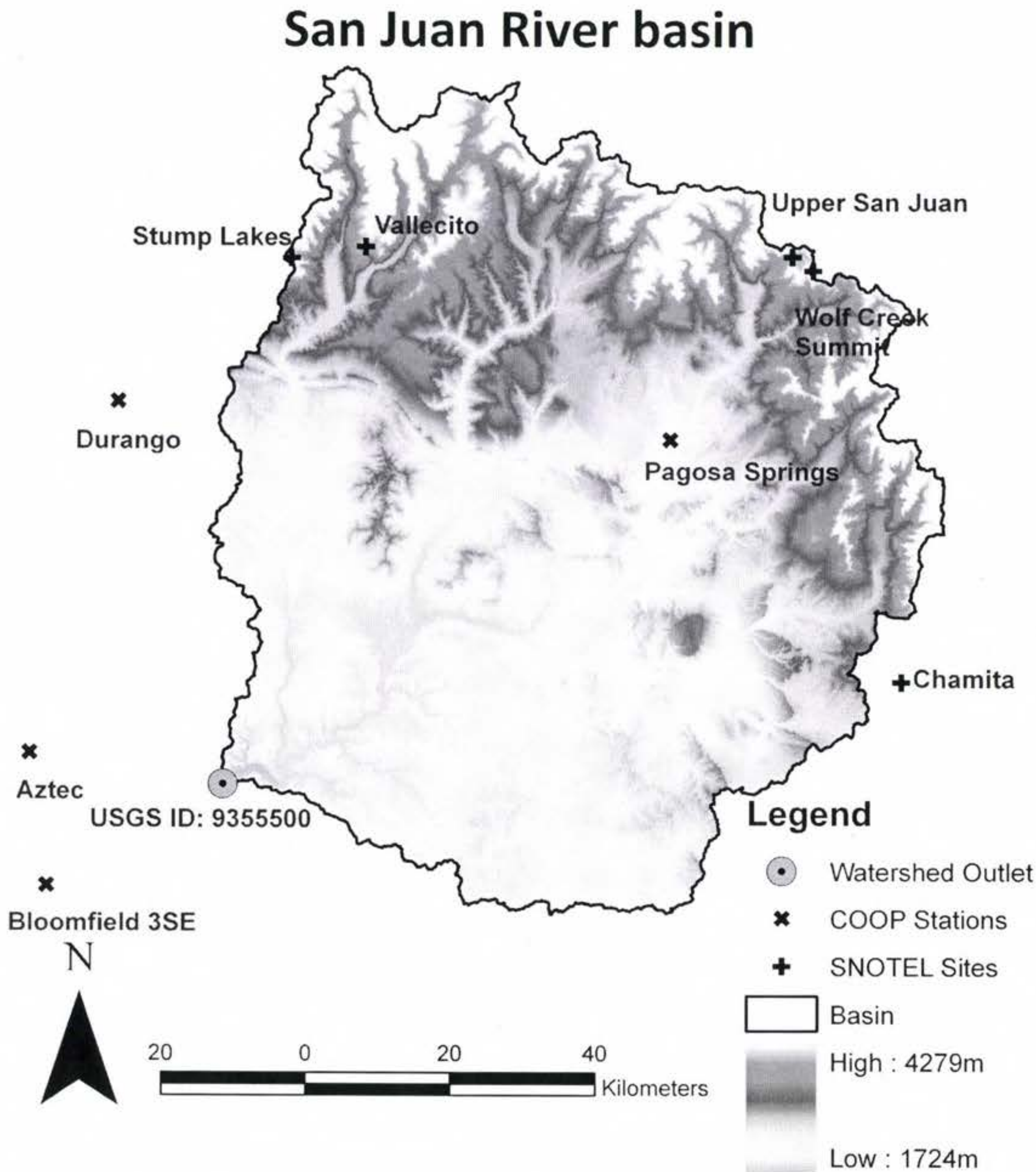


Figure 2.5. Elevation diversity in San Juan River basin along with the location of climatic stations used in the analysis.

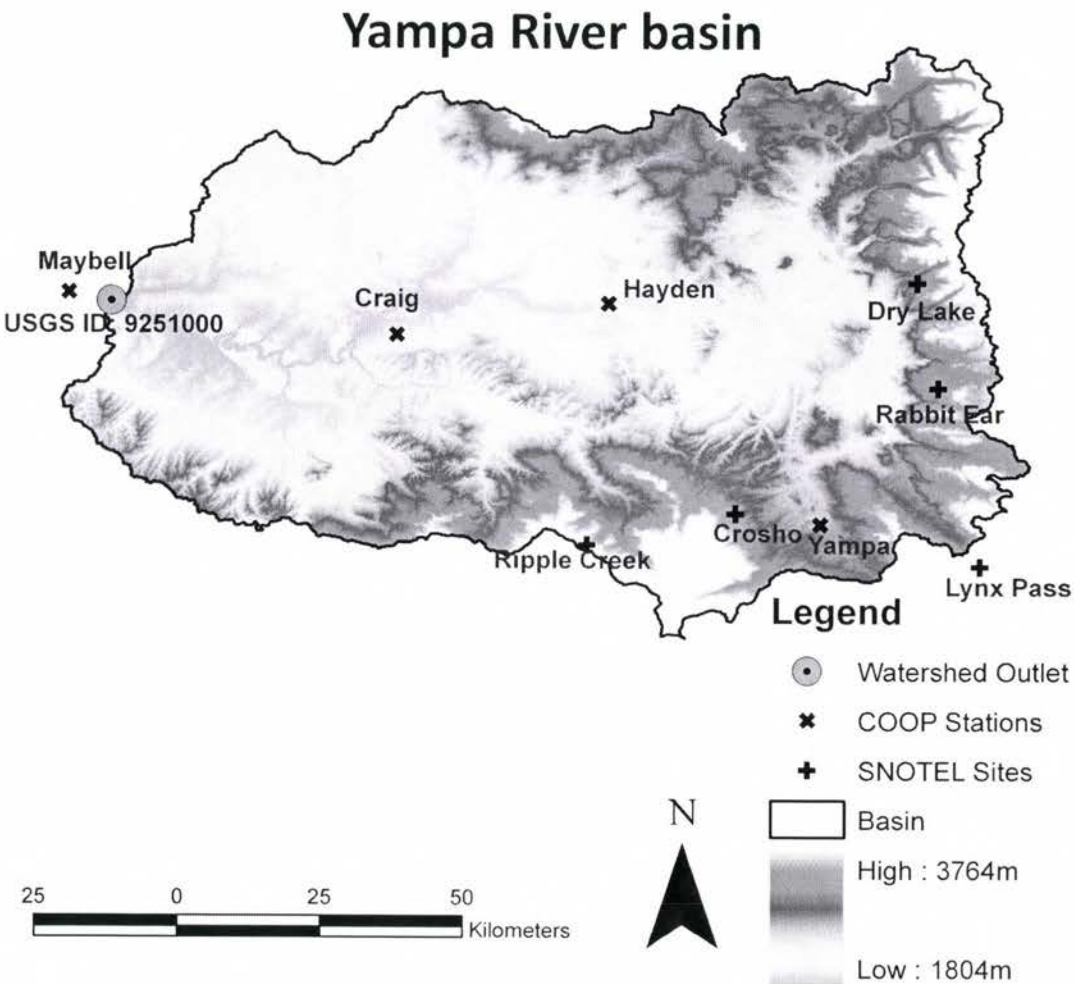


Figure 2.6. Elevation diversity in Yampa River basin along with the location of climatic stations used in the analysis.

Lapse Rates

Watersheds in Colorado have diversity in elevation; therefore, lapse rates for temperature and precipitation are provided for the true representation of these influential variables across different elevations within the watersheds. Lapse rates were determined by regression analysis of the input climatic data for individual watersheds. Table 2.2 shows the lapse rates for each of the watersheds used in this study. A non-linear relationship is observed between elevation and climatic variables (precipitation, temperature) for Colorado watersheds. However, in this study we assume a simple linear relationship and compute the lapse rates for study watersheds.

Temperature lapse rate

The temperature lapse rates were separately computed for all the watersheds using available data from the snowpack telemetry (SNOTEL) and the National Climatic Data Center (NCDC) for the stations that are within and close to the area of study. A relationship was developed between average annual temperature and station elevation. For an accurate representation of temperature in a topographically diverse watershed, the lapse rate should be assign to elevation bands (Rango and Martinec, 1979, 1994). Sub-basin temperatures are adjusted within each elevation band by comparing mean elevation of elevation band (Z_{EB}) with the station elevation (Z). Calculated temperature lapse rates were comparable to the lapse rates obtained by Fontaine et al. (2002), whose research was performed for the Upper Wind River basin in Wyoming. Adjusted temperature for an elevation band is computed as:

$$T_{EB} = T + (Z_{EB} - Z)\, dT/dz \tag{2.1}$$

where T_{EB} is the mean temperature of the elevation band, T is the temperature at the elevation where the station is located, and dT/dz is the temperature lapse rate. Mean annual temperature values computed for meteorological stations in and around the Cache la Poudre River basin were plotted against station elevation to obtain the temperature lapse rate as shown in Figure 2.7. Plots used for computing temperature lapse rates for the remaining four watersheds are shown in Appendix A1 (Figure A1.1-Figure A1.4)

Precipitation lapse rate

The lapse rate for precipitation was computed by plotting annual precipitation with weather station elevation. The study watersheds are large and have varying precipitation regimes because of elevation diversity. Therefore, the difference between the elevation of the sub-basin weather station and the elevation band was used to adjust the precipitation for all the sub-basins. Adjusted precipitation for an elevation band is computed as:

$$P_{EB} = P + (Z_{EB} - Z)dP/dz \tag{2.2}$$

where P_{EB} is the precipitation for elevation band, P is the precipitation where the station is located, and dP/dz is the precipitation lapse rate used for the calculation. Precipitation data from meteorological stations located in and around the Cache la Poudre River basin were plotted against the station elevation (Figure 2.7) to obtain the precipitation lapse rate. Plots used for computing the precipitation lapse rates for the remaining four watersheds are shown in Appendix A1 (Figure A1.1-Figure A1.4). In order to examine the variation in lapse rate the analysis period (1979-1998) was divided into 4 equal intervals and separate lapse rates were computed. Less amount of variation in precipitation lapse rate was observed from this analysis. Precipitation lapse rates for the study watersheds as computed for different periods are shown in Appendix A1 (Table A1.1), while the plots constructed for obtaining these values are shown in Appendix A1 (Figure A1.5-Figure A1.9).

This analysis was not performed for temperature datasets due to the lack of data availability for the SNOTEL stations especially during the calibration period (1979-1988).

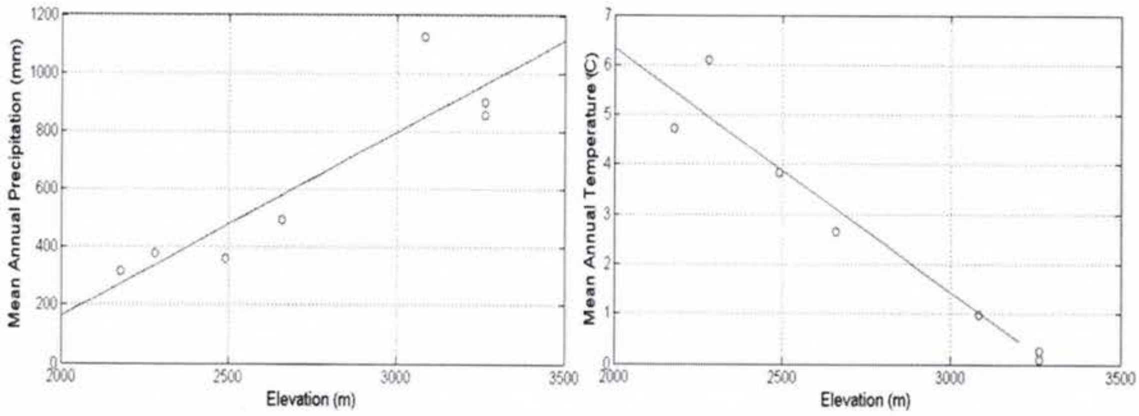


Figure 2.7. Variability of mean annual temperature and precipitation in Poudre River basin with elevation

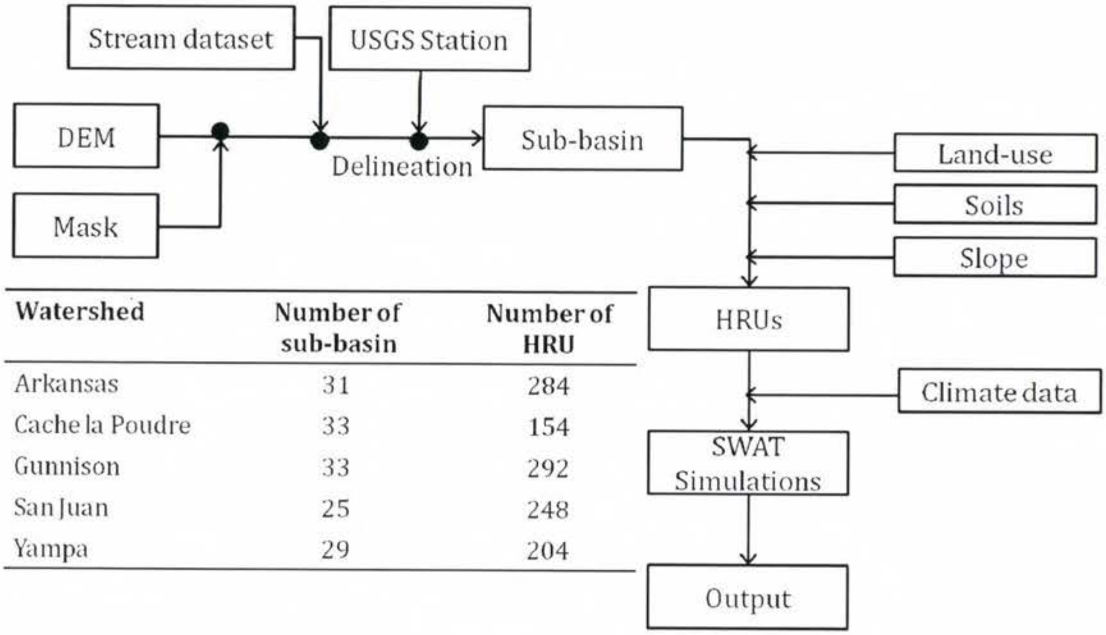
Table 2.2. Lapse rates for the watersheds

Site name	USGS site ID	Precipitation lapse rate (mm / km)	Temperature lapse rate (° C / km)
Cache la Poudre River at mouth of canyon	6752000	634	-4.9
Arkansas River at Canon City	7096000	252	-6.8
Gunnison River below Blue Mesa Dam	9124700	700	-6.5
San Juan River near Archuleta	9355500	482	-5.3
Yampa River near Maybell	9251000	567	-4.0

2.2.2. Hydrologic Model

The SWAT model was used to analyze hydrologic processes in study watersheds. SWAT was originally developed to determine the impact of land management practices on water, sediment, and agricultural contaminant chemical yields at a watershed scale. Since its development in the early 1990s, SWAT has undergone major revisions in order to enhance its capabilities (Arnold and Fohrer, 2005; Neitsch et al., 2005). Examples of revisions include the addition of hydrologic response units, the incorporation of a CO_2 component to the crop growth model, improved snowmelt routines for better simulation of hydrologic processes in mountainous watersheds, and improvement in bacterial transport and nutrient cycling routines. SWAT is currently used worldwide for many hydrologic/water quality studies, including: sediment and nutrient modeling for total maximum daily load (TMDL) development and implementation (Borah et al., 2006; Benham et al., 2006; Shirmohammadi et al., 2006; Vellidis et al., 2006), selection and implementation of best management practices (BMPs) (Arabi et al., 2006; Gitau et al., 2006), and evaluation of the impacts of climate change on various hydrologic processes (Stone et al., 2001; Rosenberg et al., 2003; Takle et al., 2005; Gosain et al., 2006; Jha et al., 2006). A comprehensive review of the development of SWAT model along with its use in various hydrologic applications over the past couple of decades can be found in Gassman et al. (2007).

SWAT uses readily available input datasets (e.g., precipitation, temperature, land use, soils, elevation, etc.) and can simulate processes such as runoff, return flow, percolation, evapotranspiration, groundwater flow, transmission losses, nutrient and pesticide loads, and reservoir storage. For modeling purposes, a watershed is divided into sub-watersheds, which are further divided into parcels possessing unique land uses, soil attributes, and slope characteristics referred to as hydrologic response units (HRUs). Input data requirements for the SWAT model are shown in Table 2.3. Daily precipitation and maximum/minimum temperature data were collected for cooperative observer program (COOP) and SNOTEL stations located in and around the study watersheds. A schematic of SWAT project set up along with the number of sub-basins and HRU's created for the study watersheds is shown in Figure 2.8.



Watershed	Number of sub-basin	Number of HRU
Arkansas	31	284
Cache la Poudre	33	154
Gunnison	33	292
San Juan	25	248
Yampa	29	204

Figure 2.8. Schematic of SWAT project set up

SWAT's hydrologic routing phase consists of main channel routing and reservoir routing. Main channel routing includes four components: water, sediment, nutrients, and organic chemicals. In this study, the soil conservation service (SCS) curve number procedure was used on the basis of the soil moisture condition to calculate the runoff, the Penman Monteith method was used to calculate the potential evapotranspiration (PET), and the variable storage method was used for channel routing.

Table 2.3. Data inputs for SWAT model

Title	Source	Data Type
National Elevation Dataset (NED)	U.S. Geological Survey (USGS) website - http://seamless.usgs.gov/	30-m Digital Elevation Model (DEM)
State Soil Geographic (STATSGO) Database	USDA/NRCS-National Cartography&Geospatial center website - http://datagateway.nrcs.usda.gov/	Soil types 1:250,000-scale map
Weather Dataset (SNOTEL Stations)	USDA/NRCS SNOTEL data and products website - http://www.wcc.nrcs.usda.gov/snow/	Daily precipitation and temperature datasets
Weather Dataset (COOP Stations)	National Climatic Data Center website - http://www.ncdc.noaa.gov/oa/ncdc.html	Daily precipitation and temperature datasets
National Land Cover Dataset (NLCD) 2001	U.S. Geological Survey (USGS) website - http://seamless.usgs.gov/	30-m Land use

SWAT accounts for sub-surface hydrology by using a kinematic storage model. The model uses the continuity equation based on mass for simulating sub-surface flows. It also accounts for lag in lateral flow in case of large sub-basins with a higher value for time of concentration. Groundwater processes are represented at the sub-basin level, while each sub-basin includes a shallow and a deep aquifer. A shallow aquifer is considered an unconfined aquifer that contributes to reach within the sub-basin, while the contribution of a deep aquifer to streamflow is considered outside the watershed and is considered lost from the system (Arnold et al., 1993). Water entering the unconfined aquifer or shallow aquifer after passing through different layers of soil profile is considered recharge to the sub-surface. SWAT partitions this recharge between the shallow aquifer and deep aquifer depending on the aquifer percolation constant represented by parameter RCHRG_DP. Baseflow contribution to reach in the sub-basin only occurs thorough shallow aquifers; it depends on the amount of water stored in the shallow aquifer, as denoted by parameter GWQMN and the baseflow recession constant denoted by ALPHA_BF. Upward movement of water from the shallow aquifer to the overlying unsaturated zone occurs when the overlying layer is dry. This process is defined as REVAP in SWAT and depends on parameters REVAPMN and GW_REVAP.

Elevation Bands

Elevation bands are generally used to handle spatial and temporal variability present in a watershed due to the elevation diversity (Rango and Martinec, 1979, 1994). Each sub-basin can represent up to 10 elevation bands in order to account for orographic effects on both temperature and precipitation. Average elevation of each band and the percentage of sub-watershed area within that band are provided as model inputs on a sub-basin basis. Elevation bands at an interval of 350m were used for this study. Precipitation and maximum/minimum temperatures were calculated for elevation bands as a function of lapse rates and the difference between the station elevation and the mean elevation of the band. An elevation band increment of 350m compares favorably with the increments that Fontaine et al. (2002) and Lemonds et al. (2007) have used for the Wind River basin in Wyoming and the Dillon Reservoir watershed in Colorado, respectively.

Representation of Snow Process in SWAT

Snow cover

SWAT represents snow hydrology at the HRU level. The type of precipitation in an HRU depends on the average temperature of air and snowfall. When the average air temperature on a daily basis is less than the snowfall temperature (SFTMP), an HRU receives precipitation in the form of snowfall. Snow exists as snowpack on the ground surface, and the snow water equivalent represents the amount of water in the snowpack. The snowpack increases with an increase in snowfall and decreases with the release of snowmelt, or sublimation. The mass balance for snowpack is shown in Equation (2.3):

$$SNO_i = SNO_{i-1} + R_{day} - E_{sub} - SNO_{mlt} \tag{2.3}$$

where SNO_i and SNO_{i-1} are the water content of snowpack on day i and $i-1$ respectively, R_{day} is the amount of precipitation on a given day and is only added to the mass balance of snowpack if the mean daily air temperature is less than or equal to the snowfall temperature (SFTMP), E_{sub} is the amount of sublimation on a given day, and SNO_{mlt} refers to the amount of snowmelt on a given day.

The snowpack in a sub-basin may not be uniformly distributed because of variables such as drifting and shading. This leads to a portion of the sub-basin area that is not covered with snow. SWAT quantifies this fraction in order to calculate snowmelt at the sub-basin level in a more realistic way. Areal coverage of snow is linked with the amount of snow present in a sub-basin using an areal depletion curve (Anderson, 1973). The curve explains the growth and slump of a snowpack on a seasonal basis. Equation (2.4) describes an areal depletion curve:

$$SNO_{cov} = \frac{SNO}{\text{SNOCOVMX}} \left(\frac{SNO}{\text{SNOCOVMX}} + \exp\left(cov_1 - cov_2 . \frac{SNO}{\text{SNOCOVMX}}\right)\right)^{-1} \quad (2.4)$$

where SNO_{cov} is the fraction of HRU covered by snow. Water content of snowpack on a particular day is denoted by SNO. The user-defined parameter SNOCOVMX refers to minimum snow water content corresponding to 100% snow cover. The coefficients cov_1 and cov_2 are computed from Equation (2.4) using 95% coverage at 95% of SNOCOVMX and 50% coverage at a user-defined fraction of SNOCOVMX. The fraction of SNOCOVMX corresponding to 50% snow cover is known as SNO50COV. The fraction of snow water content relative to 100% snow coverage is denoted as $\frac{SNO}{\text{SNOCOVMX}}$. The shape of an areal depletion curve is defined by three sets of points: (0, 0) (0.95, 0.95), and (0.5, SNO50COV). Figure 2.9 shows an areal depletion curve with the value of the input parameter SNO50COV adjusted to 0.75. The parameter SNO50COV varies between 0-1 and adjusts the shape of an areal depletion curve depending on the pattern of snow cover in a watershed. An area with uniform snow cover observes a value of SNO50COV approaching 0, while a SNO50COV value close to 1 is observed for the areas with non uniform cover.

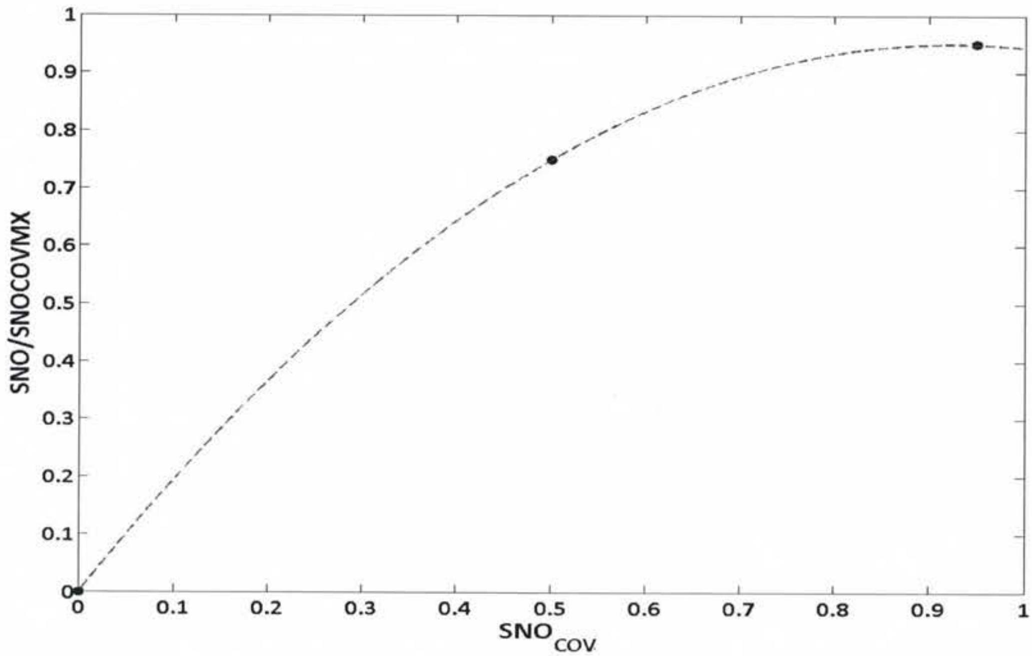


Figure 2.9. Areal depletion curve for $COV_{50} = 0.75$

Snowmelt

Snowmelt in SWAT is controlled by the mean air temperature, the temperature of the snowpack and the melting rate. SWAT computes the snowpack temperature as shown in Equation (2.5), where: the snow temperature lag factor ($TIMP$) controls the influence of the previous day's snowpack temperature ($T_{SN_{i\_1}}$) (°C) on the current day's snowpack temperature (T_{SN_i}) (°C).

$$T_{SN_i} = T_{SN_{i\_1}} (1 - TIMP) + T_B * TIMP \tag{2.5}$$

Variable $TIMP$ depends on the depth of snowpack and varies between 0-0.5 for deep snowpacks and varies from 0.5-1.0 for shallow snowpacks. Equation (2.5) shows that for deep snowpacks $T_{SN_{i\_1}}$ will have a greater influence on T_{SN_i} (°C) while in the case of shallow snowpacks the mean air temperature (T_B) (°C) will be dominating. Snowmelt in SWAT depends on the threshold temperature for snowmelt to occur, the maximum temperature of air, and the maximum snowpack temperature for the current day, as shown in Equation (2.6):

$$SNO_{mlt} = SNO_{cov} * b_{mlt}\left[\frac{T_{SNi} + T_{max}}{2} - SMTMP\right] \tag{2.6}$$

where SNO_{mlt} is the amount of snowmelt on a given day (mm H_2O), SNO_{cov} is the fraction of a HRU covered by snow as computed in Equation (2.4), b_{mlt} refers to the melt factor for the day (mm H_2O/day °C), T_{SN_i} is the snowpack temperature for the current day (°C), T_{max} is the maximum air temperature on a given day (°C), and $SMTMP$ is the threshold temperature for snowmelt to occur (°C).

The melt factor is computed using the seasonal variation with respect to maximum and minimum values occurring during the summer and winter solstices, respectively. The melt coefficient is predicted by a sine function (Anderson, 1973) as shown in Equation (2.7):

$$b_{mlt} = \frac{(SMFMX + SMFMN)}{2} + \frac{(SMFMX - SMFMN)}{2} * \sin\left(\frac{2\pi}{365}(d_n - 81)\right) \tag{2.7}$$

where $SMFMX$ is the melt factor for the June 21 (mm H_2O/day °C), $SMFMN$ is the melt factor for December 21 (mm H_2O/day °C), and d_n is the day number of the year.

Model Parameters

In order to understand the major hydrological processes represented by SWAT for the snow-dominated areas, a set of model parameters was used for sensitivity analysis. Parameters are classified depending on the process (snow cover, snowmelt, runoff, groundwater, soil percolation, channel flow, erosion, and evaporation) in which they are involved. Table 2.4 provides the acceptable range, along with the definition, of the parameters involved in the analysis. These ranges were selected based on SWAT manual (Neitsch et al., 2005). Certain empirical parameters, such as curve number (CN_F) vary with varying combinations of land use and soil. Therefore, these parameters tend to have multiple values in the watersheds comprising of several HRUs. Thus, in order to maintain the parameters' spatial variability, these parameters were changed as a fraction of their default values.

Table 2.4. List of SWAT parameters included in the analysis

No	Input parameter	Min	Max	Definition	Process
x_1	ALPHA_BF	0	1	baseflow recession constant (days)	groundwater
x_2	CANMX	0	10	maximum canopy storage	runoff
x_3	CH_KI	0	300	effective hydraulic conductivity of channel (mm/hr)	channel
x_4	CH_KII	-0.01	500	effective hydraulic conductivity of channel (mm/hr)	channel
x_5	CH_NI	0.008	0.3	manning's n for tributary channel	channel
x_6	CH_NII	0.01	0.3	manning's n for main channel	channel
x_7	CH_SII*	-0.05	0.05	Fraction change in average channel slope along channel length	channel
x_8	CN_F*	-0.15	0.15	Fraction change in curve number	runoff
x_9	DEPIMP_BSN	0	6000	Depth to impervious layer (mm)	groundwater
x_{10}	EPCO	0.01	1	Plant evaporation compensation factor	evaporation
x_{11}	ESCO	0.01	1	soil evaporation compensation factor	evaporation
x_{12}	GW_DELAY	0	500	groundwater delay (days)	groundwater
x_{13}	GW_REVAP	0.02	0.2	groundwater Revap coefficient	groundwater
x_{14}	GW_SPYLD*	-0.5	1	Fraction change in specific yield of the shallow aquifer	groundwater
x_{15}	GWHT	0	25	initial groundwater height	groundwater
x_{16}	GWQMN	0	5000	threshold water level in shallow aquifer for baseflow to occur (mm)	groundwater
x_{17}	OV_N	0.01	0.3	manning's n for overland flow	runoff
x_{18}	RCHRG_DP	0	1	groundwater recharge to deep aquifer (fraction)	groundwater
x_{19}	REVEP_MN	0	500	threshold water level in the shallow aquifer for Revap to occur (mm)	groundwater
x_{20}	SFTMP	-5	5	snowfall temperature (°C)	snow cover
x_{21}	SLOPE*	-0.1	0.1	Fraction change in slope of HRU	geomorphology
x_{22}	SMFMN	0	10	melt factor on June 21 (mm /°C/day)	snowmelt
x_{23}	SMFMX	0	10	melt factor on Dec 21(mm/°C/day)	snowmelt
x_{24}	SMTMP	-5	5	threshold temperture for snowmelt (°C)	snowmelt
x_{25}	SNO50COV	0	1	fraction of snow volume represented by SNOCOVMX that corresponds to 50% snow cover	snow cover
x_{26}	SNOCOVMX	0	650	minimum snow water content that corresponds to 100% snow cover (mm)	snow cover
x_{27}	SOL_AWC*	-0.1	2	Fraction change in available water capacity of the soil layer	soil
x_{28}	SOL_K*	-0.5	5	Fraction change in soil conductivity	soil
x_{29}	SURLAG	1	24	surface runoff lag coefficient	Runoff
x_{30}	TIMP	0.01	1	Snow temperature lag factor	snowmelt

* These parameters were varied as a percentage of their default values to maintain their relative spatial variability

2.2.3. Sensitivity Analysis

Sensitivity analysis is considered a prerequisite for model building irrespective of the field of study. It helps in assessing the quality of a model for environmental practices and provides guidelines for developing decision support systems that are used in creating and modifying environmental policies (Saltelli et al., 2000; Tarantola et al., 2002). It is considered a key technique in providing assistance to risk assessments (Baker et al., 1999). Sensitivity analysis assists in analyzing the measures that can mitigate the risk of climate change (Jones, 2000). This study uses a global sensitivity analysis method, FAST, to identify the individual and interaction effects of SWAT parameters on the generation of streamflow with respect to magnitude as well as timing in snow-dominated mountainous watersheds. Sensitivity analysis methods can be categorized into three general classes: local sensitivity analysis methods, screening methods and global sensitivity analysis methods (Saltelli et al., 2000).

Local sensitivity analysis methods consider only the local impact of input parameters on the model and the results obtained are related to a particular point in the entire parameter space. These methods require the relative uncertainty of each parameter to be weighed when comparing the effects of various input parameters on the output and therefore are considered less efficient methods. The majority of the previous studies related to sensitivity analysis of SWAT parameters have used local methods. These studies were mainly based on identifying sensitive SWAT parameters related to flow, sediments or nutrients in different study watersheds (Wang et al., 2005; Plus et al., 2006; Muleta et al., 2007; Rouhani et al., 2007; Shen et al., 2009).

Screening methods are considered simple and economical in terms of time and computational cost. Such methods rank the input parameters in order of their importance, but quantitative measurements, that is, how much a parameter is more important than another parameter, are beyond the scope of this method. Screening methods do not provide any information about the interactions between different input parameters and thus have very limited use in the study of mountainous watersheds where interdependency between different parameters governs the hydrology. Most of the studies incorporating screening methods with SWAT have either used the LH-OAT method or the Morris-OAT method (Holvoet et al., 2005; Arabi et al., 2007; Mulungu et al., 2007; Ahl et al., 2008; Arabi et al., 2008; Coffey et al., 2010).

Global sensitivity analysis apportions the output uncertainty to the uncertainty in the input parameters (Saltelli, 2000), and can be used to carry out a number of tasks. Global sensitivity analysis is used to provide guidelines for the implementation of model-based system assessments, and to assess the robustness of decisions in the presence of uncertainty (Tarantola et al., 2002). It provides improvement in the reliability and credibility of decisional processes by clarifying the range of uncertainty associated with policies for environmental assessments. To the best of our knowledge, only Francos et al. (2003) have used the global sensitivity analysis method with SWAT in order to identify sensitive parameters related to flow, sediments and nutrients in the Oust watershed situated in England.

Global Sensitivity Analysis

Various model approximation techniques such as regression analysis, correlation measures, and rank transformation are grouped together as global sensitivity analysis methods (Kiparissides et al., 2008). However, variance-based methods have increasingly gained popularity because they not only provide a quantitative measure of the importance of model parameters individually, but also explicitly reveal the importance of interactions between model parameters. First order sensitivity indices (S_i) and total order sensitivity indices (TS_i) are computed as shown below in Equation (2.8) and Equation (2.9), respectively (Saltelli et al., 2000) :

$$S_i = {V\big(E(Y|x_i)\big)}\Big/{V(Y)} \tag{2.8}$$

$$TS_i = \Big(V(Y) - V\big(E(Y|x_{\sim i})\big)\Big)/V(Y) \tag{2.9}$$

where $V\big(E(Y|x_i)\big)$ represents the variance of the expected value of the output (Y) with respect to input parameter (x_i), $V(Y)$ is the total variance in the output (Y) and, $V\big(E(Y|x_{\sim i})\big)$ represents the variance of the expected value of the output (Y) with respect to input parameters other than x_i. Computation of expected value and variance terms in these equations varies and depends on the method used for the analysis.

Fourier Amplitude Sensitivity Test (FAST)

FAST is one of the most popular techniques developed for global sensitivity and uncertainty analysis (Cukier et al., 1973; Schaibly and Shuler, 1973; Cukier et al., 1975, 1978; Saltelli et al., 1998; Lu et al., 2001; Xu et al., 2008). FAST estimates the expected value (E(Y)) and variance (V(Y)) of the output variable Y and the contribution of each input parameter to this variance (Saltelli et al., 2000). The FAST methodology is based on transformation the *p*-dimensional parameter space to a one-dimensional space using a Fourier transformation function. Implementation of FAST in conjunction with SWAT follows these steps:

Step 1: A distributed hydrologic model (SWAT) with a multi-objective function (Y) and p different input parameters is selected as shown in Equation (2.10). Ranges of the input parameters are shown in Table 2.5.

$$\mathrm{Y} = f(x_1, x_2, \dots \dots \dots . x_p) \tag{2.10}$$

Step 2: A transformation function (Equation (2.11)) is introduced for each input parameter in order to convert a multi-dimensional integral in x (Equation (2.10)) into a one-dimensional integral in s (Equation (2.12)). A number of transformation functions have been proposed by Cukier et al. (1973), Koda et al. (1979) and Saltelli et al. (1999). This study uses the transformation function proposed by Saltelli et al. (1999).

$$x_i = \ 1/2 \ + 1/\pi \arcsin(sin\omega_i s) \tag{2.11}$$

$$f(s) = f\left(T_1(sin\omega_1 s), \dots \dots \dots, T_p\left(sin\omega_p s\right)\right) \tag{2.12}$$

where s is a scalar variable ranging from - π to π and ω_i is a set of angular frequencies consisting of only integers. The transformation function allows the parameter to oscillate periodically at the corresponding ω_i, thus changing the model output to a periodic function of s. If the ω_i's are positive integers, the corresponding function will have a period 2π. Thus, Fourier expansion can be used for expanding the model output as shown in Equation (2.13):

$$f(s) = A_0 + \sum_{h=1}^{\infty}\{A_h \cos(hs) + B_h \sin(hs)\} \tag{2.13}$$

where A_0 is a constant computed as shown in Equation (2.15), while A_h and B_h are the Fourier coefficients.

Step 3: The Fourier coefficients in Equation (2.13) are computed by using discrete samples, denoted as: s_1, s_2, s_3 etc. The transformation function is applied to each sample element of S shown in Equation (2.14) to obtain the sampled values of each parameter. Model runs are performed on these obtained sample values, and the Fourier coefficients are computed using elements of S as shown in Equation (2.16) and Equation (2.17):

$$S = \{s_1, s_2, \ldots.s_k, \ldots\ldots.s_N\} \tag{2.14}$$

$$A_0 = 1/N \sum_{k=1}^{(N-1)/2} f(s_k) \tag{2.15}$$

$$A_h = 2/N \sum_{k=1}^{(N-1)/2} f(s_k)\cos(s_k h) \tag{2.16}$$

$$B_h = 2/N \sum_{k=1}^{(N-1)/2} f(s_k) \sin(s_k h) \tag{2.17}$$

Step 4: The obtained Fourier coefficients from Equation (2.16) and Equation (2.17) are used to compute the variance of the output Y by Equation (2.18):

$$V(Y) = \frac{1}{2} \sum_{h=1}^{(N-1)/2} (A_h^2 + B_h^2) \tag{2.18}$$

Step 5: In order to compute the partial variance (G_{w_i}) of each parameter on the model output, different values of ω_i and the number of samples (N) are required. The minimum sample size requirement for computing G_{w_i} is shown in Equation (2.19):

$$N = 2M\omega_{\max}+1 \tag{2.19}$$

where $\omega_{\max}$ is the maximum frequency from the set of ω_i, M refers to the maximum harmonic which is usually 4 or 6, and N is a user-defined number for the FAST samples. After values for N and M, $\omega_{\max}$ can be computed in order to determine values for other frequencies. A high value is assigned to ω_i, and complementary frequencies ($\omega_{\sim i}$) receive lower values. The maximum value of complimentary frequencies is determined using Equation (2.20):

$$Max\ (w_{\sim i}) = \frac{w_i}{2M} \tag{2.20}$$

Later, frequencies $(w_{\sim i})$ for complementary set $[1, Max\ (w_{\sim i})]$ are assigned depending on the number of input parameters. The basic rule for assigning these frequencies is that the difference between two consecutive frequencies should be as large as possible.

Step 6: In this step the partial variance in the model output with respect to the uncertainty of each input parameter x_i is computed as shown in Equation (2.21):

$$G_{w_i} = \frac{1}{2} \sum_{u=1}^{(N-1)/2} (A^2_{u\omega_i} + B^2_{u\omega_i}) \tag{2.21}$$

Step 7: Total variance of Y computed from step 4, and variance in model output with respect to each input parameter computed from step 6, are now used to obtain the individual contribution of each input parameter to the total variance of Y. This is also known as the first order sensitivity indices and is computed as shown in Equation (2.22), which is equivalent to Equation (2.8).

$$S_i^{\text{FAST}} = {G_{\omega_i}}/{V(Y)} \tag{2.22}$$

Step 8: Finally, FAST total order indices are computed in order to understand the interactions between the input parameters. To determine the total order indice for an input parameter x_i, an angular frequency ω_i is assigned to it, while all the other input parameters are allotted the angular frequencies of $\omega_{\sim i}$ and its higher harmonics $u\omega_{\sim i}$, where $\sim i$ refers to all but i. A partial variance $G_{\omega_{\sim i}}$ that measures the effect of all the input parameters (except x_i) on the model output is computed by using Equation (2.23).

Later, the result from Equation (2.23) is used to obtain the total order indice ($TS(i)$) or the total effect of input parameter x_i from Equation (2.24), which is equivalent to Equation (1.9).

$$G_{\omega_{-i}} = \frac{1}{2} \sum_{u=1}^{(N-1)/2} (A_{u\omega_{\sim i}}^2 + B_{u_{\omega_{\sim i}}}^2) \tag{2.23}$$

$$TS(i) = 1 - {G_{\omega_{\sim i}}}/{V(Y)} \tag{2.24}$$

Stability Analysis

Previous studies have shown that the accuracy and consistency of results from FAST analysis could be influenced by the number of model evaluations (Lu et al, 2001). Francos et al. (2003) obtained three subsets of SWAT parameters, each composed of 14 parameters as a result of sensitivity analysis based on the Morris screening method. These subsets were used for the FAST analysis of 19 output variables related to flow, sediments, and nutrients. Computational limitations in this study allowed for only three different subsets of 14 input parameters to be included in the FAST analysis; this led to exclusion of some important SWAT parameters that were related to a particular output variable from the analysis. Stability analysis was not addressed in this study, and was most likely due to a lower number of SWAT parameters included in the FAST analysis. The number of simulations required for obtaining consistent results from FAST depends on the number of input parameters used in the analysis. FAST has a limitation to its applicability when the number of inputs is large, as the algorithm can only be applied to 50 or fewer inputs (Mokhtari et al., 2006).

In order to determine the adequate number of model evaluations required to obtain consistent sensitivity analysis results, a stability analysis was performed for the Cache la Poudre River basin. The number of model evaluations required for a stable FAST analysis depends on the number of input parameters selected for the sensitivity analysis. Since the FAST analysis for all the watersheds in this study was based on 30 SWAT parameters, the stability analysis was performed for one watershed, that is, the Cache la Poudre watershed, and model evaluations corresponding to stable results were used for all other watersheds.

Three replications of FAST runs were performed for the Cache la Poudre River basin with the number of samples varying between 2,000 and 15,000. Three different values of sensitivity indices were obtained for each parameter as a result of three identical runs and were used to compute the absolute difference between these values for each parameter, separately. An average value (v_j) was computed for each of the three identical sets by taking the mean of the absolute difference computed for each parameter, as shown in Equation (2.25). The obtained values were then used to calculate a mean and a standard deviation for each number of FAST samples used in this analysis by using Equation (2.26) and (2.27):

$$v_j = \frac{\sum_{i=1}^{30} |x_{i_m} - x_{i_n}|}{30}\ ; m, n = 1,2,3, m \neq n, \qquad (2.25)$$

$$and\ j = \{2000, 3000, 4000, 5000, 10{,}000, 15{,}000\}$$

$$v_{j_{mean}} = \frac{v_{j_1}+v_{j_2}+v_{j_3}}{3} \tag{2.26}$$

$$v_{j_{stdev}} = \sqrt{\frac{1}{2}\sum_{k=1}^{3}\left(v_{j_k} - v_{j_{mean}}\right)^2} \tag{2.27}$$

Mean and standard deviation values of less than 5% and 1%, respectively, were obtained from the FAST analysis with 15,000 model evaluations. Thus, FAST analysis for all watersheds in the study was performed with 15,000 model evaluations.

2.3. Results and Discussion

The results of the integrated SWAT/FAST analysis exhibit a strong agreement on the important parameters for all study watersheds. However, sensitivity indices varied depending on the objective function utilized in the analysis. The stability analysis in the Poudre River watershed indicated that a minimum of 15,000 model evaluations were required to obtain consistent results. Thus, sensitivity analysis for all study watersheds was performed using 15,000 model evaluations. Figure 2.10 shows the importance of selecting an appropriate number of samples from the parameter space while performing a sensitivity analysis using FAST. Error plots for the two objective functions as displayed in Figure 2.10 clearly show that as the number of model evaluations increased, the disparity between sensitivity indices from three replicates diminished. Mean and standard deviation values corresponding to 15,000 model evaluations indicated stability in the sensitivity analysis results from FAST analysis, as shown in Figure 2.10. It should be noted that these findings are specific to this study where 30 SWAT parameters were altered.

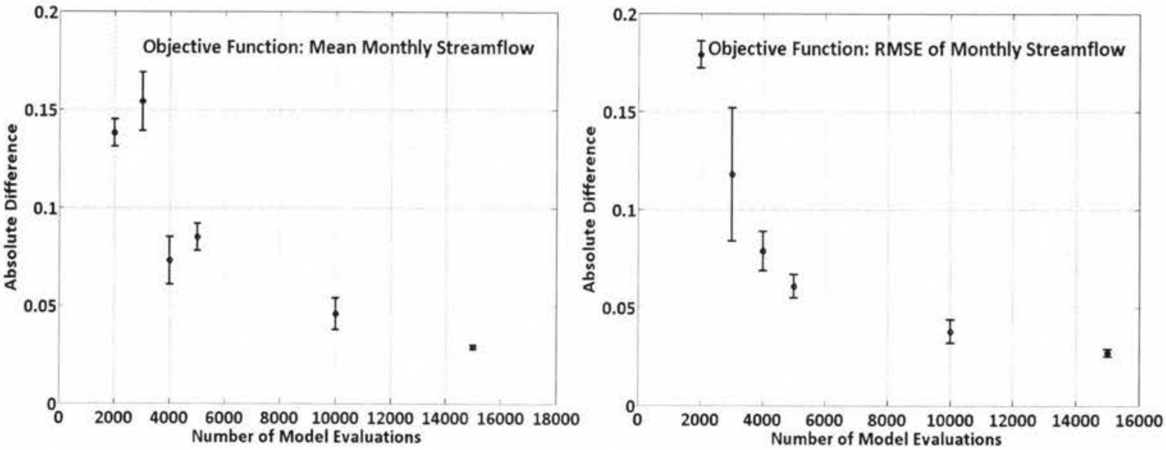


Figure 2.10. Illustration of the importance of number of model evaluations on the result of FAST

Sensitivity analysis of 30 SWAT input parameters corresponding to the two objective functions mean monthly streamflow and the corresponding root mean square error, assisted in identifying the SWAT parameters that play an important role in hydrologic modeling of mountainous watersheds. Multiple objective functions were selected in order to identify the parameters and the hydrologic processes that play a vital role in the generation of streamflow in terms of both volume and timing in snow-dominated mountainous watersheds. Major findings of this analysis are discussed below.

Case 1. Objective Function: Mean Monthly Streamflows

Main Effects: First Order Indices

The first order indices obtained as a FAST output help in determining whether the objective function is dominated by the interaction effect or the individual effect of the parameters. Figure 2.11 shows that the individual effect of the parameters dominated when monthly streamflow was used as the objective function. Hydraulic conductivity of the soil, represented by the parameter SOL_K, and effective hydraulic conductivity of channel alluvium, represented by the parameter CH_Kl, were observed to be the most important parameters for the majority of watersheds. Other important parameters obtained from the analysis of FAST first order indices of mean monthly streamflow were mainly related to groundwater processes and are shown in Table 2.5. Figure 2.11 only shows the parameters with sensitivity indices greater than 0.1. However, a detailed list of important parameters can be seen in Table 2.5.

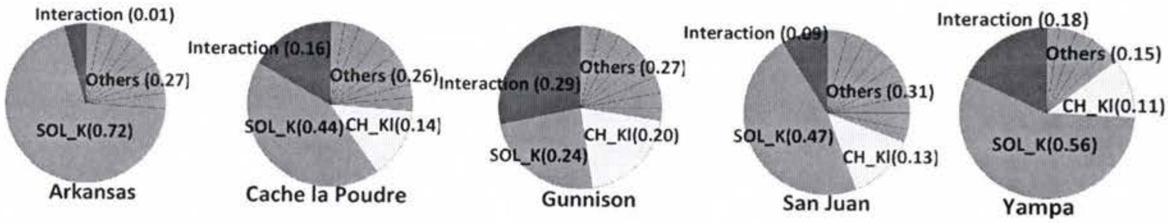


Figure 2.11. FAST first order sensitivity indices for the objective function mean monthly streamflow. where, SOL_K: hydraulic conductivity of soil and CH_Kl: effective hydraulic conductivity of channel alluvium

Interaction Effects: Total Order Indices

The interaction effect was not observed to be dominant in most of the watersheds when mean monthly streamflow was used as the objective function. This shows that the interaction between different hydrologic processes does not play a major role when the analysis is corresponding to volume of flow. Interactions were mainly observed for some groundwater parameters. Few snow parameters were also observed to have an interaction effect especially in case of the Gunnison River basin. Figure 2.12 shows the parameters corresponding to the interaction portion of the pie charts in Figure 2.11. The importance of sub-surface hydrologic processes for the generation of streamflow in mountainous watersheds was realized from this analysis.

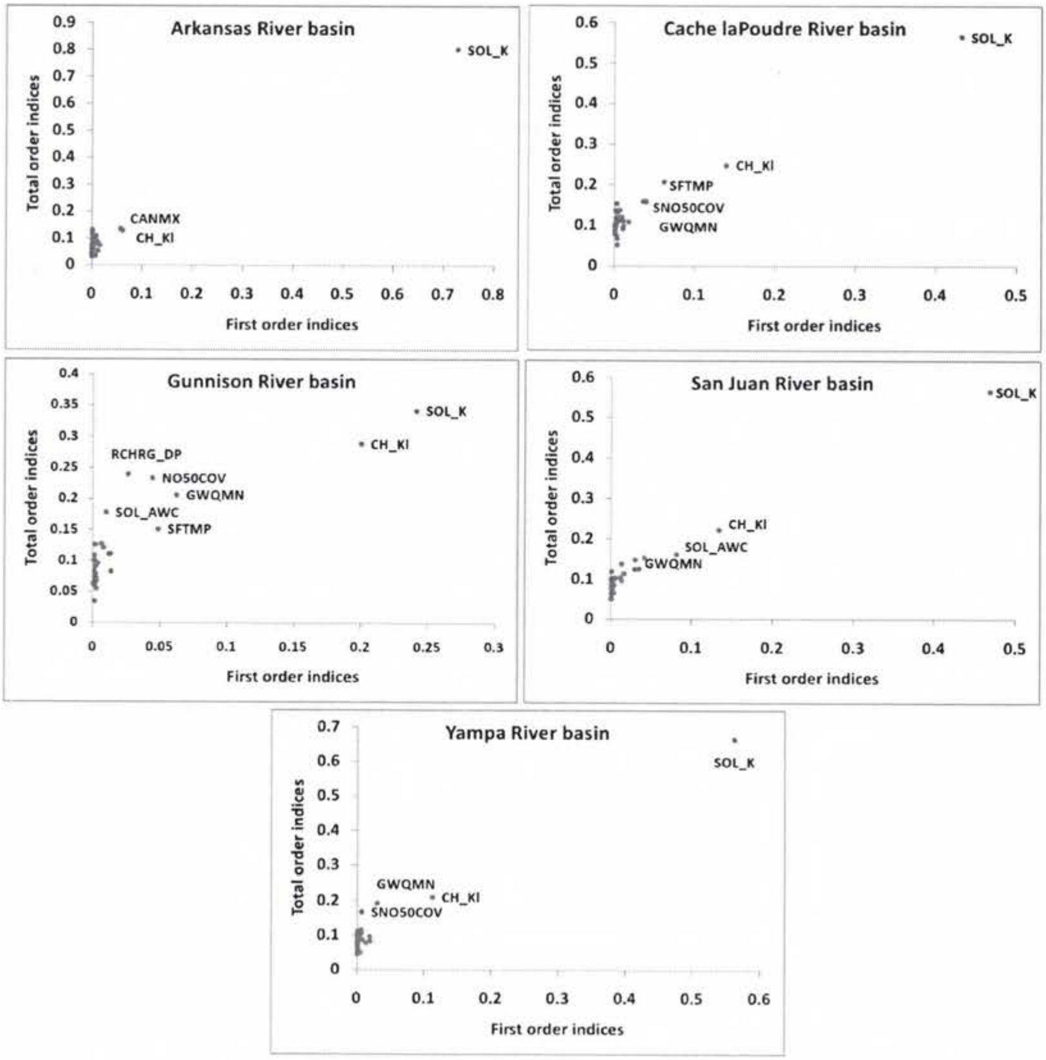


Figure 2.12. Parameters contributing to a higher interaction effect in the case of MSF as the objective function.

Case 2. Objective Function: RMSE of Mean Monthly Streamflows

Main Effects: First Order Indices

The first order indices obtained as a FAST output from the analysis of the RMSE of monthly streamflow show the dominance of interactions between different hydrologic processes in the generation of streamflow with respect to magnitude, as well as timing.

Figure 2.13 shows that the baseflow parameter, ALPHA_BF, was observed to be the most sensitive for all the watersheds. This shows that the contribution of sub-surface or groundwater flow to streamflow is a dominant process for generation of streamflow in snow-dominated mountainous watersheds. Only important parameters with FAST first order indices greater than 0.1 are shown in Figure 2.13. However, the complete list of important parameters can be seen in Table 2.5.

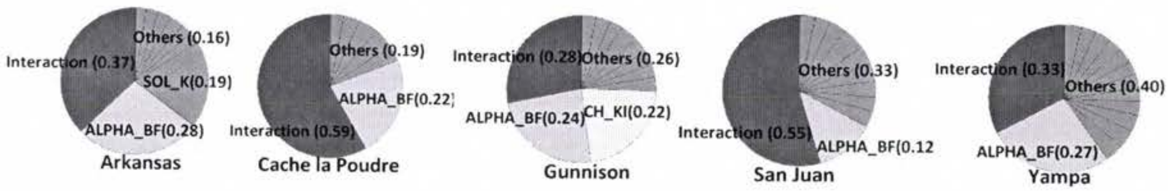


Figure 2.13. FAST first order sensitivity indices for the objective function RMSE of mean monthly streamflow. where, ALPHA_BF: Baseflow recession constant and CH_Kl: effective hydraulic conductivity of channel alluvium

Interaction Effects: Total Order Indices

In order to identify the parameters that are contributing to the interaction portions in Figure 2.13, total order indices from the FAST output were analyzed. Figure 2.14 shows the parameters contributing most to the interaction division of the pie charts for all five watersheds. These parameters were mainly related to snow cover, snowmelt, baseflow and lateral flow; which support the finding of Dincer et al. (1970), Martinec (1975), Rodhe (1981), and Flerchinger (1992) for mountainous watersheds. Generation of streamflow in snow-dominated mountainous regions depends on the snowmelt and the snowmelt recharge pattern to groundwater systems (Flerchinger et al., 1992), which helps in understanding the higher interaction effect obtained for these parameters from the FAST analysis of the RMSE of monthly streamflows.

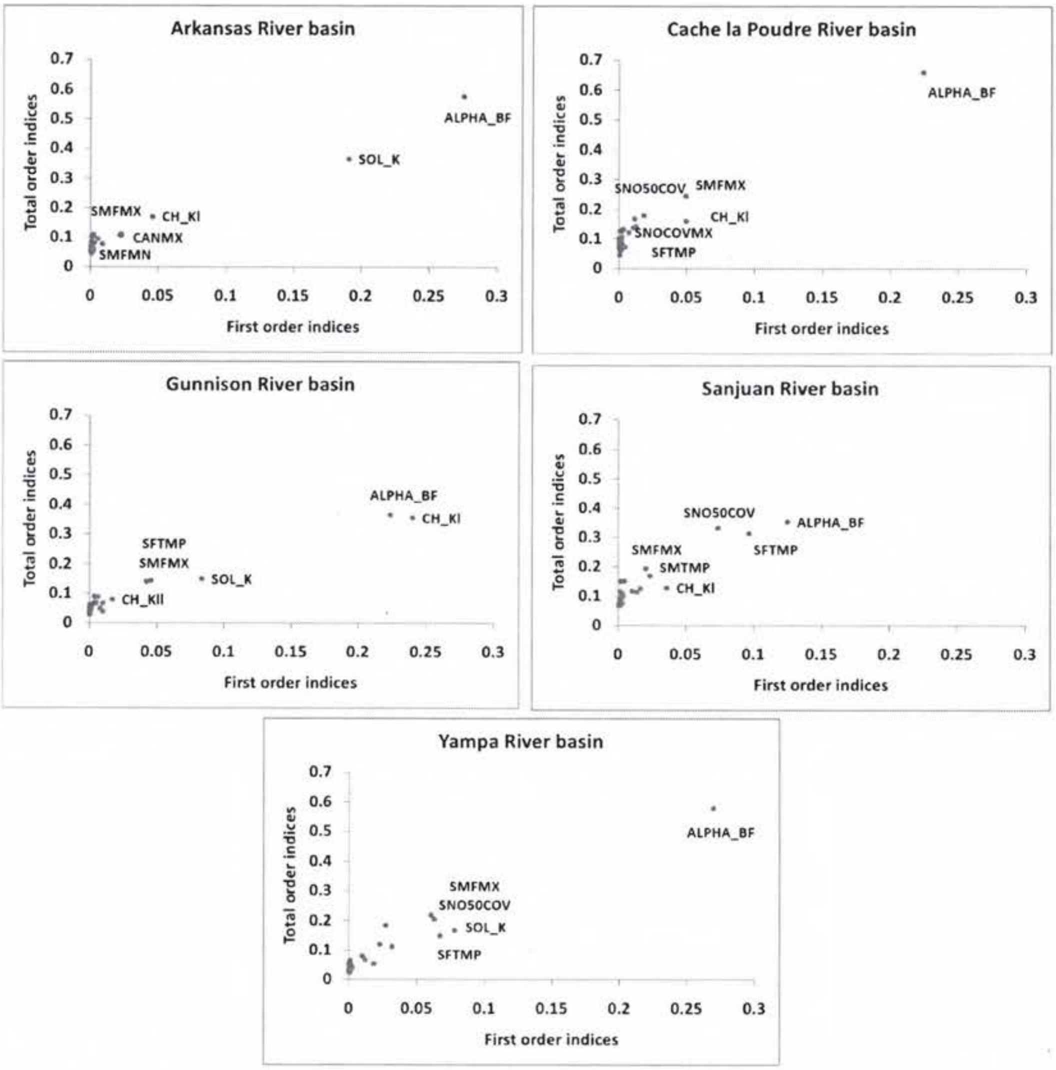


Figure 2.14. Parameters contributing to higher interaction effect in case of RMSE of the mean monthly streamflow as the objective function

Sensitivity indices of parameters were obtained for both the mean monthly streamflow and the corresponding RMSE, separately. Table 2.5 shows the rank of the parameters for the two objective functions, starting with the mean monthly streamflow (Q) and followed by the RMSE of monthly streamflow (e), for all five watersheds. The last column for each watershed shows the global (G) or the overall rank of parameters, which was decided by selecting the higher of the assigned ranks from the two objective functions. It can be seen from Table 2.5 that the majority of important parameters are similar irrespective of the watershed. Parameters corresponding to hydrological processes such as snow cover, snowmelt, soil, groundwater, etc., were observed to be important for all the watersheds. However, few parameters were observed to be important only for particular watersheds.

Table 2.5. Rank of SWAT parameters for average monthly streamflow (Q), RMSE of monthly streamflow (e) along with their global rank (G) in the study watersheds.

Parameters	Arkansas			Cache la Poudre			Gunnison			San Juan			Yampa		
	Q	e	G	Q	e	G	Q	e	G	Q	e	G	Q	e	G
ALPHA_BF	28	1	1	23	1	1	11	1	1	16	1	1	23	1	1
CANMX	2	8	2	16	13	13	12	9	9	11	22	11	17	21	17
CH_KI	4	3	3	2	5	2	2	2	2	2	8	2	2	11	2
CH_KII	17	9	9	24	4	4	15	8	8	20	11	11	10	4	4
CH_NI	8	24	8	29	12	12	23	26	23	26	24	24	9	15	9
CH_NII	6	23	6	25	15	15	20	18	18	27	13	13	16	25	16
CH_SII	3	22	3	26	18	18	9	24	9	17	26	17	24	26	24
CN_F	19	15	15	30	25	25	26	14	14	21	6	6	7	22	7
DEPIMP_BSN	26	19	19	8	27	8	27	29	27	9	30	9	25	24	24
EPCO	30	13	13	19	29	19	14	30	14	15	25	15	27	29	27
ESCO	14	17	14	15	22	15	19	11	11	8	18	8	13	12	12
GW_DELAY	22	5	5	18	17	17	28	27	27	25	15	15	14	28	14
GW_REVAP	18	30	18	9	14	9	25	22	22	19	20	19	28	23	23
GW_SPYLD	27	18	18	27	19	19	24	23	23	30	23	23	21	17	17
GWHT	21	25	21	12	23	12	21	21	21	28	27	27	30	19	19
GWQMN	12	26	12	4	9	4	5	20	5	4	10	4	3	18	3
OV_N	5	10	5	17	21	17	17	17	17	18	29	18	26	30	26
RCHRG_DP	20	29	20	20	11	11	3	6	3	10	14	10	5	20	5
REVEP_MN	13	14	13	22	24	22	22	16	16	14	21	14	8	13	8
SFTMP	15	16	15	3	8	3	7	4	4	5	3	3	19	6	6
SLOPE	7	28	7	10	26	10	29	15	15	12	19	12	29	16	16
SMFMN	25	12	12	14	16	14	18	10	10	22	16	16	20	10	10
SMFMX	9	11	9	28	2	2	10	5	5	13	4	4	12	2	2
SMTMP	24	20	20	13	10	10	16	28	16	24	5	5	11	8	8
SNO50COV	10	6	6	5	3	3	4	12	4	7	2	2	4	3	3
SNOCOVMX	11	7	7	11	7	7	8	7	7	6	7	6	18	7	7
SOL_AWC	16	4	4	7	20	7	6	13	6	3	12	3	15	14	14
SOL_K	1	2	1	1	6	1	1	3	1	1	9	1	1	5	1
SURLAG	29	27	27	6	28	6	30	25	25	23	17	17	6	27	6
TIMP	23	21	21	21	30	21	13	19	13	29	28	28	22	9	9

Highlighted numbers in the table correspond to the top 5 parameters obtained from the multi-objective sensitivity analysis of the SWAT parameters for the study watersheds.

2.3.1 Important Parameters

The hydraulic conductivity of soil, SOL_K, and the baseflow parameter, ALPHA_BF, were observed to be the most important parameters for the two objective functions (mean monthly streamflow and RMSE of monthly streamflow) used for the sensitivity analysis of SWAT parameters in Colorado watersheds. Higher sensitivity indices for these parameters show that the movement or flow of water through soil and the contribution of baseflow to streamflow generation both play an important role in the hydrology of snow-dominated mountainous watersheds of Colorado.

Other generally important parameters include the snow cover and snowmelt parameters: SNO50COV, SNOCOVMX, SMFMX, SMTMP, SMFMN, and SFTMP. The effective hydraulic conductivity in channel alluvium, CH_K1, soil water capacity, SOL_AWC, and groundwater parameter GWQMN, were also observed to be sensitive in most of the study watersheds. Sensitivity of these parameters explains the importance of snow-related processes, sub-surface hydrology and, in-channel transmission losses in the hydrology of snow-dominated mountainous watersheds.

Results show variation in parameter sensitivity depending on the objective function selected for the analysis. Higher sensitivity indices for parameters SOL_K, SOL_AWC, GWQMN, and CH_K1 were observed when analysis was performed with mean monthly streamflow as the objective function. On the contrary, the groundwater parameter ALPHA_BF and the snow parameters SNOCOVMX, SNO50COV, SMFMX, SMFMN, and SMTMP emerged with higher sensitivity indices when RMSE of monthly streamflow was evaluated as the objective function.

2.4 Conclusion

A stability analysis of FAST, performed on the Cache la Poudre River basin, clearly showed the importance of the number of model evaluations required for obtaining stable sensitivity analysis results. The result of this analysis suggests that at least 15,000 model evaluations should be used when sensitivity analysis is performed for 30 input parameters in the distributed hydrologic model SWAT. This analysis will help researchers in understanding the relation between the number of input parameters and the corresponding number of FAST evaluations required for stable sensitivity analysis.

The importance and applicability of the variance-based global sensitivity analysis method FAST were demonstrated in five major river basins of Colorado. The results indicated the significance of objective function while performing sensitivity analysis; it became evident that the sensitivity of parameters varied depending on the objective function selected in the FAST analysis. Sensitivity analysis performed with the mean monthly streamflow used as the objective function showed that the streamflow volume in Colorado watersheds was mostly influenced by groundwater processes. On the other hand, sensitivity analysis performed with the RMSE of monthly streamflow suggested the importance of interactions between snow-related and sub-surface hydrologic processes for generation of streamflow with respect to timing and flow pattern in monthly flow hydrographs. This result should motivate researchers to use variance-based global sensitivity analysis methods like FAST that not only include multiple objective functions for the analysis, but also address the importance of parameters in terms of both their individual and interaction effects on the objective function. This genre of sensitivity analysis is especially important in the case of mountainous watersheds, where interactions between different parameters and corresponding hydrologic processes are observed to play an important role in streamflow generation.

The analysis performed with FAST for flow-related parameters of SWAT using mean monthly streamflow and corresponding RMSE as the objective functions showed that similar hydrologic processes are critical in the major river basins of Colorado. This suggests that a common parameter set can be selected for the snow-dominated and mountainous watersheds of Colorado. The obtained important parameters can be used for the flow calibration in some other Colorado watersheds in order to examine the reliability of the results obtained from this study. Future studies may now use these findings in ungaged watersheds located in Colorado, where use of hydrologic model is difficult. This should help to effectively manage water resources in areas where there is scarcity or no availability of flow data.

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CHAPTER 3: REGIONALIZATION APPROACH FOR COLORADO RIVER BASINS

Abstract

Over the past couple decades, hydrologic models have been increasingly used to aid in the management of water resources around the world. However, their application to ungaged basins where data availability is limited present a challenge. Especially, the utility of highly parameterized, process based, and distributed models in mountainous watersheds is still questionable. In this study, we examine various regionalization approaches that can be used for estimating model parameters in watersheds with an unreliable or nonexistent record of streamflow data. The present work uses a distributed hydrologic model known as the Soil and Water Assessment Tool (SWAT) for hydrologic modeling of streamflow in five major river basins of Colorado. Thirty flow related parameters of the SWAT model were calibrated and corroborated over a 20 year period starting in January of 1979. The focus of this paper is to: first, evaluate the suitability of SWAT model for flow simulations in mountainous and snow dominated watersheds of Colorado, and second, analyze the performance of various regionalization methods for flow simulations in ungaged watersheds. These methods range from vicinity, similarity approach in terms of physiographic attributes (land use, soil etc), and multi-site calibration of a watershed model to gaged sites in a region. The jack-knife cross

validation technique was later used in order to analyze the accuracy of these regionalization approaches.

Results indicated the suitability of SWAT model for flow simulations in mountainous watersheds. Regionalization of distributed hydrologic models like SWAT in snow dominated mountainous regions was observed to be possible and the importance of two methods used for regionalization was realized. The first method is based on a similarity approach that involves computation of parameter values for an ungaged watershed based on similarity index (SI) with respect to physiographic attributes. The second method is multi-site calibration of gaged watersheds with the goal to minimize RMSE between the observed and simulated streamflows and apply the best obtained parameter set for flow predictions in ungaged watershed. This study performed regionalization of SWAT based on only five watersheds and therefore suggests inclusion of more watersheds in the analysis in order to have better representation of watershed characteristics of a region. Additional regionalization approaches based on kriging, artificial neural network (ANNs), etc. may be examine in future studies in order to reinforce applicability of SWAT for flow predictions in ungaged watersheds.

Keywords: mountainous regions; hydrologic modeling; SWAT; similarity indices; physiographic attributes; Ungaged- watershed; regionalization

3.1 Introduction

Predicting the hydrologic response of an ungaged or poorly gaged basin is complex and is considered a key field of research in hydrologic sciences (Sivapalan et al., 2003). These predictions are even more difficult for mountainous regions like Colorado because of the extent of spatial and temporal variability present in the terrain. Reasonable estimates of hydrologic response in ungaged watersheds are vital to effective planning and management of water resources, especially in assisting quantifications of water storage and yield from such watersheds (Bledsoe et al., 2006). These estimates are usually obtained by transferring parameters of a hydrologic model from a gaged watershed to an ungaged watershed located in the same geographical region in an approach known as regionalization (Bloschl and Sivapalan, 1995). General approach for regionalization is based on a two-step procedure: First, estimation of model parameters for each gaged catchment in a region, followed by implementation of a regionalization technique to relate model parameters to watershed characteristics (Fernandez et al., 2000).

Researchers have used different methods such as bi-multivariate regression, clustering, kriging and neural networks for regionalization, but with limited success (Jarboe and Haan, 1974, Magette et al., 1976, Lall and Olds, 1987, Hughes, 1989, Gupta et al., 1999, Nijssen et al., 2001, Heuvelmans et al., 2006). Hydrologic response was observed to be non-homogenous for geographically close watersheds of Great Britain in the study performed by Shu and Burn (2003), which exposed the use of proximity as a criterion for regionalization. However, proximity is one of the commonly used methods for modeling ungaged watersheds around the world (Egbuniwe et al., 1976, Vandewiele et al., 1991, Merz and Bloschl, 2004, Oudin et al., 2008). Burn and Boorman (1992) suggested a "similarity index" approach with respect to watershed attributes in order to transfer a complete parameter set from a gaged to an ungaged watershed. This study was performed on a set of watersheds located in the UK. Later, Parajka et al. (2005) used this approach for regionalization of a semi-distributed hydrologic model in Austrian catchments. They employed watershed attributes such as land use, soil, mean annual precipitation and temperature, to reflect the similarity between watersheds. This study showed the importance of a similarity approach and a kriging approach for regionalization of a semi-distributed hydrologic model.

Fernandez et al. (2000) used a regional calibration procedure for their study in a region of the southeastern U.S comprising of 33 sites. It involved calibration of all the sites in the study area in a concurrent manner, with the dual goal of obtaining ideal relationship between model parameters and basin characteristics, and predicting model parameters in order to simulate streamflows close to observed values. The performance of this approach was evaluated by comparing the simulated and observed flows for three sites that were not used for developing regional relationships. The study showed adequate relationships between model parameters and catchment attributes, but the predicted streamflows for ungaged watersheds were not satisfactory.

Beven and Binley (1992) pointed out the limitation of distributed hydrologic models due to their excessive number of input parameters, and suggested uncertainty estimation as a possible remedy. Regionalization of parameters reduces the uncertainty associated with overparameterization and therefore, provides an efficient solution to this problem common to distributed hydrologic models (Beven, K.J., 2001, Gotzinger and Bardossy, 2006). Engeland et al. (2001) used a Bayesian methodology for regionalizing the

ECOMAG model for nine catchments located in the NOPEX region of Sweden. They computed likelihood estimates of parameters using the observed and simulated streamflow values and applied Baye's theorem for obtaining probabilistic distribution of parameters. Two sampling methods: regular and Metropolis-Hastings were used in this study. This study suggested the usefulness of Bayesian method in regionalizing model parameters.

Regionalization of a hydrologic model in an alpine climate is considered difficult due to scarcity of data, as well as the spatial and temporal variability present in these areas. Merz and Bloschl (2004) regionalized the parameters of a hydrologic model in a snow-dominated Austrian region comprising of 308 gaged watersheds. The analysis revealed the importance of spatial proximity method for performing regionalization. However, the model used in this study was a lumped hydrologic model, which may not be suitable for Austrian catchments because of the elevation diversity present in the region. Later, Parajka et al. (2005) used a semi-distributed hydrologic model and included elevation zones in the analysis for more accurate predictions in ungaged catchments with diverse elevations. Different regionalization methods were analyzed in this study, but the method based on the use of similarity indices to compute parameter values for an ungaged watershed was not evaluated.

Comprehensive watershed models, such as SWAT, have been rarely used by researchers and scientists for performing regionalization. Heuvelmans et al. (2006) is the only study, to our knowledge, that performed regionalization of SWAT parameters for 25 watersheds located in the Flemish region of Belgium. Their study showed the importance of land use in the regionalization of SWAT model parameters and also highlighted the superiority of artificial neural nets over the linear regression methods. However, regionalization of comprehensive hydrologic models like SWAT in snow-dominated mountainous regions has yet to be addressed, which is the scope of this study.

The overall goal of this study is to evaluate the performance of various regionalization methods for estimating SWAT parameters in major watersheds located in snowmelt-dominated, mountainous region of Colorado. To this end, the following objectives are defined: (1) evaluate the suitability of SWAT for hydrologic simulations in major river basins in Colorado, (2) apply range of regionalization methods for estimating SWAT model parameters that are important in study watersheds, and (3) evaluate the performance of these regionalization methods and identify the ones performing efficiently for snow-dominated mountainous watersheds of Colorado.

3.2 Methods and Materials

Shuffle Complex Evolution (SCE-UA) algorithm was used to investigate the adequacy of SWAT model for flow simulation in snow dominated and mountainous regions by performing single site calibration of SWAT models prepared for study watersheds. Later, six different approaches were evaluated for the regionalization of SWAT parameters in snow-dominated and mountainous watersheds of Colorado. These include an arithmetic mean approach, two different approaches based on similarity index (SI) related to watershed attributes, spatial proximity approach, a Bayesian statistical analysis and a multi-site calibration approach. Each of these approaches was evaluated in the following five major river basins of Colorado, which include: the Arkansas River at Canon City, the Cache la Poudre River at mouth of canyon, the Gunnison River above Blue Mesa Dam, the San Juan River near Archuleta, and the Yampa River near Maybell.

Performances of single site calibration along with diverse approaches applied for regionalization of SWAT were evaluated on a monthly basis over a simulation period of 20 years starting from January 1979 to December 1998. A 3-year warm up period was used to adjust the initial conditions for hydrologic simulations. Performances of regionalization methods were examined by jack-knife cross validation technique. In this technique a watershed is considered as ungaged and flow predictions are obtained by utilizing the estimated parameter values from different regionalization approaches. This technique was used in order to examine the decrease in SWAT model performance as it is applied from gaged to an ungaged watershed. Streamflow in Colorado River basins is considerably affected by man-made influences such as dams and reservoirs, diversion of water to nearby streams, evaporation and return flows etc. Therefore, naturalized flows that were only available on a monthly basis were used for valid comparison of observed and simulated streamflows.

3.2.1. Study Area

The present study encompasses five major river basins located primarily in Colorado. The Cache la Poudre and San Juan River basins include small areas in the neighboring states of Wyoming and New Mexico, respectively. Figure 3.1 shows the location of the watersheds. The Cache la Poudre and Arkansas River basins are located on the eastern side of the Continental Divide and therefore drain into the Mississippi River. The remaining three watersheds are on the Western side of the Continental Divide and drain into the Colorado River, which later flows into the Gulf of California. All the watersheds have a typical characteristic of high relief, with an elevation range of 1,500 meters to 4,400 meters as shown in Figures 2.2-2.6.

Diversity in elevation leads to significant variability in the amount and form of precipitation within these watersheds. Average precipitation in the Rocky Mountains at an elevation of 3230 meters is almost six times more than the western slope, which has an elevation of 1,520 meters (Hjermstad, 1970). The climate of these basins is greatly influenced by topography. Average annual precipitation recorded at weather stations in and around these watersheds varies from 268 mm/year to 1,480 mm/year, with an average annual temperature variation of -2.65° C to 13° C. These watersheds mainly receive precipitation in the form of snow, and thus, the observed streamflow in these watersheds displays seasonal variation dominated by spring and summer snowmelt (NRDC, 2008). Snow cover in these areas can start as early as mid-October and persist well into mid-June (NRCS, 2007). Around May, the snowpack begins releasing meltwater to surface and sub-surface hydrologic systems. Studies show that the runoff generated from snow acts much differently than runoff generated from rainfall since snowmelt is a slow and gradual process and therefore takes time to become a part of the water balance.

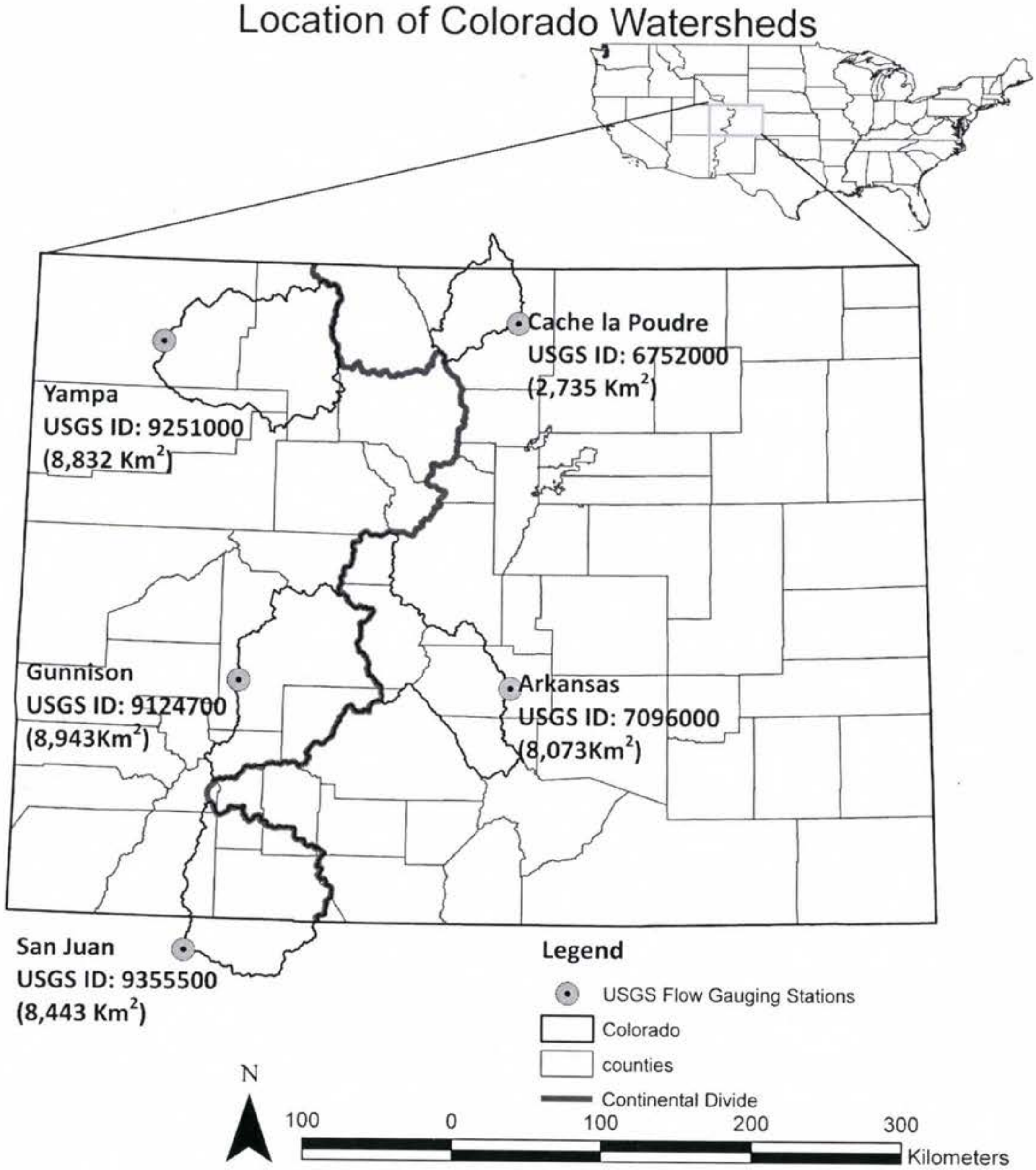

Figure 3.1. Location of study watersheds and corresponding USGS streamflow gaging stations.

Table 3.1. Land use, soil, and topographic attributes of study watersheds

Watershed	Land use*[1]		Hydrologic Soils*[2]		Elevation Range (meters)
	Description	%	Group	%	
Arkansas River 8,073 (km^2)	Forest-Evergreen	48.7	A	8.45	1632-4396
	Range-Brush	9.16	B	40.5	
	Range-Grasses	37.1	C	9.15	
	Southwestern range land	5.05	D	42.0	
Cache la Poudre River 2,735 (km^2)	Forest-Evergreen	64	A	0.0	1593-4131
	Range-Brush	18.4	B	11.0	
	Range-Grasses	15.3	C	41.6	
	Water	2.36	D	47.4	
Gunnison River 8,943 (km^2)	Forest-Evergreen	44	A	10.3	2183-4351
	Forest-Deciduous	9.52	B	32.5	
	Range-Brush	25.9	C	50.0	
	Range-Grasses	17.8	D	7.19	
	Southwestern range land	2.88			
San Juan River 8,443 (km^2)	Forest-Evergreen	50.1	A	0.0	1724-4279
	Forest-Deciduous	9.76	B	20.2	
	Range-Brush	29.6	C	36.7	
	Range-Grasses	7.58	D	43.1	
	Hay	2.98			
Yampa River 8,832 (km^2)	Forest-Deciduous	32.7	A	4.9	1804-3763
	Forest-Evergreen	17.8	B	69.1	
	Range-Brush	47.0	C	17.2	
	Range-Grasses	2.56	D	8.82	

*[1]Land use classification was obtained using National Land Cover Dataset, 2001

*[2]Hydrologic soil group classification was obtained from State Soil Geographic (STATSGO) database. Group A and D refer to soil having high and very low infiltration rate respectively, while Group B and C refer to soil with moderate and slow infiltration rate.

Land use in the state of Colorado is mainly comprised of evergreen and deciduous forests at high elevation, while lowlands are mostly covered by shrubs and grasslands. Soils in the area have very low to moderate infiltration rates. Details related to land use, soils, and other information is provided in Table 3.1.

Lapse Rates

Watersheds in Colorado have diversity in elevation; therefore, lapse rates for temperature and precipitation are provided for the true representation of these influential variables across different elevations within the watersheds. Lapse rates were determined by regression analysis of the input climatic data for individual watersheds. Table 3.2 shows the lapse rates for each of the watersheds examined in this study. A non-linear relationship is observed between elevation and climatic variables (precipitation, temperature) for Colorado watersheds. However, in this study we assume a simple linear relationship and compute the lapse rates for study watersheds.

Temperature lapse rate

The temperature lapse rates were separately computed for all the watersheds using available data from the snowpack telemetry (SNOTEL) and the national climatic data center (NCDC) websites for the stations that are within and close to the area of study. A relationship was developed between average annual temperature and station elevation. For an accurate representation of temperature in a topographically diverse watershed, the lapse rate should be added to elevation bands (Rango and Martinec, 1979, 1994). Sub-basin temperatures are adjusted within each elevation band by comparing mean elevation of elevation band (Z_{EB}) with the station elevation (Z). Calculated temperature lapse rates were comparable to the lapse rates obtained by Fontaine et al. (2002), whose research was performed for the Upper Wind River basin in Wyoming. Adjusted temperature for an elevation band is computed as:

$$T_{EB} = T + (Z_{EB} - Z)\, dT/dz \tag{3.1}$$

where T_{EB} is the mean temperature of the elevation band, T is the temperature at the elevation where the station is located, and dT/dz is the temperature lapse rate. Mean annual temperature values computed for meteorological stations in and around the Cache la Poudre River basin were plotted against station elevation to obtain the temperature lapse rate, as shown in Figure 3.2. Plots used for computing temperature lapse rates for the remaining four watersheds are shown in Appendix A1 (Figure A1.1-Figure A1.4)

Precipitation lapse rate

The lapse rate for precipitation was computed by plotting annual precipitation with weather station elevation. The study watersheds are large and have varying precipitation regimes because of elevation diversity. Therefore the difference between the elevation of the sub-basin weather station and the elevation band was used to adjust the precipitation for all the sub-basins. Adjusted precipitation for an elevation band is computed as:

$$P_{EB} = P + (Z_{EB} - Z)dP/dz \tag{3.2}$$

where P_{EB} is the precipitation for the elevation band, P is the precipitation where the station is located, and dP/dz is the precipitation lapse rate used for the calculation. Precipitation data from meteorological stations located in and around the Cache la Poudre River basin were plotted against the station elevation (Figure 3.2) to obtain the precipitation lapse rate. Plots used for computing the precipitation lapse rates for the remaining four watersheds are shown in Appendix A1 (Figure A1.1-Figure A1.4)

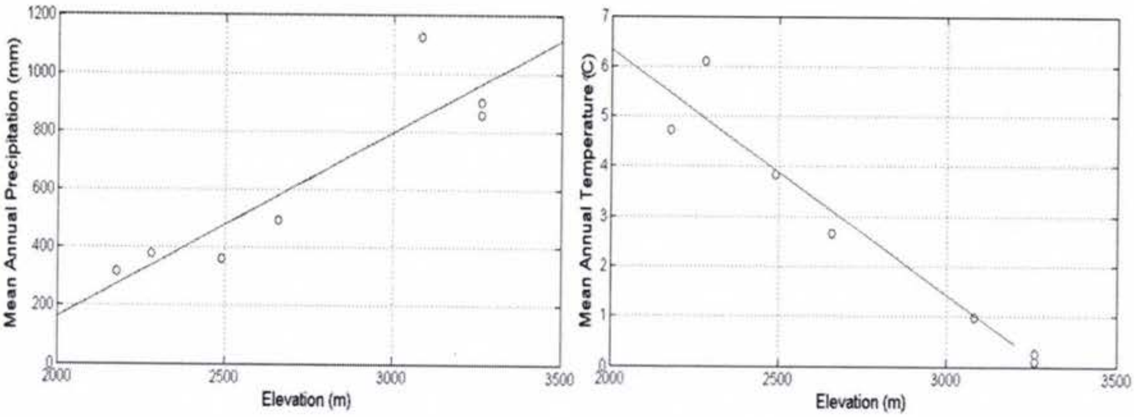

Figure 3.2. Variability of mean annual temperature and precipitation in Poudre River basin with elevation

Table 3.2. Lapse rates for the watersheds

Site name	USGS site ID	Precipitation lapse rate (mm / km)	Temperature lapse rate (° C / km)
Cache la Poudre River at mouth of canyon	6752000	634	-4.9
Arkansas River at Canon City	7096000	252	-6.8
Gunnison River below Blue Mesa Dam	9124700	700	-6.5
San Juan River near Archuleta	9355500	482	-5.3
Yampa River near Maybell	9251000	567	-4.0

3.2.2. Hydrologic Model

The SWAT model was used to analyze hydrologic processes in study watersheds. SWAT was originally developed to determine the impact of land management practices on water, sediment, and agricultural contaminant chemical yields at a watershed scale. Since its development in the early 1990s, SWAT has undergone major revisions in order to enhance its capabilities (Arnold and Fohrer, 2005; Neitsch et al., 2005). Examples of the revisions include the addition of hydrologic response units, the incorporation of a CO_2 component to the crop growth model, improved snowmelt routines for better simulation of hydrologic processes in mountainous watersheds, and improvement in bacterial transport and nutrient cycling routines. SWAT is currently used worldwide for many hydrologic/water quality studies, including: sediment and nutrient modeling for total maximum daily load (TMDL) development and implementation (Borah et al., 2006; Benham et al., 2006; Shirmohammadi et al., 2006; Vellidis et al., 2006), selection and implementation of best management practices (BMPs) (Arabi et al., 2006; Gitau et al., 2006), and evaluation of the impacts of climate change on various hydrologic processes (Stone et al., 2001; Rosenberg et al., 2003; Takle et al., 2005; Gosain et al., 2006; Jha et al., 2006). A comprehensive review of the development of the SWAT model, along with its use in various hydrologic applications over the past couple of decades, can be found in Gassman et al. (2007).

SWAT uses readily available input data and can simulate processes such as runoff, return flow, percolation, evapotranspiration, groundwater flow, transmission losses, nutrient and pesticide loads, and reservoir storage. For modeling purposes, a watershed is divided into sub-watersheds, which are further divided into parcels possessing unique land uses, soil attributes, and slope characteristics referred to as hydrologic response units (HRUs). Input data requirements for the SWAT model are shown in Table 3.3. Daily precipitation and maximum/minimum temperature values were collected for cooperative observer program (COOP) and SNOTEL stations located in and around the study watersheds.

SWAT's hydrologic routing phase consists of main channel routing and reservoir routing. Main channel routing includes four components: water, sediment, nutrients, and organic chemicals. In this study, the soil conservation service (SCS) curve number procedure was used on the basis of the soil moisture condition to calculate the runoff, the Penman Monteith method was used to calculate the potential evapotranspiration (PET), and the variable storage method was used for channel routing.

Table 3.3. Data inputs for SWAT model

Title	Source	Data Type
National Elevation Dataset (NED)	U.S. Geological Survey (USGS) website - http://seamless.usgs.gov/	30-m Digital Elevation Model (DEM)
State Soil Geographic (STATSGO) Database	USDA/NRCS-National Cartography&Geospatial center website - http://datagateway.nrcs.usda.gov/	Soil types 1:250,000-scale map
Weather Dataset (SNOTEL Stations)	USDA/NRCS SNOTEL data and products website - http://www.wcc.nrcs.usda.gov/snow/	Daily precipitation and temperature datasets
Weather Dataset (COOP Stations)	National Climatic Data Center website - http://www.ncdc.noaa.gov/oa/ncdc.html	Daily precipitation and temperature datasets
National Land Cover Dataset (NLCD) 2001	U.S. Geological Survey (USGS) website - http://seamless.usgs.gov/	30-m Land use

SWAT accounts for sub-surface hydrology by using a kinematic storage model. The model uses the continuity equation based on mass for simulating sub-surface flows. It also accounts for lag in lateral flow in case of large sub-basins with a higher value for time of concentration. Groundwater processes are represented at the sub-basin level, while each sub-basin includes a shallow and a deep aquifer. A shallow aquifer is considered an unconfined aquifer that contributes to reach within the sub-basin, while the contribution of a deep aquifer to streamflow is considered outside the watershed and is considered lost from the system (Arnold et al., 1993). Water entering the unconfined aquifer or shallow aquifer after passing through different layers of soil profile is considered recharge to the sub-surface. SWAT partitions this recharge between the shallow aquifer and deep aquifer depending on the aquifer percolation constant represented by parameter RCHRG_DP. Baseflow contribution to reach in the sub-basin only occurs thorough shallow aquifers; it depends on the amount of water stored in the shallow aquifer, as denoted by parameter GWQMN and the baseflow recession constant denoted by ALPHA_BF. Upward movement of water from the shallow aquifer to the overlying unsaturated zone occurs when the overlying layer is dry. This process is defined as REVAP in SWAT and depends on parameters REVAPMN and GW_REVAP.

Elevation Bands

Elevation bands are generally used to handle spatial and temporal variability present in a watershed due to the elevation diversity (Rango and Martinec, 1979, 1994). Each sub-basin can represent up to 10 elevation bands in order to account for orographic effects on both temperature and precipitation. The average elevation of each band and the percentage of sub-watershed area within that band are provided as model inputs on a sub-basin basis. Elevation bands at an interval of 350m were used for this study. Precipitation and maximum/minimum temperatures were calculated for elevation bands as a function of lapse rates and the difference between the station elevation and the mean elevation of the band. An elevation band increment of 350m compares favorably with the increments that Fontaine et al. (2002) and Lemonds et al. (2007) have used for the Wind River basin in Wyoming and the Dillon Reservoir watershed in Colorado, respectively.

3.2.3. Model Calibration Procedure

Shuffle Complex Evolution (SCE-UA) is one of the most popular and widely used single objective, global optimization techniques (Duan et al., 1994; Muttil and Jayawardena, 2008). The SCE-UA procedure starts with the sampling of a number of points selected randomly from a feasible parameter space. These sampled points are sorted depending upon the increasing criterion value and are partitioned into complexes containing fix number of points. Later, each complex is evolved separately by the number of evolution steps, and the complex shuffling is performed. Convergence is checked depending upon either the maximum number of trials before optimization is terminated or improvement in the criterion value by a certain percentage within definite shuffling loops. Finally, by examining complex numbers and removing complexes with lowest ranked points, global optimum is obtained. Details about the algorithm and methodology of the SCE-UA are explained by Duan.et.al (1992, 1993, and 1994).

The SCE-UA algorithm has been used for the calibration of hydrologic models such as SWAT. For example, Eckhardt and Arnold (2001) performed automatic calibration of SWAT model using SCE-UA method for a mesoscale catchment in central Germany. The SCE-UA method was used for calibration and validation of SWAT model for the baseline period and later used to analyze the impact of climate change on the hydrologic response of the Luohe River basin (Hao et al, 2001). Breuer et al. (2005) used the SCE-UA algorithm for automatic calibration of discharge and nitrate load in the Dill catchment located in mid-Hesse, Germany. A comprehensive list of studies that have used SWAT and SCE-UA algorithm for various hydrologic applications over the past couple of decades can be found in Gassman et al. (2007).

3.2.4. Model Performance Criteria

Performance criteria in the field of hydrology can be defined as the rules or characteristics or the statistical measures that evaluate the performance and behavior of a hydrologic model through comparison between observed and simulated variables (Krause et al., 2005; Moriasi et al., 2007) The performance criteria examined in this study are: Relative error (RE), bias in a model (BIAS), coefficient of correlation (R^2), Nash-Sutcliffe efficiency coefficient (NS), and root mean square error (RMSE).

Relative error (RE)

The relative error (RE) is considered as a statistical measure for goodness of fit (Du et al., 2009). It is based on agreement between observed and simulated values and is computed as:

$$RE = \frac{(Q_i - \widehat{Q_\iota})}{Q_i} \tag{3.3}$$

where Q_i and $\hat{Q}_i$ refer to observed and modeled discharges.

Bias (BIAS)

The bias is the difference between the observed and the predicted values. It provides an evaluation of the tendency of the measured values to be larger or smaller than the observed record (Gupta et al., 1999). Overestimation of measured values by a model leads to a negative bias, while underestimation of measured values by a model leads to a positive bias. Bias in a model can be defined as shown in Equation (3.4):

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}(Q_i - \widehat{Q_\iota}) \tag{3.4}$$

where Q_i and $\widehat{Q}_i$ refer to observed and modeled discharge, and n denotes the number of time steps included in the calibration.

Coefficient of correlation (R^2)

The coefficient of correlation explains the correlation between the simulated and observed streamflows and is computed as shown in Equation (3.5). It ranges between 0-1. The higher value for R^2 indicates better agreement between the observed and simulated values. It is one of the widely used statistical measures for model evaluation but is observed to be more sensitive to outliers as compared to observations near the mean (Legates and McCabe, 1999).

$$R^2 = \frac{\sum_{i=1}^{n}(Q_i - Q_{mean})^2 - \sum_{i=1}^{n}(\hat{Q}_i - \hat{Q}_{mean})^2}{(n-1)s_Q s_{\hat{Q}}} \tag{3.5}$$

where $\hat{Q}_{mean}$ refer to the mean of the modeled discharge while, s_Q and $s_{\hat{Q}}$ refers to standard deviation of observed and simulated discharge respectively. All other variables in the equation are same as described for Equation (3.3) and Equation (3.4).

Nash-Sutcliffe efficiency coefficient (E_{NS})

The Nash-Sutcliffe efficiency coefficient is one of the most common statistical measures used in hydrologic modeling for assessing goodness of fit (Knight et al, 2006) and is shown in Equation (3.6).

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n}(Q_i - Q_{mean})^2} \tag{3.6}$$

where Q_i and $\hat{Q}_i$ refer to observed and modeled discharge, Q_{mean} is the mean of observed discharge for the time step, and n denotes the number of time steps included in the calibration. The value of NS ranges from -∞ to 1. The higher the value of NS the better the model.

Root mean square error (RMSE)

Root mean square error (RMSE) is one of the most commonly used statistical measures (Singh et al., 2004; Vazquez-Amabile and Engel, 2005). It computes the error between the observed and simulated values as shown in Equation (3.7). Comparison of RMSE values between the observed and simulated streamflow values denotes a time scale analysis and provides a comparison with respect to both magnitude and timing of streamflows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_i - \widehat{Q_i})^2} \quad (3.7)$$

3.2.5. Single-site model calibration and testing

Model calibration can be defined as the fine tuning of model parameters within acceptable ranges in order to obtain the best agreement between observed and simulated results. Testing refers to model testing and is often considered as an evidence for the performance of a calibrated model. Single-site calibration and testing of the SWAT model was performed on the basis of monthly streamflow data by using the SCE-UA method with RMSE as the objective function. A 3-year warm-up period was used to adjust the initial conditions prior to simulations over the study period. The time period for the calibration was January 1979 to December 1988 while the testing or validation was performed for the period January 1989 to December 1998.

3.2.6. *Regionalization methods*

Diverse regionalization methods were examined in this study. These regionalization methods estimate value of SWAT parameters that were identified as sensitive for five major river basins of Colorado. Regionalized parameter sets obtained from different methods were then examined on the SWAT model setups for study watersheds and their performance was evaluated. Regionalization methods used in this study are discussed below.

Method 1: Arithmetic mean approach

In this method each parameter for an ungaged watershed is computed as the arithmetic mean of calibrated values of the parameter in gaged watersheds. This method assumes that the watersheds located in the same geographical region will display similar hydrological behavior. Equation (3.8) represents a method for computing parameter values for an ungaged watershed using the arithmetic mean approach. It is one of the most common methods, and has been utilized in previous regionalization studies (Kokkonen et al., 2003, Parajka et al., 2005, Kim and Kaluarachchi, 2008):

$$x_{iU} = \frac{1}{g}\sum_{i=1}^{g} x_{iG} \tag{3.8}$$

where, x_{iU} refers to the value of a parameter x_i for an ungaged watershed, x_{iG} is value of the same parameter in gaged watersheds, and g refers to number of gaged watersheds used in the analysis.

Method 2: Similarity index (SI) approach

This method is based on computation of SI with respect to different physiographic attributes of the watersheds located in same geographical region, and identifying the extent of similarity between them. The main thought behind this method is to select a donor watershed that is most similar in terms of physiographic attributes to an ungaged watershed. First, an ungaged watershed is selected and SI ($\emptyset_\gamma$) between this watershed and other watersheds located in a study area are computed separately by using Equation (3.9). Watershed having smallest SI ($\emptyset_\gamma$) with the ungaged watershed is selected as a donor and its complete parameter set is transferred to the ungaged watershed. Merz and Bloschl (2004) and Parajka et al. (2005) have used this method in their regionalization studies on Austrian catchments. Following watershed attributes were examined in this method: mean elevation of watershed, land use, soil, long term average annual precipitation, and long term average annual temperature. The similarity indices (SI) examined in this method were computed as shown in Equation (3.9).

$$\emptyset_\gamma = \sum_{\gamma=1}^{\partial} (\rho_\gamma^G - \rho_\gamma^U)/\Delta\rho_\gamma \qquad (3.9)$$

where $\emptyset_\gamma$ refers to the SI between the watersheds with respect to physiographic attributes, ∂ refer to number of physiographic attributes selected for the analysis, ρ_γ^G and ρ_γ^U refer to the attribute value for the gaged and ungaged watersheds, respectively, and $\Delta\rho_\gamma$ refers to the range of each attribute. The following combinations of ungaged and donor catchment were selected from this analysis: Arkansas: Cache la Poudre, Cache la Poudre: San Juan, Gunnison: San Juan, San Juan: Cache la Poudre and, Yampa: San Juan. Similarity indices between the watersheds are shown in Appendix A2 (Table A2.1).

Method 3: Weighted arithmetic mean using SI

The third method is based on computing the parameter value by using the SI obtained in Method 2. Parameter values are computed with respect to each watershed attribute separately, after which the obtained parameter set may be used for the regionalization study. The SI between the attributes of each of the four watersheds, considered as gaged, and the remaining watershed, considered as ungaged, were used to compute parameter values for the ungaged watershed using Equation (3.10). The obtained parameter set was later used for calibration and testing of the ungaged watershed.

$$x_i = \frac{\sum_{j=1}^{g-1} x_j / \emptyset_j}{\sum_{j=1}^{g-1} 1 / \emptyset_j} ; j \neq i \tag{3.10}$$

where x_i refers to the value of a parameter for a watershed considered as ungaged, which is computed using the value of that same parameter in gaged watersheds denoted by x_j, along with their similarity index SI ($\emptyset_j$) with ungaged watershed. g refers to number of gaged watersheds, i varies from 1 to p depending upon the number of parameters. The following watershed attributes were used for computing SI: mean elevation of watershed, land use, soil, long term average annual precipitation, and long term average annual temperature. Later, arithmetic mean (AM) and geometric mean (G) of these SI ($\emptyset_\gamma$) related to different watershed attributes were also computed using Equation (3.11) and Equation (3.12), respectively, and the performance was analyzed.

$$AM\left(\emptyset_1, \emptyset_2 \ldots \emptyset_\gamma\right) = \frac{1}{\gamma}\left(\emptyset_1 + \emptyset_2 + \cdots + \emptyset_\gamma\right) \tag{3.11}$$

$$G\left(\emptyset_1, \emptyset_2 \ldots \emptyset_\gamma\right) = \sqrt[\gamma]{\emptyset_1\, \emptyset_2 \ldots \ldots \emptyset_\gamma} \tag{3.12}$$

Method 4: Spatial proximity

The fourth method is based on spatial proximity between the watersheds. Spatial proximity was measured by Euclidean distance between centroids of the watersheds. The gaged watershed closest to the ungaged watershed was selected as a donor, and the ungaged watershed was calibrated using the set of parameters from donor watershed. This method is considered one of the most commonly used regionalization techniques, and has been applied all over the world (Egbuniwe et al., 1976, Vandewiele et al., 1991, Vandewiele and Elias, 1995, Merz and Bloschl, 2004, Oudin et al., 2008). The following pairs were used as ungaged-gaged watersheds: Arkansas-Gunnison, Cache la Poudre-Yampa, Gunnison-Arkansas, San Juan-Gunnison, and Yampa-Poudre. Table 3.4 shows the Euclidean distance between the centroids of these watersheds.

Table 3.4. Proximity Analysis.

Watershed	Distance (km)				
	Arkansas	Cache la Poudre	Gunnison	San Juan	Yampa
Arkansas	-	244	89	197	239
Cache la Poudre	244	-	282	426	153
Gunnison	89	282	-	148	222
San Juan	197	426	148	-	365
Yampa	239	153	222	365	-

Method 5: Bayesian statistical analysis

The fifth method includes computation of likelihood estimates for the most important parameters, in order to understand their posterior distribution in study watersheds. Important parameters were obtained as a result of sensitivity analysis performed using the Fourier amplitude sensitivity test (FAST).

Bayes' theorem explains the posterior distribution of the parameter vector (θ) based on observations as shown in Equation (3.13):

$$f(\theta|Q) = k * f(e|\theta) * f(\theta) \tag{3.13}$$

where $f(\theta|Q)$ denotes the posterior density function (pdf) of θ with respect to the observed streamflow data Q, k is a constant used for normalization, $f(e|\theta)$ refers to the likelihood function of model error $(Q - \hat{Q})$ denoted by e, $\hat{Q}$ refers to predicted value of streamflow, and $f(\theta)$ denotes the prior distribution of θ.

Christensen (2004) and Stedinger et al. (2008) assumed the model error (e) to be normally distributed with zero mean and standard deviation of σ. Therefore, the pdf for error e, depending upon θ, was represented by Equation (3.14).

$$f(e|\theta) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left[-\frac{(Q-\widehat{Q})^2}{2\sigma^2}\right] \tag{3.14}$$

Equation (3.13) can be modified to Equation (3.15) by substituting $f(e|\theta)$ from Equation (3.14).

$$f(\theta|Q) = k.\frac{1}{\sqrt{2\pi}\,\sigma} \exp\left[-\frac{(Q-\widehat{Q})^2}{2\sigma^2}\right] f(\theta) \tag{3.15}$$

In order to compute the posterior pdf of model parameters from Equation (3.15), one needs to calculate σ^2, which in turn requires the maximum likelihood estimates of model parameters, as explained in Stedinger et al. (2008). In this study, maximum likelihood estimates of parameters were not available, and therefore, the parameter values obtained from shuffled complex evolution (SCE-UA), with root mean square error (RMSE) as the objective function, were used for the analysis. We used Equation (3.16), developed by Griensven et al. (2008), and Equation (3.17) to compute the likelihood values of input parameters.

$$\vartheta = \sum_{n=1}^{2500} \frac{RMSE_n}{RMSE_{n,min}} \tag{3.16}$$

where n refers to number of simulations, $RMSE_n$ is the root mean square error for the n^{th} simulation, and $RMSE_{n,min}$ is the minimum RMSE value from all simulations. Likelihood estimate (l) of θ was computed by using Equation (3.17):

$$l(\theta) = \exp(-\xi * \vartheta) \tag{3.17}$$

where variable ξ refers to the sensitivity coefficients that were computed for each parameter, separately. These values were computed from the first order and total order sensitivity indices obtained from the FAST analysis performed with mean monthly streamflow and RMSE of monthly streamflow as the objective functions. Sensitivity coefficients were added in above equation in order to consider the impact of parameter sensitivity in the analysis. ξ was computed by selecting the highest sensitivity indice value from the FAST output for 30 SWAT parameters and later, dividing sensitivity indices of all the parameters by that value. ξ was 1 for the most important parameter while it varied between 0 and 1 for other parameters, depending upon the value of sensitivity indices. Separate likelihoods were computed with respect to important parameters by using the first order and total order ξ'^{S}. Later, cumulative likelihood values were computed and normalized by dividing by the sum of the likelihood values. Cumulative distribution functions (CDF) were developed for the sensitive parameters in order to understand their posterior distribution in study watersheds. Finally, parameter values corresponding to 50^{th} percentile were obtained from these plots for each gaged watershed and the mean of these values was used for calibration of the ungaged watershed.

Method 6: Multi-site calibration

The sixth method was based on the multi-site calibration of all gaged watersheds with the goal to minimize RMSE between the observed and simulated monthly streamflows (Equation (3.18)). The best obtained parameter set as a result of multi-site calibration was used for flow predictions in ungaged watersheds. The SCE-UA, one of the most popular, single objective, global optimization techniques was used for the analysis.

$$OF_i = \min(\sum_{j=1}^{g-1}(RMSE_j)); \; j \neq i \tag{3.18}$$

Performance measure

The performance of these regionalization approaches was examined using the jack-knife cross validation technique. This technique uses the parameter set computed from regionalization approaches to simulate the monthly streamflow for a watershed considered as ungaged. Finally, a performance measure (E) was obtained using Equation (3.19) in order to evaluate the performance of regionalization approaches. The closer the E value is to one, the better it is. Equation (3.19) was used in order to account for structural uncertainties associated with SWAT; e.g., Performance measures obtained from single site calibration of SWAT were not perfect which shows that the model has some limitations and does not account for all the hydrologic processes. Also, the performance of regionalization approaches should be evaluated when compared to default.

$$E = \frac{E_{NS}^{R} - E_{NS}^{D}}{E_{NS}^{B} - E_{NS}^{D}} \tag{3.19}$$

where E_{NS}^{R}, E_{NS}^{D}, and E_{NS}^{B} refer to the regionalized, default, and best Nash Sutcliffe coefficients (E_{NS}) obtained for each watershed. Value for E_{NS}^{R} varies depending upon the regionalization approach and the selected watershed attribute used for the analysis, while

E_{NS}^{D} and E_{NS}^{B} are constant and computed with the default and calibrated set of parameters, respectively and are shown in Table 3.6 & 3.7.

In addition to the previously discussed regionalization methods, results from the single-site calibration performed using the SCE-UA method were also examined for all study watersheds. Plots were constructed for the most important parameters in order to understand their behavior in mountainous and snow-dominated watersheds of Colorado. These plots show values of an input parameter corresponding to selected number of function evaluations of SCE-UA. Plots demonstrate the converging pattern of a parameter in terms of its optimal values in a watershed. These plots were also developed for the results from multi-site calibration analysis and are shown in Appendix A2 (Figure A2.6-A2.15) along with the parameter plots from the single-site calibration results. All the analyzes based on single-site and multi-site calibration were performed for 2500 number of function evaluations.

3.3 Results and discussion

Flow calibration and testing

Table 3.5 shows the best value for different performance measures obtained for each of the study watersheds based on the single-site flow calibration and testing or validation of the SWAT model. Simulated and observed monthly streamflow hydrographs compared better for the validation period, as shown in Figure 3.3-3.7. The probable reason for this outcome was the availability of more reliable precipitation and temperature records from the weather stations for the validation period, and lack of such climatic data record during the calibration period. Especially, for the SNOTEL stations which had temperature data points available only from late 1980's. Total number of precipitation and temperature data points available during the calibration and validation period for all the study watersheds are shown in Appendix A2 (Table A2.2, Table A2.3). Scatter plots corresponding to the observed and simulated streamflows showed under-prediction of streamflow by SWAT for the high peaks observed during the calibration period, while these plots indicated over-estimation of streamflow during the validation period as shown in Appendix A2 (Figure A2.1-A2.5). Table 3.5 reveal the best and the default values for different performance measures examined in this study and shows the improvement in values of these measures as a result of calibration and validation of the SWAT model for study watersheds.

Table 3.5. Performance measures for the study watersheds based on the single-site calibration.

Watersheds	Performance Measures															
	Adjusted (RE)		Default (RE)		Adjusted (BIAS)		Default (BIAS)		Adjusted (R^2)		Default (R^2)		Adjusted (E_{NS})		Default (E_{NS})	
	Cal*	Val*	Cal	Val	Cal	Val	Cal	Val	Cal	Val	Cal	Val	Cal	Val	Cal	Val
Arkansas	18.2	-12	-26.3	-62.6	4.6	-2.6	-6.6	-13.5	0.79	0.88	0.18	0.24	0.58	0.74	-0.68	-2.21
Cache la Poudre	15.5	-11	-36.0	-87.3	2.2	-1.2	-5.0	-9.4	0.93	0.93	0.35	0.36	0.83	0.82	-0.19	-1.22
Gunnison	14.2	-17	-113	-202	6.6	-6.8	-52.5	-82.1	0.82	0.92	0.14	0.36	0.65	0.83	-2.71	-6.05
San Juan	35.9	-13	-24.7	-113	18.3	-5.2	-12.6	-44.3	0.80	0.91	0.20	0.59	0.52	0.75	-0.45	-1.19
Yampa	26.0	-17	-7.40	-77.7	14.6	-8.43	-4.1	-37.9	0.88	0.96	0.33	0.54	0.70	0.87	-0.06	-0.55

*Calibration and validation was performed for the period 1979-1988 & 1989-1998 respectively for all the watersheds.

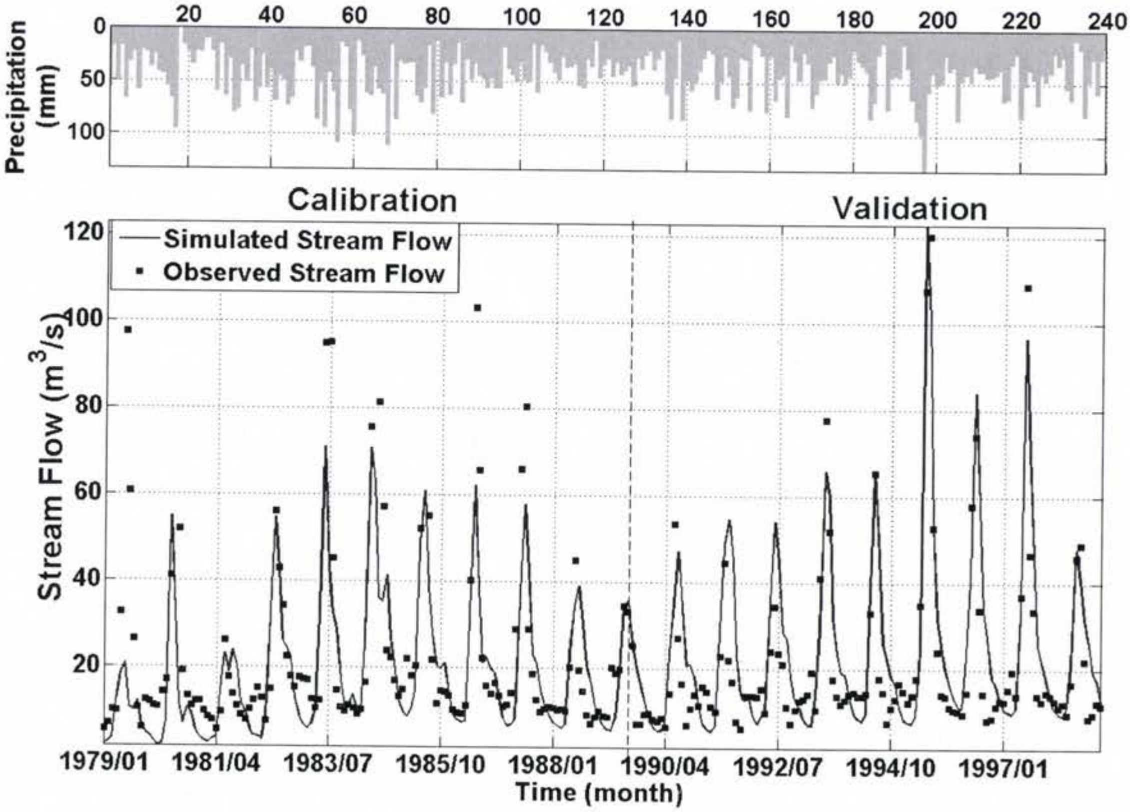

Figure 3.3. Measured and simulated total monthly streamflow for calibration and validation period from the single-site calibration of SWAT model for Arkansas River basin.

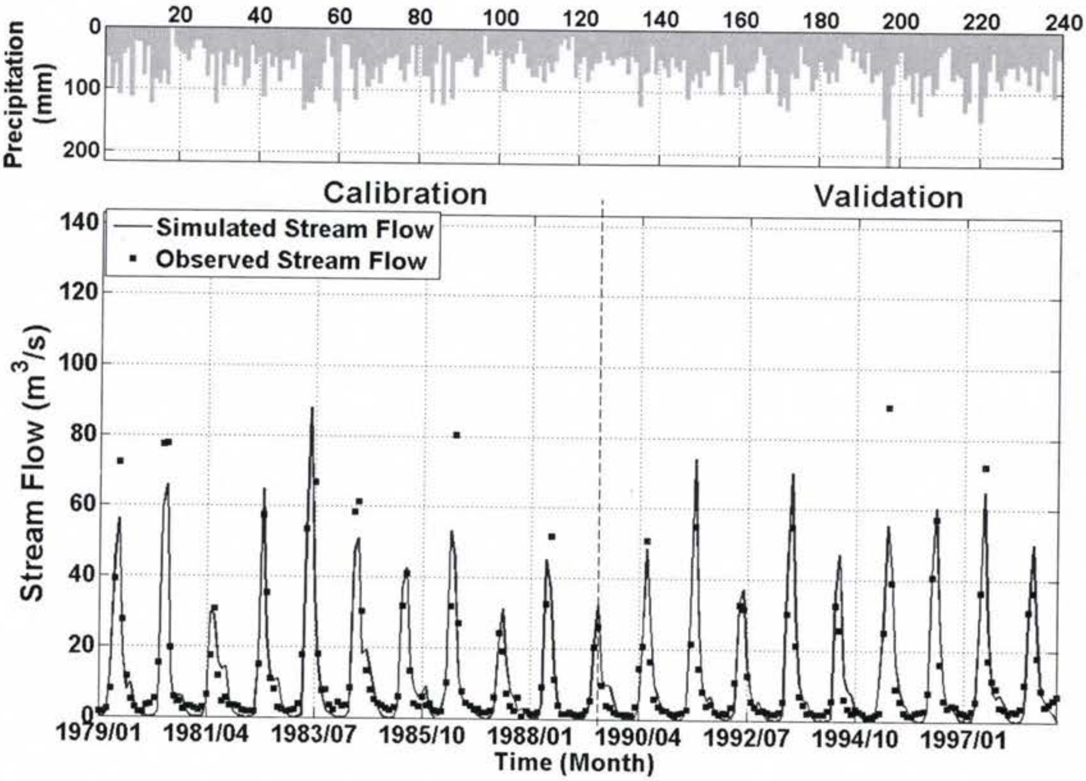

Figure 3.4. Measured and simulated total monthly streamflow for calibration and validation period from the single-site calibration of SWAT model for Cache la Poudre River basin

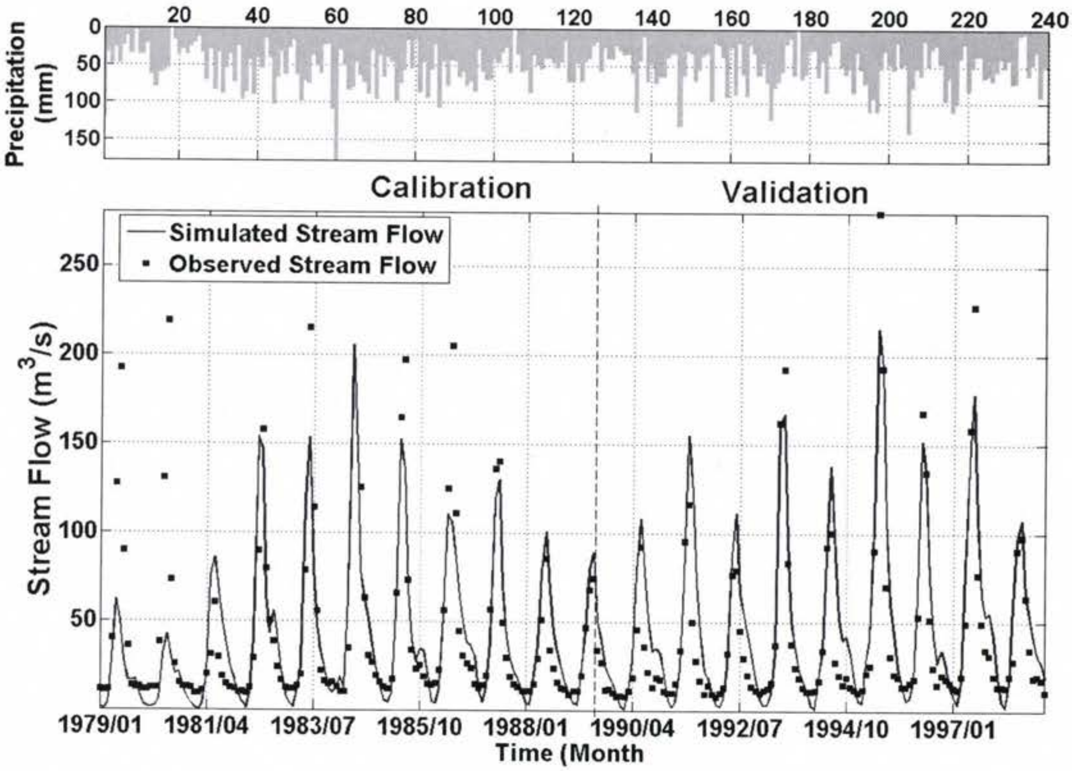

Figure 3.5. Measured and simulated total monthly streamflow for calibration and validation period from the single-site calibration of SWAT model for Gunnison River basin.

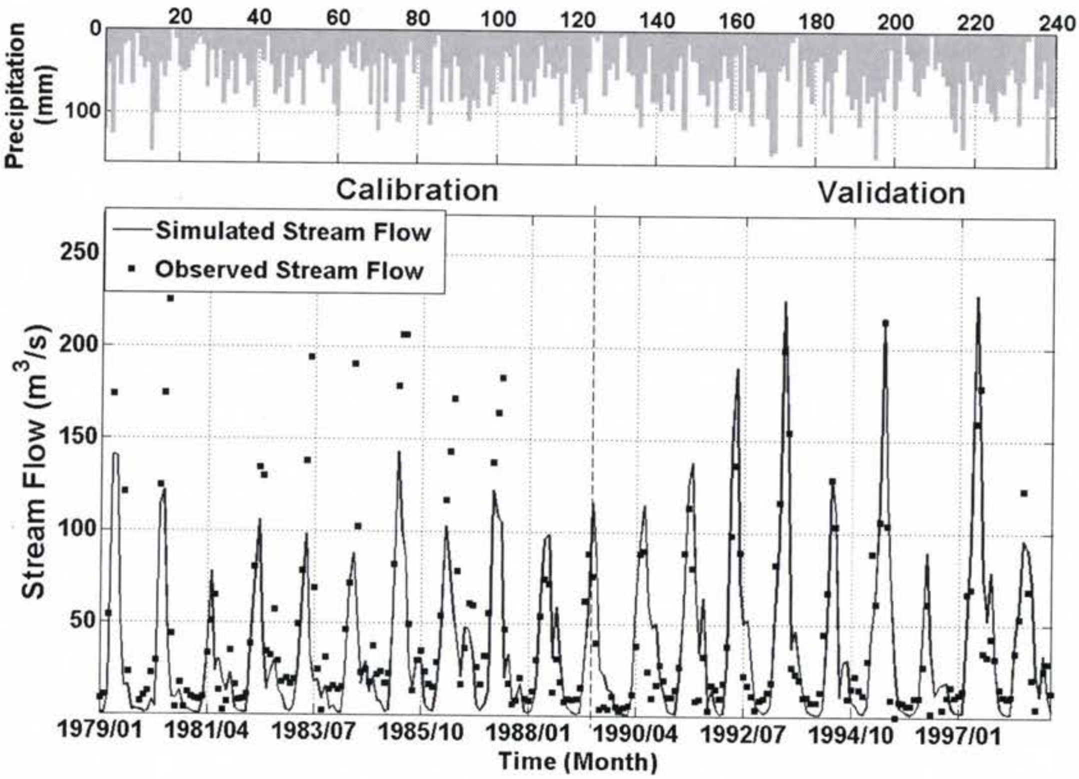

Figure 3.6. Measured and simulated total monthly streamflow for calibration and validation period from the single site calibration of SWAT model for San Juan River basin.

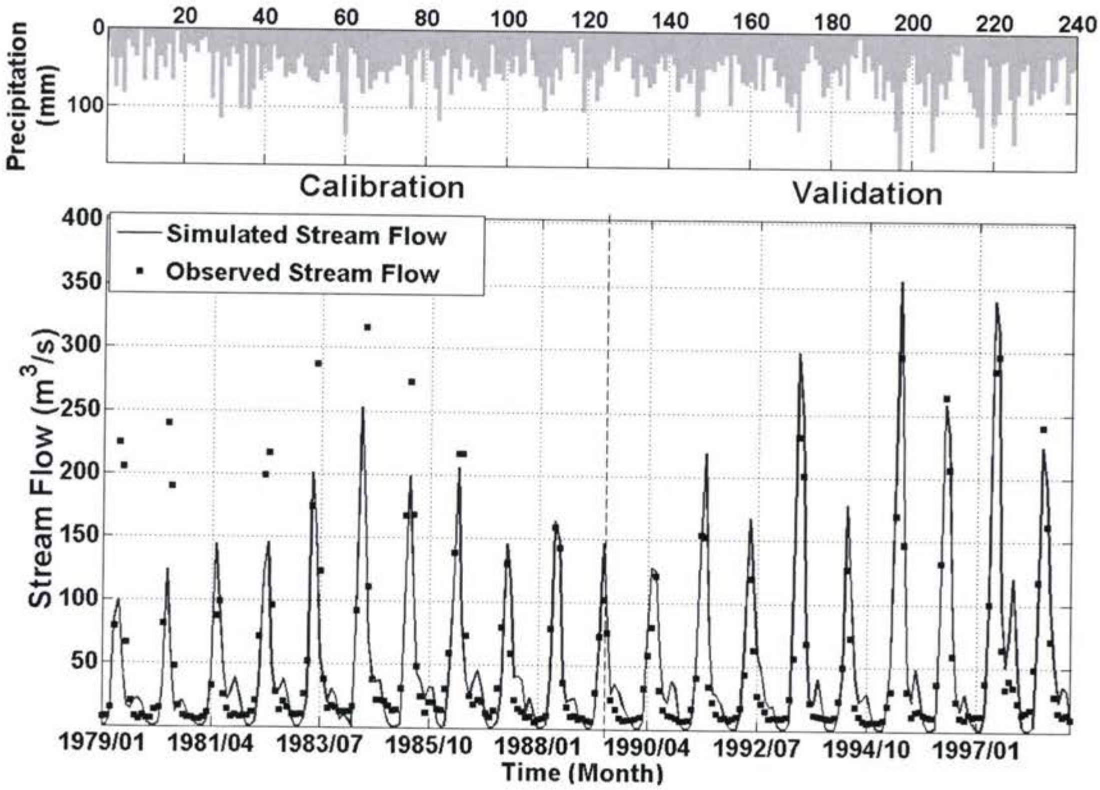

Figure 3.7. Measured and simulated total monthly streamflow for calibration and validation period from the single-site calibration of SWAT model for Yampa River basin.

Performance of regionalization methods

The performance of regionalization methods is presented in terms of E value computed from Equation (3.18). For a favorable performance of regionalization method the E value should be close to 1. Tables 3.6 and 3.7 show the results of these regionalization methods for calibration and validation period respectively. A graphical representation of the performance of different regionalization methods for the study watersheds is shown in Figure 3.10. Methods based on the weighted arithmetic mean, and the multi-site calibration of gaged watersheds performed relatively well as compare to other methods for most of the watersheds. Major findings with respect to performance of different regionalization methods are discussed below.

Method 1: Arithmetic mean approach

The first method, based on the arithmetic mean of calibrated parameters, was observed to perform well when compared to other methods as shown in Figure 3.10. However, the performance of this approach varied depending upon the extent of similarity between the watersheds selected for the analysis. For example, there may be variation amongst the watersheds with respect to snow cover and snowmelt pattern. Hence, the SWAT parameters associated to snow related processes will exhibit different values in such watersheds. Therefore, the arithmetic mean approach may not be the best method for predicting parameter values of an ungaged watershed in such cases. This approach should only be used when watersheds located in a region have great extent of similarity between them.

Method 2: Similarity indices approach

The second approach, based on calibration of an ungaged watershed by using the parameter set from a gaged watershed, gave competent results. This shows that the direct transfer of parameters from a gaged to an ungaged watershed having smallest similarity indices can be used for regionalization of a comprehensive hydrologic model like SWAT in mountainous watersheds. The performance of this method is consistent with the findings of Kokkonen et al. (2003), and Parajka et al. (2005) who performed their study on the catchments of North Carolina and Austria, respectively.

Method 3: Weighted arithmetic mean using SI

The third method, based on computation of parameter values using a weighted approach, was observed to perform better for the majority of the watersheds as compared to most of the other methods used in this study. However, the best results from the third method did not correspond to a particular watershed attribute, which shows the intricacy involved in performing regionalization with respect to a particular watershed attribute. Computation of parameter values of an ungaged watershed by this method depends upon the extent of similarity between the gaged-ungaged watersheds in terms of physiographic attributes. Therefore, this method provides a more realistic approach for regionalization of a distributed hydrologic model.

Method 4: Spatial proximity

The fourth method, based on spatial proximity, was observed with an average performance. This method assumes that the watersheds in a similar geographical region have identical response of hydrological behavior. However, this is not the case in the real world as shown by Shu and Burn (2003) in their study in Great Britain. Contradictory to this finding, Merz and Bloschl suggested the importance of this method for regionalization of a watershed model with their study on Austrian watersheds. Therefore, whether the method should be used for regionalization or not depends on geographical location and requires a careful analysis of watersheds characteristics located in proximity. The method was observed to be performing fairly well for Arkansas, Cache la Poudre and Gunnison River basins, while the performance was rather poor for San Juan and Yampa river basins. Therefore, predicting the applicability of this approach as a regionalization method is ambiguous and varies from region to region, as well as from watershed to watershed.

Method 5: Bayesian statistical analysis

Performance of The Bayesian statistical analysis as a regionalization method was observed to be poor for most of the watersheds. However, this method highlights the importance of Bayesian analysis as a way to determine the posterior distribution of important parameters by using their likelihood estimates. Greater variation in CDF's was observed for the parameters identified as sensitive from FAST analysis. This is due to the fact that the parameters with higher sensitivity indices tend to have ξ close to one and therefore more variation is observed in their likelihood estimates as compare to parameters with ξ close to zero. Figure 3.8-3.9 shows the results of this analysis for the parameters related to hydraulic conductivity of soil SOL_K and baseflow ALPHA_BF respectively. Plots for the CDF's of other parameters are shown in Appendix A2 (Figure A2.16-A2.18). This method requires further research and analysis in order to enhance its applicability as a regionalization method.

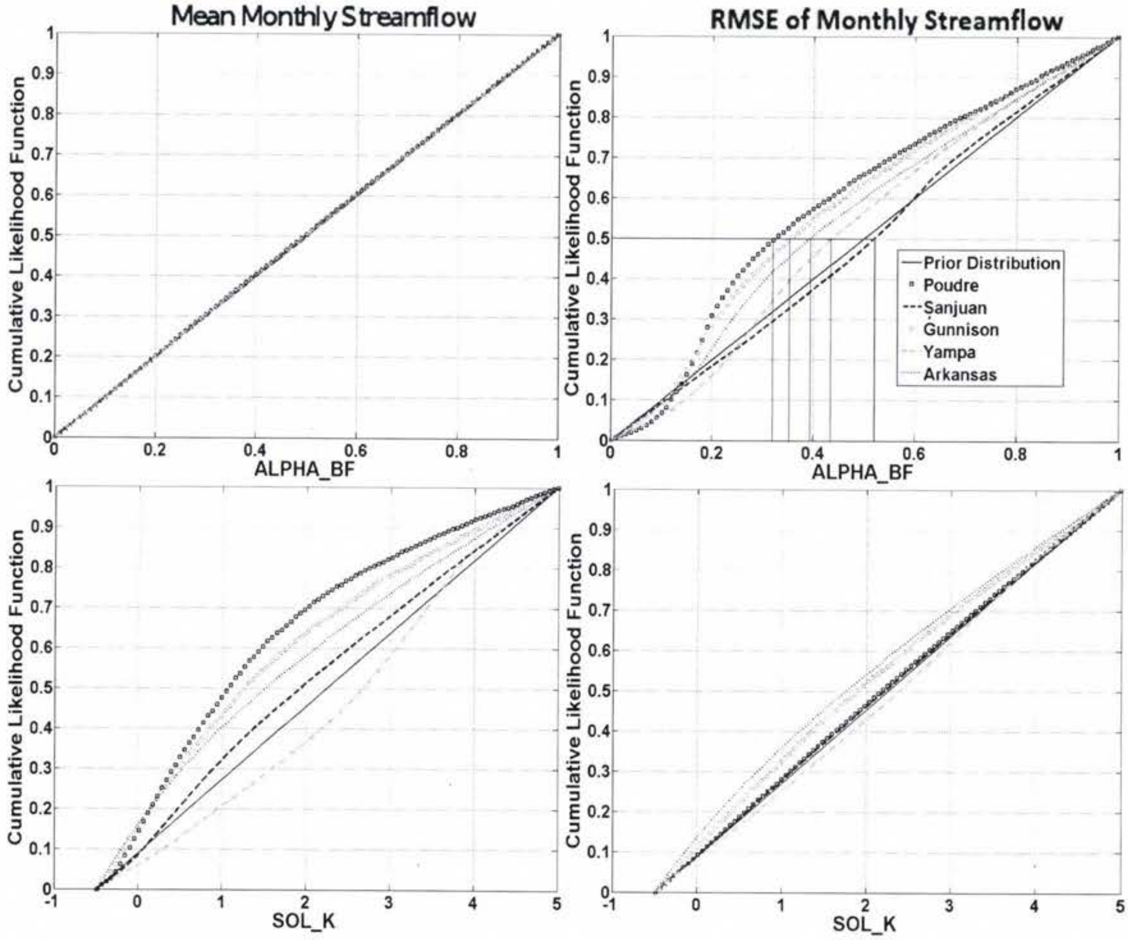

Figure 3.8. CDF's of the most important parameters ALPHA_BF and SOL_K using the FAST first order indices for MSF and corresponding RMSE

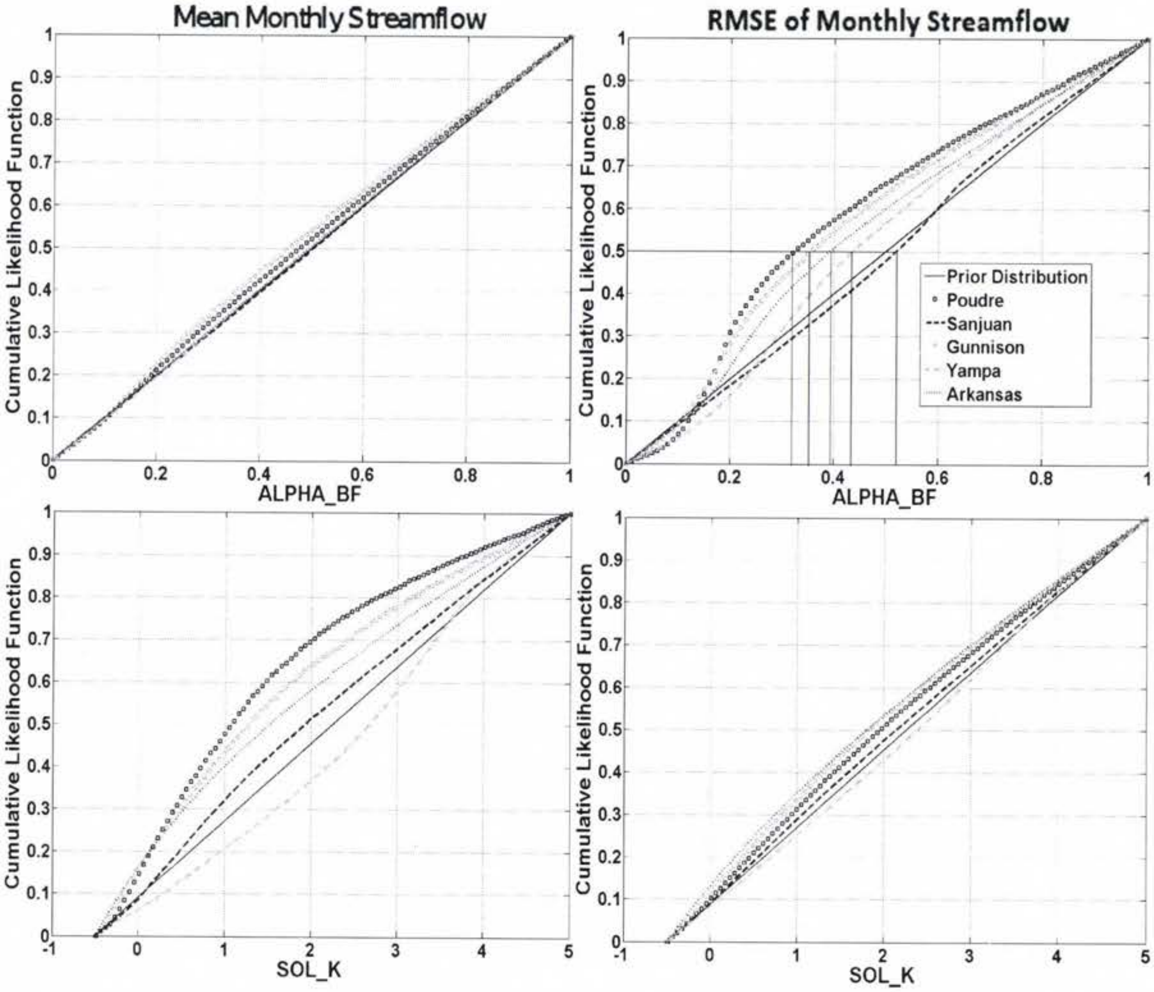

Figure 3.9. CDF's of the most important parameters ALPHA_BF and SOL_K using the FAST total order indices for MSF and corresponding RMSE

Method 6: Multi-site calibration

The sixth method was observed to perform efficiently for most of the watersheds, which supports the use of this method for regionalization of comprehensive hydrologic models such as SWAT. The method was observed to be computationally intensive since it requires multi-site calibration of several gaged watersheds located in a region. However, with advancements in computational techniques and availability of high performance processors, this method can be extremely efficient in regionalization studies of distributed watershed models. A great extent of similarity was observed between the parameter plots from the results based on multi-site and single-site calibration for the majority of important parameters (Figure A2.6-A2.15). This supports the employment of multi-site calibration approach as a regionalization method for distributed hydrologic models like SWAT.

After analyzing the plots prepared for the important parameters by using the single-site calibration results as shown in Appendix A2 (Figure A2.6-A2.15); it was observed that the parameter values were converging to a similar range for most of the watersheds examined in this study. The observed similarity between these converging patterns will help in reducing the range (lower-upper bound) of SWAT input parameters in snow-dominated region of Colorado. This in turn will assist in improving the efficiency of various hydrologic modeling tools like automatic calibration, sensitivity analysis, uncertainty analysis etc. For example: the actual range of the SWAT input parameter related to melt factor 'SMFMN' is between 0-10, however after analyzing Figure A2.10 (Appendix A2) one can easily change this range to 0-3 for the study area. However, this is not true for all the parameters and therefore, a proper analysis should be done before modifying the parameter range.

Table 3.6. Results from different regionalization methods used for the analysis during the calibration period.

METHODS		Watersheds				
		Arkansas	Cache la Poudre	Gunnison	San Juan	Yampa
Method I (Arithmetic mean)		0.71	0.62	0.82	0.69	0.77
Method II (Similarity indices)		0.84	0.67	0.55	0.67	0.56
Method III (Weighted arithmetic mean approach)	Mean Elevation	0.83	0.37	0.86	0.90	0.79
	Land use	0.79	0.64	0.74	0.89	0.80
	Soils	0.64	0.42	0.80	0.85	0.74
	Precipitation	0.75	0.62	0.65	0.96	0.87
	Temperature	0.60	0.73	0.88	0.84	0.74
	AM of SI	0.72	0.56	0.80	0.88	0.78
	GM of SI	0.72	0.54	0.78	0.89	0.78
Method IV (Proximity)		0.74	0.74	0.60	0.60	0.50
Method V (Bayesian statistical analysis)	MSF	0.37	0.42	0.84	0.55	0.40
	RMSE	0.40	0.45	0.86	0.55	0.37
Method VI (Multi-site calibration)		0.79	0.94	0.79	0.22	0.66

Numbers in the table correspond to ***E*** value, closer the ***E*** value to one better is the performance of regionalization method.

Table 3.7. Results from different regionalization methods used for the analysis during the testing or validation Period.

METHODS		Watersheds				
		Arkansas	Cache la Poudre	Gunnison	San Juan	Yampa
Method I (Arithmetic mean)		0.76	0.49	0.90	0.94	0.60
Method II (Similarity indices)		0.93	0.36	0.76	0.85	0.90
Method III (Weighted arithmetic mean approach)	Mean Elevation	0.83	0.20	0.93	0.88	0.73
	Land use	0.83	0.35	0.89	0.98	0.71
	Soils	0.75	0.24	0.90	0.97	0.74
	Precipitation	0.79	0.33	0.83	0.94	0.71
	Temperature	0.73	0.35	0.94	0.95	0.71
	AM of SI	0.79	0.30	0.91	0.95	0.71
	GM of SI	0.79	0.27	0.90	0.94	0.71
Method IV (Proximity)		0.82	0.62	0.72	0.78	0.78
Method V (Bayesian statistical analysis)	MSF	0.58	0.33	0.92	0.85	0.33
	RMSE	0.58	0.34	0.92	0.84	0.31
Method VI (Multi-site calibration)		0.92	0.88	0.88	0.74	0.80

Numbers in the table correspond to ***E*** value, closer the ***E*** value to one better is the performance of regionalization method. Highlighted value corresponds to the best result obtained for each of the study watersheds during the validation period.

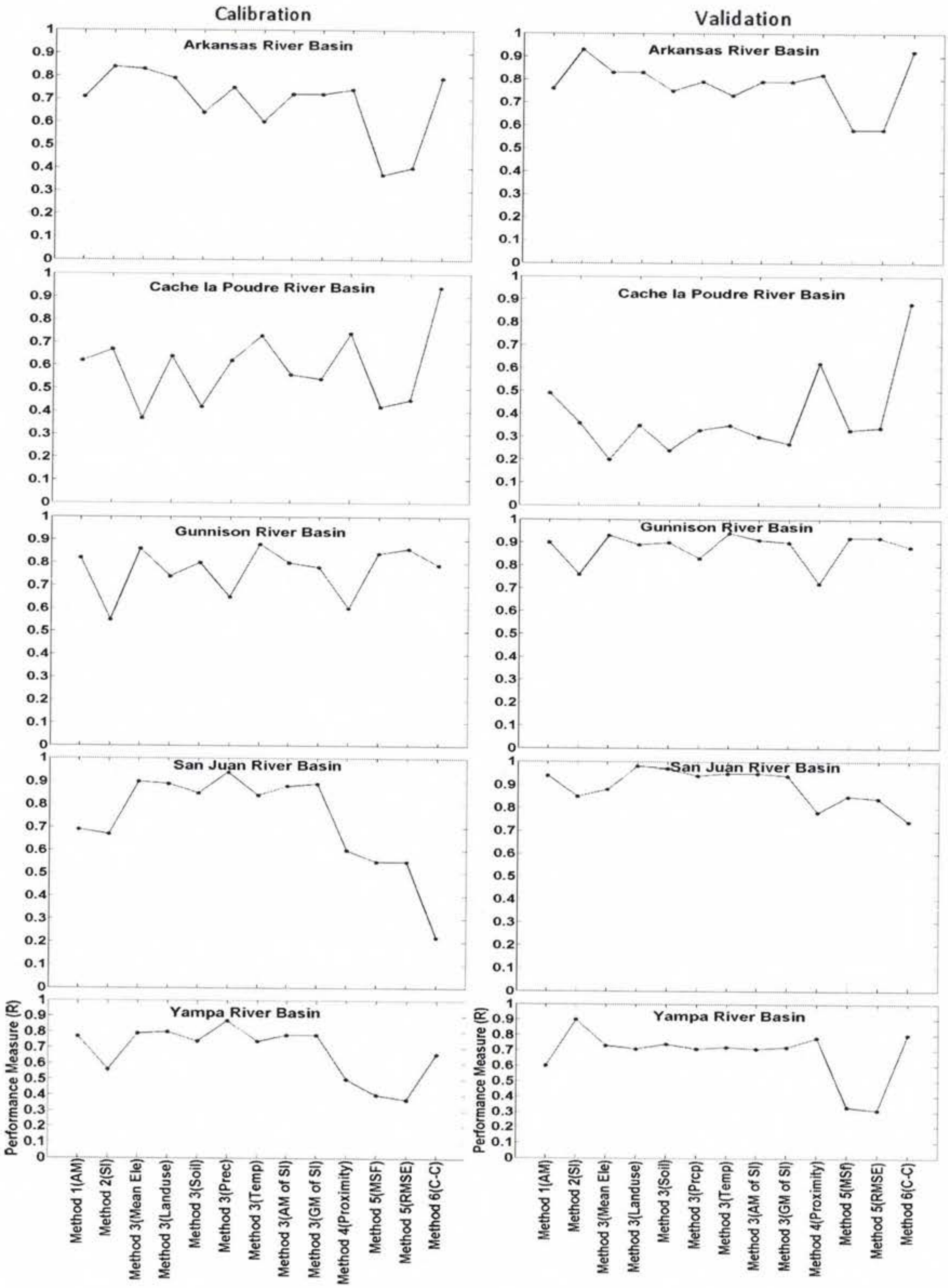

Figure 3.10. Graphical representation of the performance of different regionalization methods for the calibration and the validation period.

3.4 Conclusions

Different regionalization methods, as analyzed in this work, clearly show the importance between physiographic attributes and model parameters of watersheds located in similar geographical regions. Comparison between the results from different regionalization approaches indicate the importance of the methods based on the use of SI related to watershed attributes for performing the analysis in mountainous watersheds. The performance of these methods depends upon the number of physiographic attributes included in the analysis. Therefore, the maximum number of attributes representing different watershed characteristics should be examined for better comparison between watersheds. Performance of regionalization methods, as evaluated in this study, will certainly assist watershed modelers and SWAT users in efficient hydrologic modeling of ungaged watersheds located in snow-dominated mountainous regions.

This study also introduces a new approach for regionalization of distributed hydrologic models like SWAT. The approach, termed multi-site calibration, calibrates the hydrologic model at gaged sites in a concurrent manner and minimizes the RMSE between the observed and simulated flows. The best obtained parameter set from the previous step is then used for the flow calibration in an ungauged watershed. This approach proved to be an efficient method that can be used for regionalization of distributed hydrologic models.

Further research for regionalization of a distributed hydrologic model in mountainous watersheds can be performed by using additional watersheds located in Colorado; which would provide a better feel of watershed characteristics in the region. Additional physiographic attributes such as FARL index, topographic index, snow similarity measure and areal proportion of porous aquifers could possibly used for computing SI in the future. Finally, additional methods such as kriging and artificial neural network (ANNs), should be researched for applicability to regionalization of SWAT in Colorado watersheds.

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CHAPTER 4: CONCLUSIONS

In this study, hydrologic modeling of five major river basins in Colorado, including Arkansas River at Canon City, Cache la Poudre River at Mouth of Canyon, Gunnison River above Blue Mesa Dam, San Juan River near Archuleta and, Yampa River near Maybell, was performed using the Soil and Water Assessment Tool (SWAT). The main goals that led to this study were to: (1) identify the critical hydrological processes that govern the magnitude and timing of streamflow generation in mountainous and snow-dominated watersheds of Colorado, (2) recognize the similarities between the watersheds with respect to dominant hydrological processes identified as a result of sensitivity analysis performed using Fourier Amplitude Sensitivity Test (FAST), and (3) analyze different regionalization methods based on diverse criteria and identify the methods performing efficiently in major river basins of Colorado.

Performance measures obtained from the calibration and testing of the SWAT models for the period 1979-1998, indicates applicability of SWAT in non-agricultural and snow-dominated mountainous watersheds. The capability of SWAT in handling complex hydrologic processes like snow cover, snowmelt, and sub-surface hydrologic processes was realized. The SWAT model was observed to be competent in incorporating lapse rates and elevation bands in order to account for the spatial and temporal variability attributable to orographic effects in mountainous watersheds. Efficient performance of

SWAT in major river basins of Colorado suggest the importance of hydrologic models that can incorporate snow processes with simulation of various components of the water balance.

The significance of variance based global sensitivity analysis methods that can incorporate multiple objective functions during analysis was realized. Sensitivity analysis performed with mean monthly streamflow as the objective function suggested the influence of sub-surface hydrologic processes on streamflow volume in Colorado watersheds. In addition, the impact of interactions between the snow related and sub-surface hydrologic processes on the timing and flow pattern in monthly flow hydrographs of Colorado watersheds was realized from the sensitivity analysis based on RMSE of monthly streamflow. This Study suggests the inclusion of SWAT input parameters related to these hydrologic processes while performing hydrologic modeling in mountainous regions. Moreover, a higher extent of similarity between the sensitivity analysis results for the study watersheds suggests a common set of SWAT parameters that is capable of achieving an appropriate fit for the SWAT model representing mountainous watersheds in Colorado.

Predictions in an ungaged watershed are one of the biggest concerns in the field of hydrologic sciences and engineering. Identifying the extent of resemblance between the watersheds in terms of SI related to various watershed attributes was observed to be significantly important for the regionalization of SWAT for mountainous watersheds. The method based on use of these SI to compute parameter values and the multi-site calibration approach were observed to be the most efficient methods for performing regionalization of SWAT in snow-dominated and mountainous regions.

Although researchers and scientists around the globe have addressed the problems related to ungaged basins and have provided necessary recommendations, there is still a need of extensive research in order to achieve considerable progress in this key research area of hydrologic sciences. This research introduces some new regionalization methods along with addressing the ones previously used in ungaged basins. The analysis provides a broader picture of complexity present in mountainous watersheds and suggests some regionalization techniques that may be suitable for predictions in ungaged mountainous basins. This study shows only a preliminary analysis of these regionalization methods with respect to five major river basins of Colorado, and thus, calls for further detailed analysis in order to reinforce their applicability in mountainous regions.

Appendix A1

Table A1.1 Precipitation lapse rates for the study watersheds during different analysis periods.

Site name	USGS site ID	Precipitation lapse rate (mm/km)			
		1979-1983	1984-1988	1989-1993	1994-1998
Cache la Poudre River at mouth of canyon	6752000	760	654	633	639
Arkansas River at Canon City	7096000	298	233	238	234
Gunnison River below Blue Mesa Dam	9124700	665	757	698	737
San Juan River near Archuleta	9355500	500	392	433	484
Yampa River near Maybell	9251000	Limited Data	515	553	670

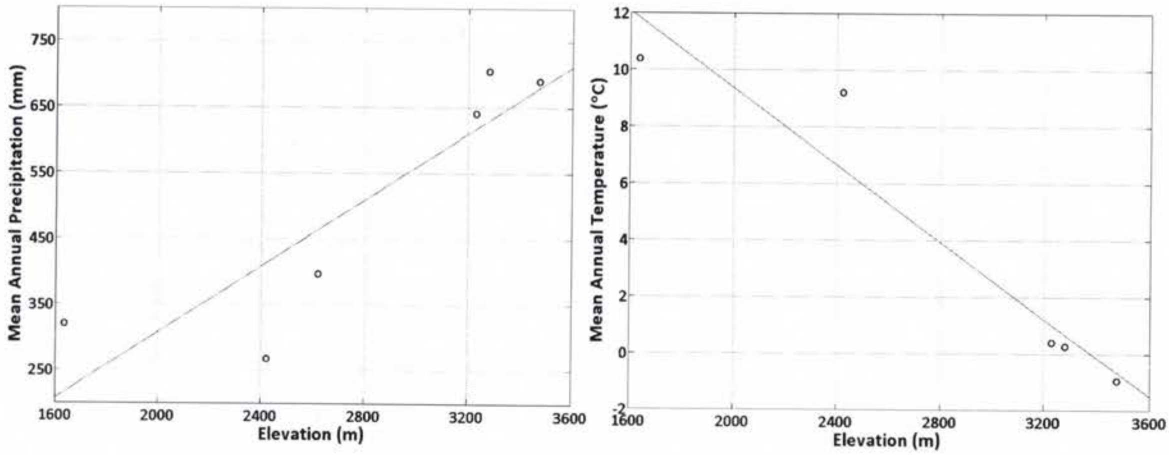

Figure A1.1. Variability of mean annual temperature and precipitation in Arkansas River basin with elevation

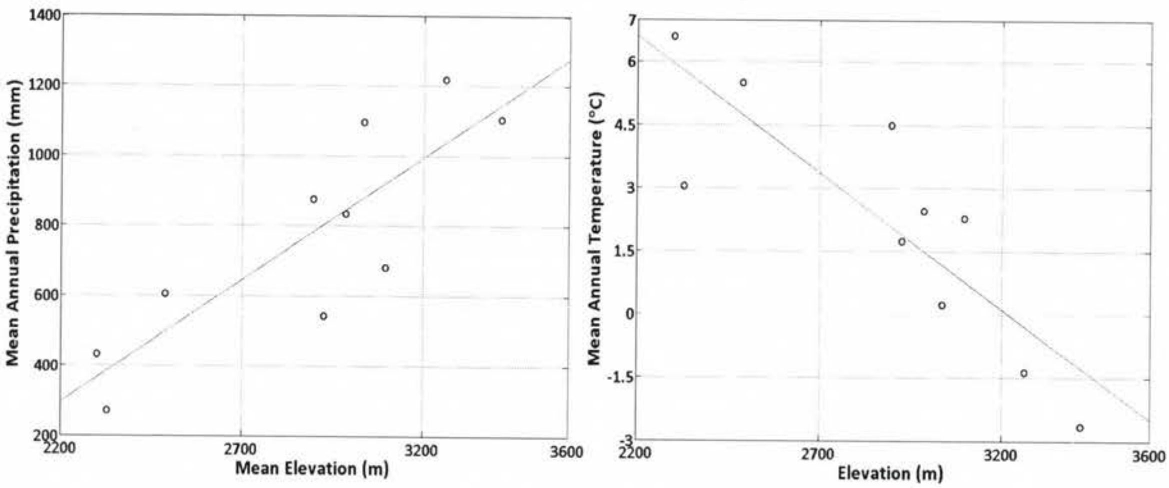

Figure A1.2. Variability of mean annual temperature and precipitation in Gunnison River basin with elevation

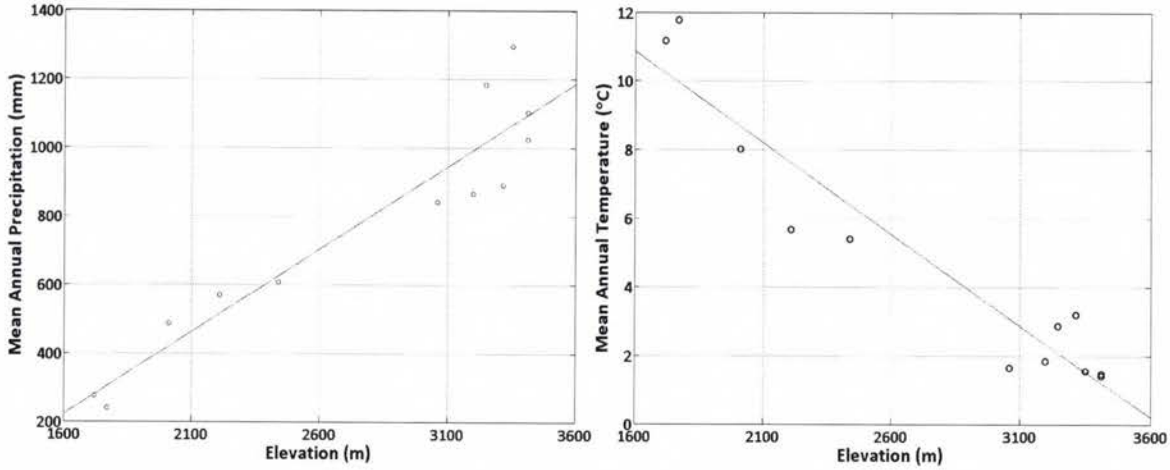

Figure A1.3. Variability of mean annual temperature and precipitation in San Juan River basin with elevation.

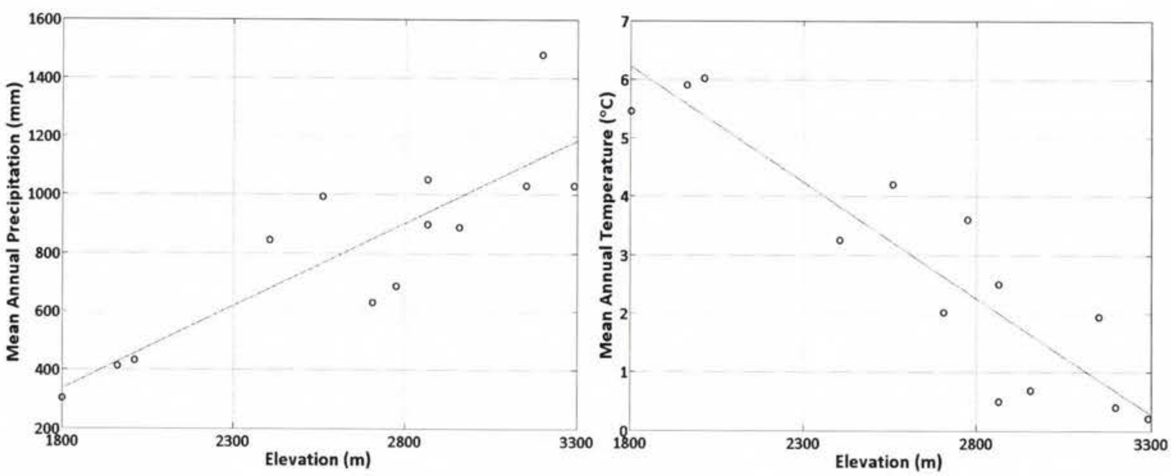

Figure A1.3. Variability of mean annual temperature and precipitation in Yampa River basin with elevation.

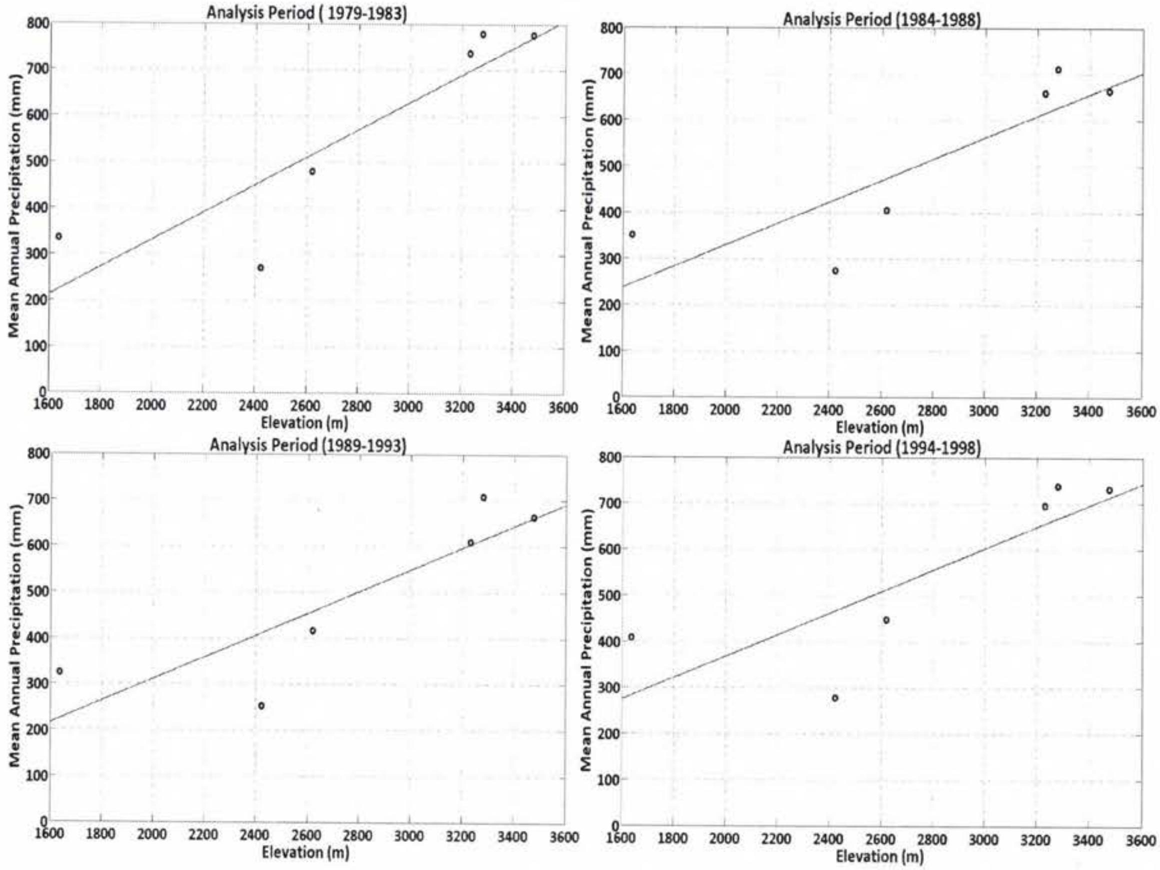

Figure A1.5. Variability of mean precipitation in Arkansas River basin with elevation for different analysis period.

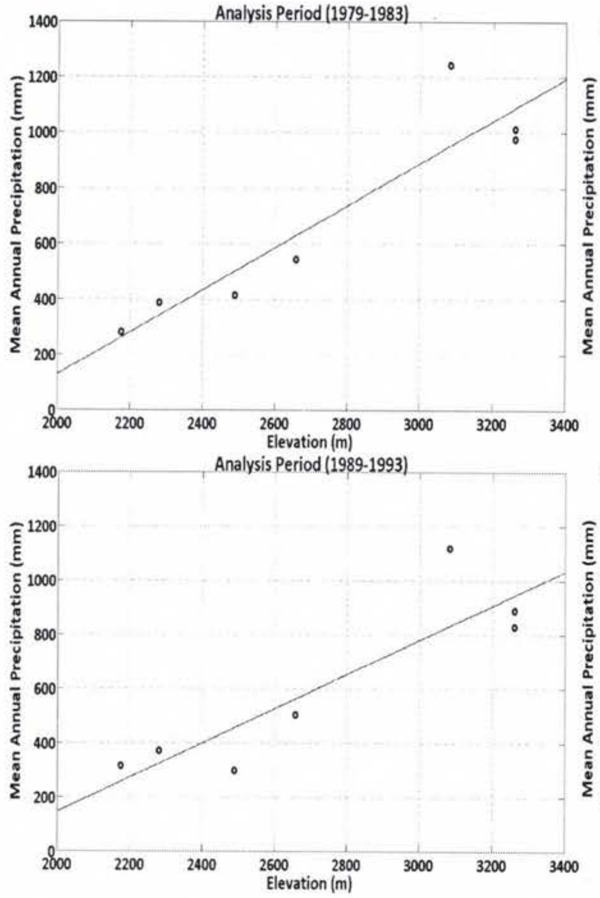

Figure A1.6. Variability of mean precipitation in Cache la Poudre River basin with elevation for different analysis period.

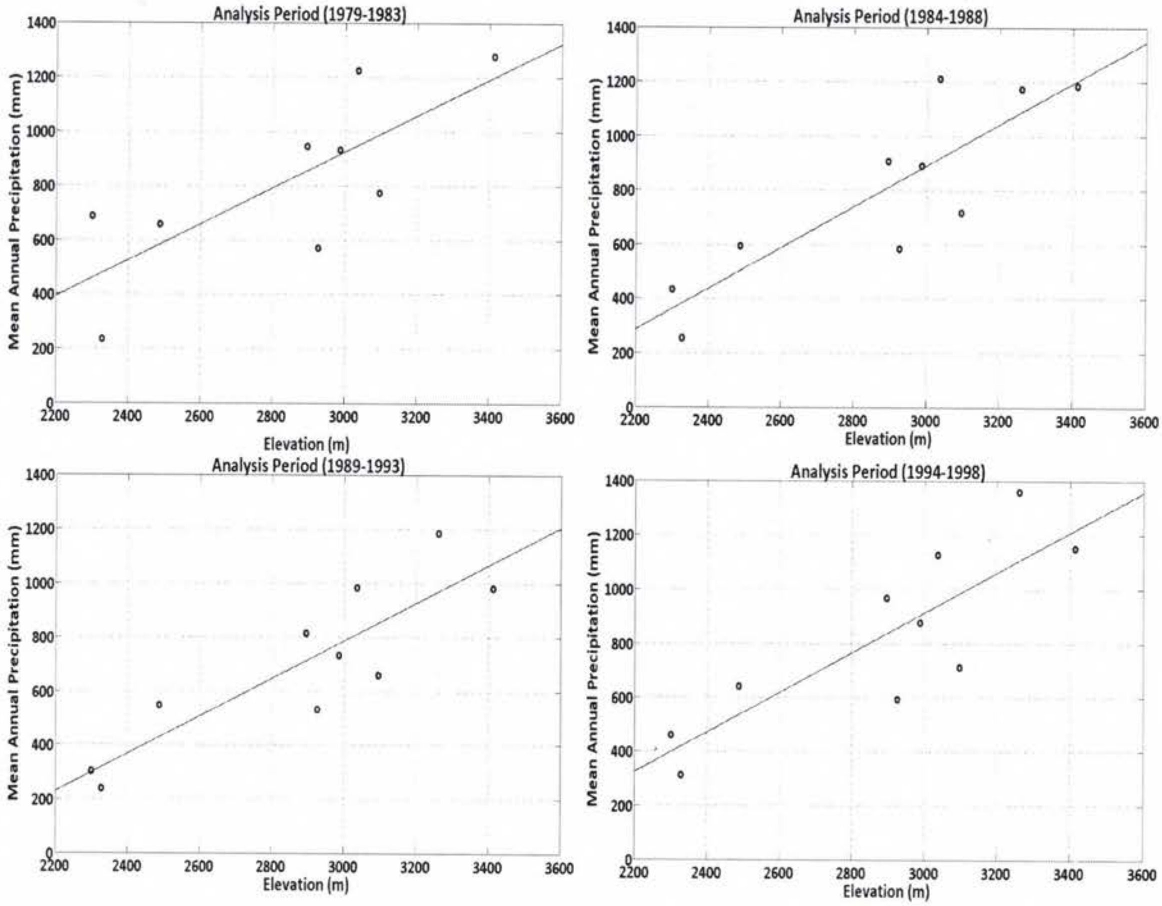

Figure A1.7. Variability of mean precipitation in Gunnison River basin with elevation for different analysis period.

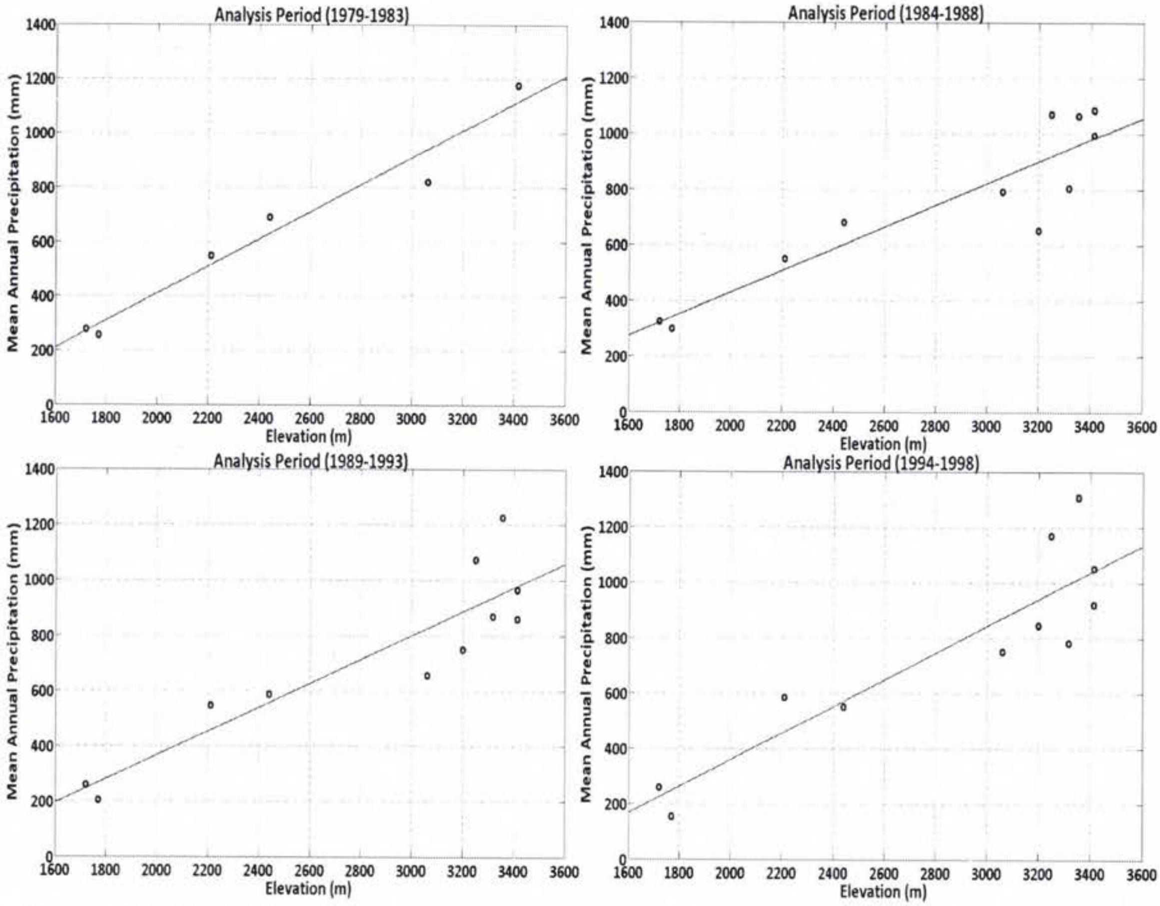

Figure A1.8. Variability of mean precipitation in San Juan River basin with elevation for different analysis period.

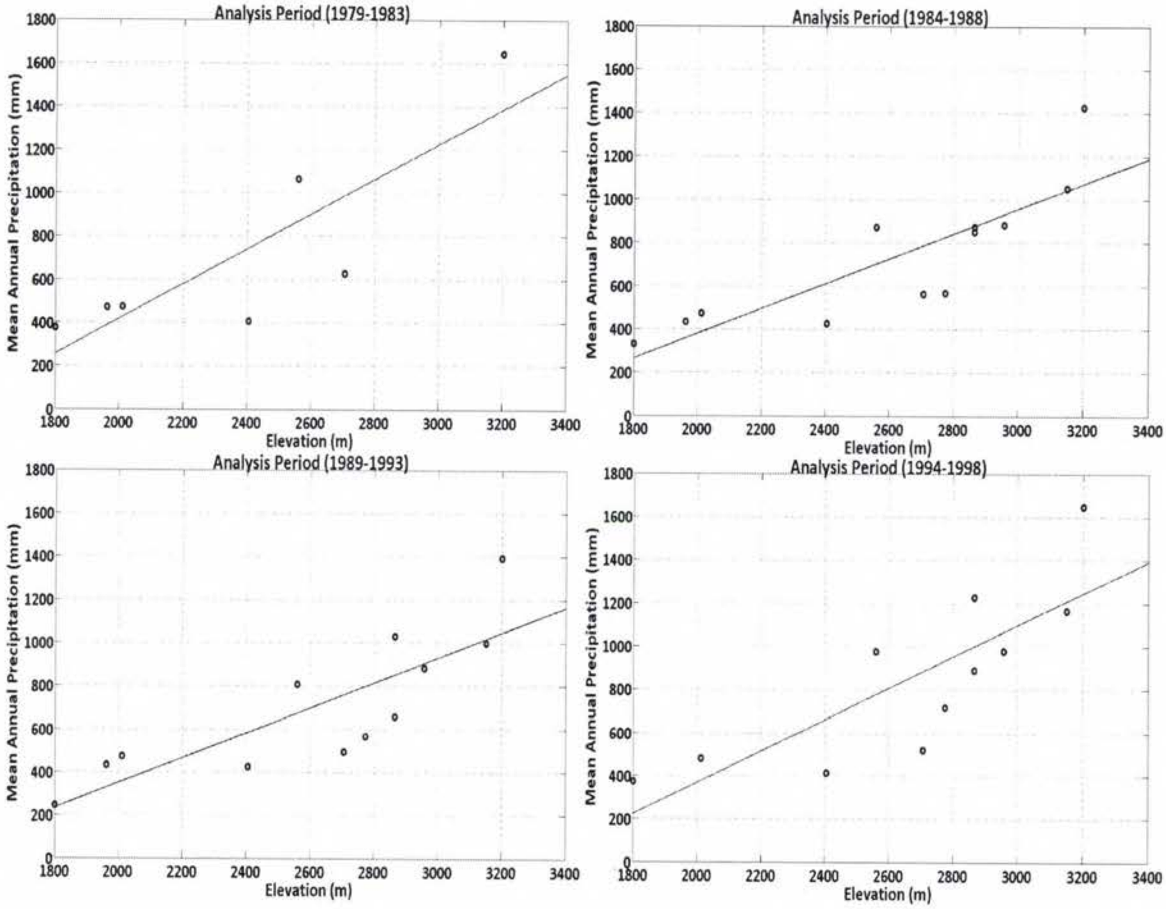

Figure A1.9. Variability of mean precipitation in Yampa River basin with elevation for different analysis period.

APPENDIX A2

Table A2.1 Similarity indices between the watersheds with respect to different physiographic attributes.

Ungaged Watershed	Gaged Watershed	Mean Elevation	Land use	Soil	Precipitation	Temperature	Arithmetic Mean	Geometric Mean
Arkansas	Cache la Poudre	0.103	0.128	0.224	0.152	0.117	0.145	0.139
	Gunnison	0.060	0.107	0.279	0.276	0.137	0.172	0.147
	San Juan	0.134	0.141	0.163	0.264	0.064	0.153	0.139
	Yampa	0.178	0.271	0.233	0.263	0.101	0.209	0.197
Cache la Poudre	Arkansas	0.103	0.122	0.224	0.152	0.117	0.144	0.138
	Gunnison	0.166	0.080	0.234	0.140	0.049	0.134	0.116
	San Juan	0.030	0.087	0.061	0.141	0.172	0.098	0.082
	Yampa	0.080	0.225	0.403	0.160	0.027	0.179	0.126
Gunnison	Arkansas	0.061	0.105	0.279	0.276	0.137	0.171	0.146
	Cache la Poudre	0.166	0.084	0.234	0.140	0.049	0.134	0.117
	San Juan	0.204	0.046	0.205	0.015	0.169	0.128	0.087
	Yampa	0.259	0.177	0.237	0.046	0.068	0.157	0.128
San Juan	Arkansas	0.134	0.128	0.163	0.264	0.064	0.151	0.136
	Cache la Poudre	0.030	0.091	0.061	0.141	0.172	0.099	0.083
	Gunnison	0.204	0.046	0.205	0.015	0.169	0.128	0.087
	Yampa	0.048	0.161	0.342	0.032	0.178	0.152	0.109
Yampa	Arkansas	0.178	0.340	0.126	0.263	0.101	0.202	0.183
	Cache la Poudre	0.072	0.301	0.279	0.160	0.027	0.168	0.121
	Gunnison	0.238	0.214	0.232	0.046	0.068	0.160	0.130
	San Juan	0.048	0.194	0.232	0.032	0.178	0.137	0.104

Closer the value to zero higher is the similarity between the gaged and ungaged watershed.
Highlighted value represents smallest similarity index between the ungaged and gaged watersheds with respect to different physiographic attributes

Table A2.2 Precipitation and temperature data points available during the calibration and validation period for study watersheds from COOP climatic stations.

Watershed	Total number of data points			
	Precipitation		Temperature	
	Calibration	Validation	Calibration	Validation
Arkansas	10551	10327	4573	7165
Cache la Poudre	6775	4109	6631	4002
Gunnison	3101	3154	3160	3278
San Juan	18100	14767	17991	14818
Yampa	12557	13596	12716	13761

Table A2.3 Precipitation and temperature data points available during the calibration and validation period for study watersheds from SNOTEL climatic stations.

Watershed	Total number of data points			
	Precipitation		Temperature	
	Calibration	Validation	Calibration	Validation
Arkansas	9627	10926	5155	10375
Cache la Poudre	7240	7284	92	7000
Gunnison	15405	18210	5767	17725
San Juan	9107	18210	3877	17834
Yampa	8408	18210	4192	17907

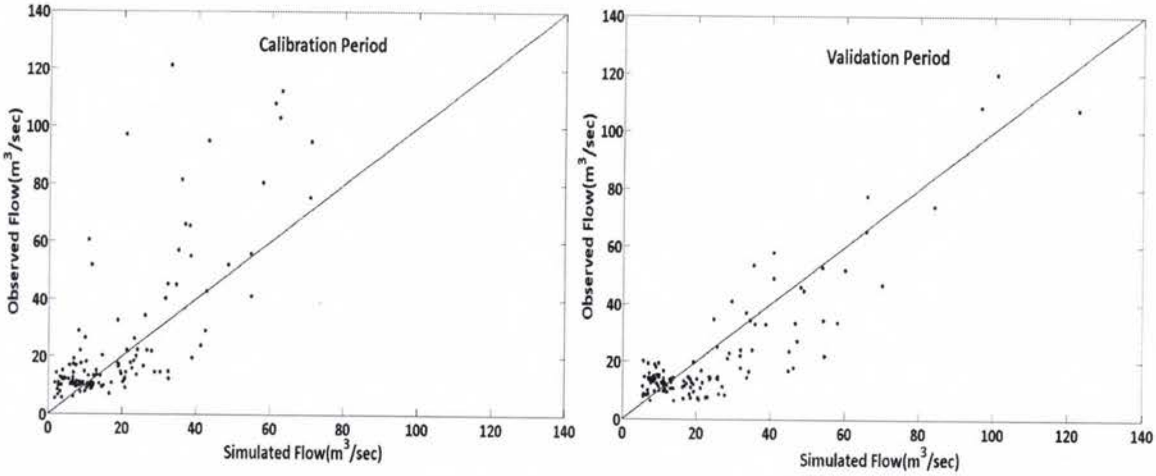

Figure A2.1. Scatter plot between the observed and simulated flows during the calibration and validation period for Arkansas River basin

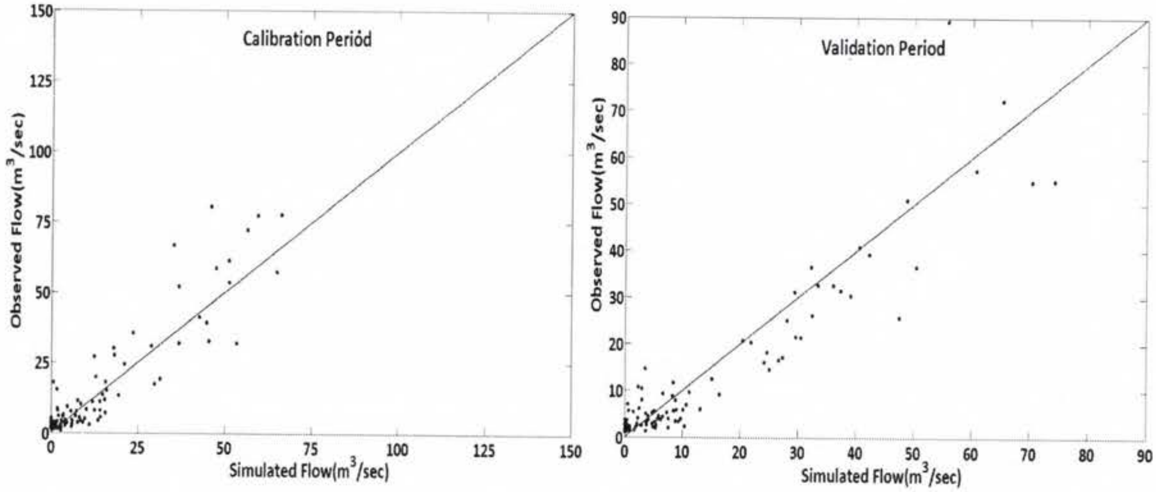

Figure A2.2. Scatter plot between the observed and simulated flows during the calibration and validation period for Cache la Poudre River basin

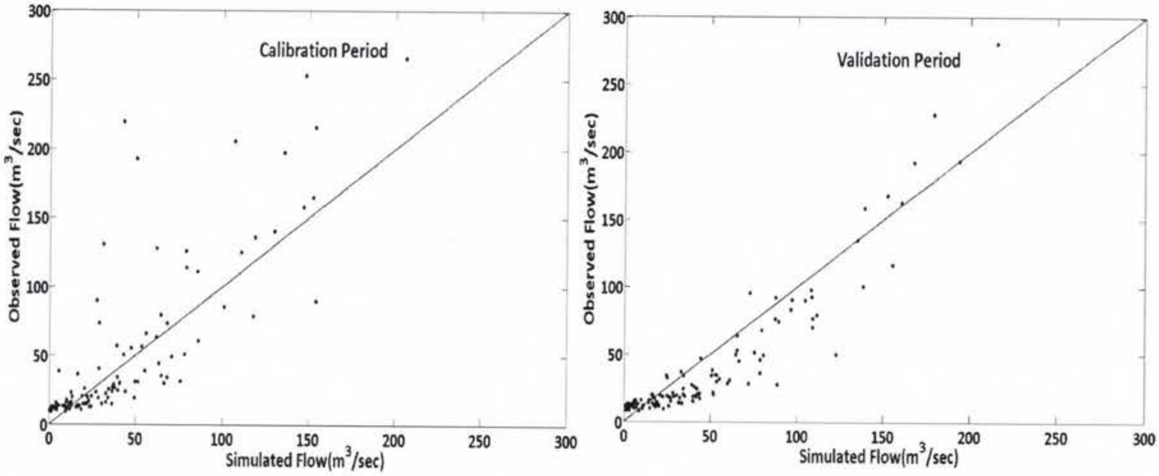

Figure A2.3. Scatter plot between the observed and simulated flows during the calibration and validation period for Gunnison River basin

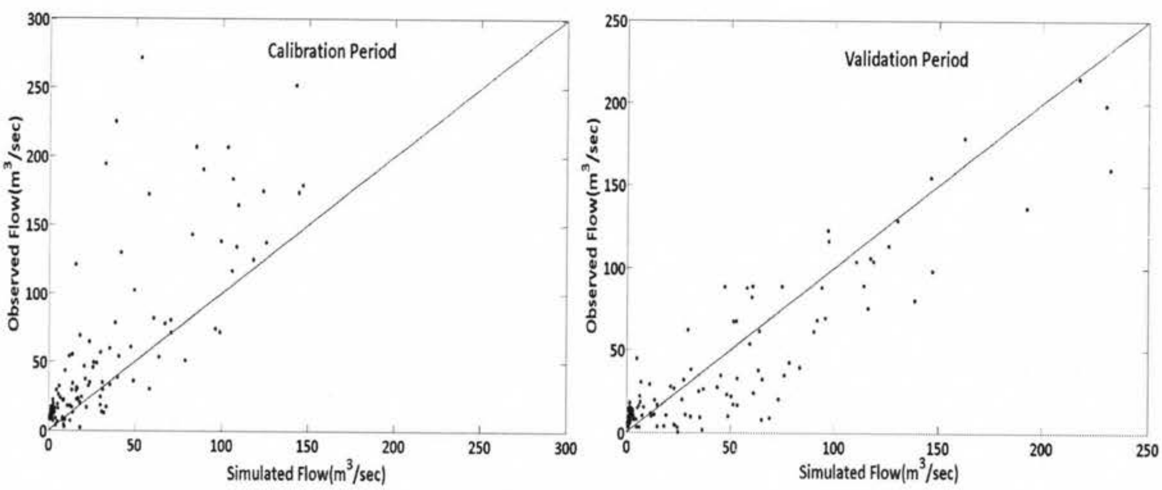

Figure A2.4. Scatter plot between the observed and simulated flows during the calibration and validation period for San Juan River basin

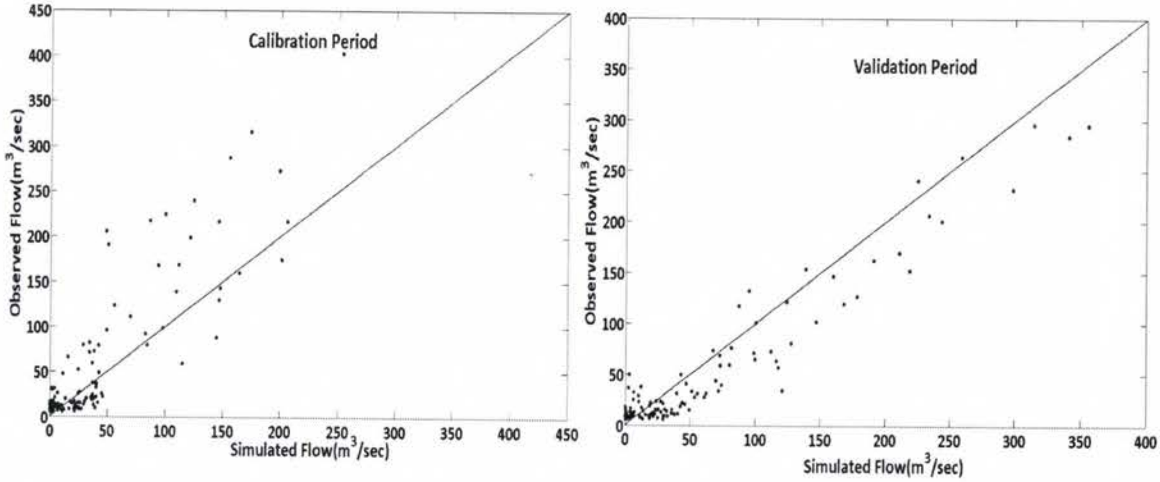

Figure A2.5. Scatter plot between the observed and simulated flows during the calibration and validation period for Yampa River basin

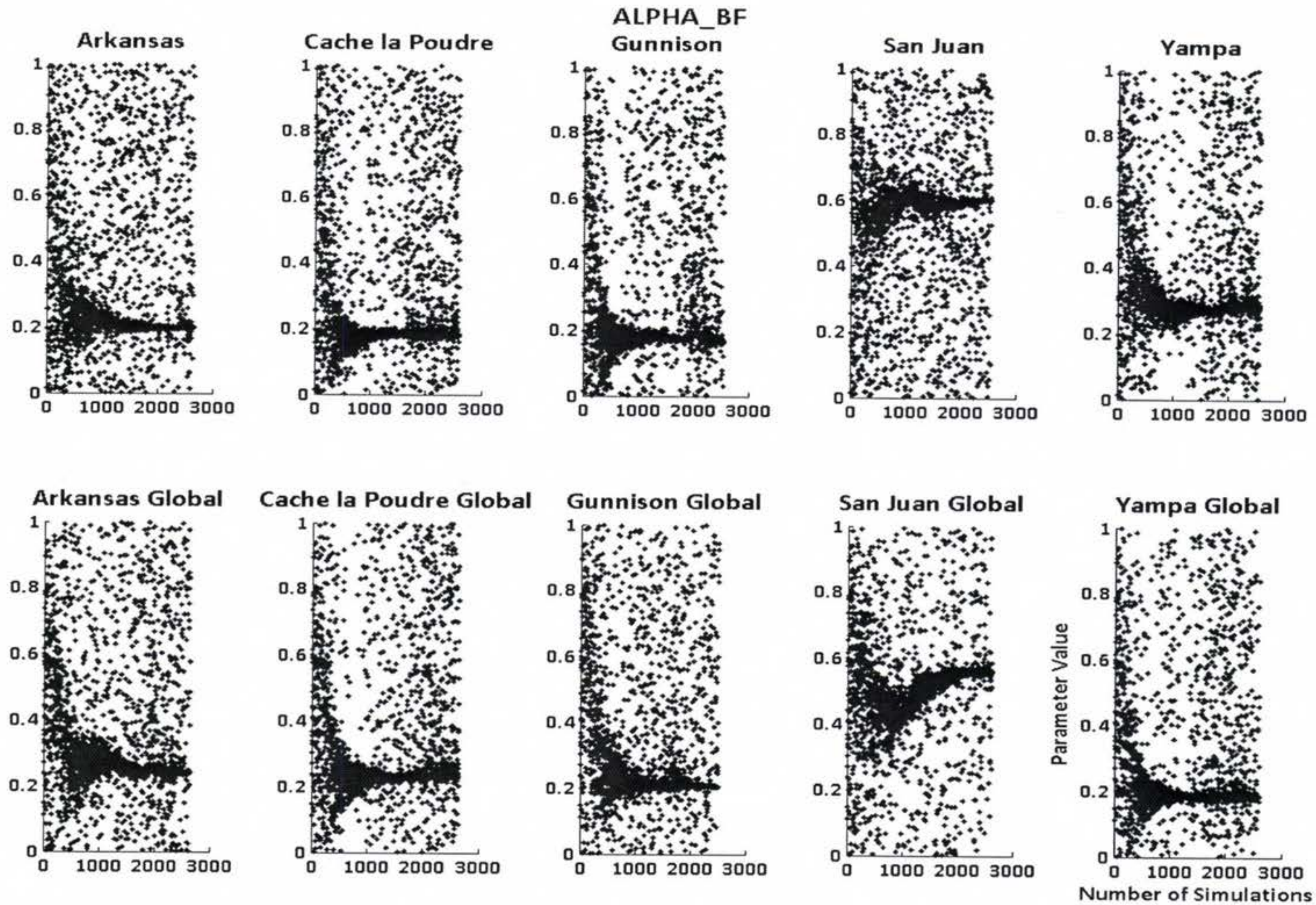

Figure A2.6. Convergence of parameter value for ALPHA_BF from single-site and multi-site calibration of SWAT model for the study watersheds.

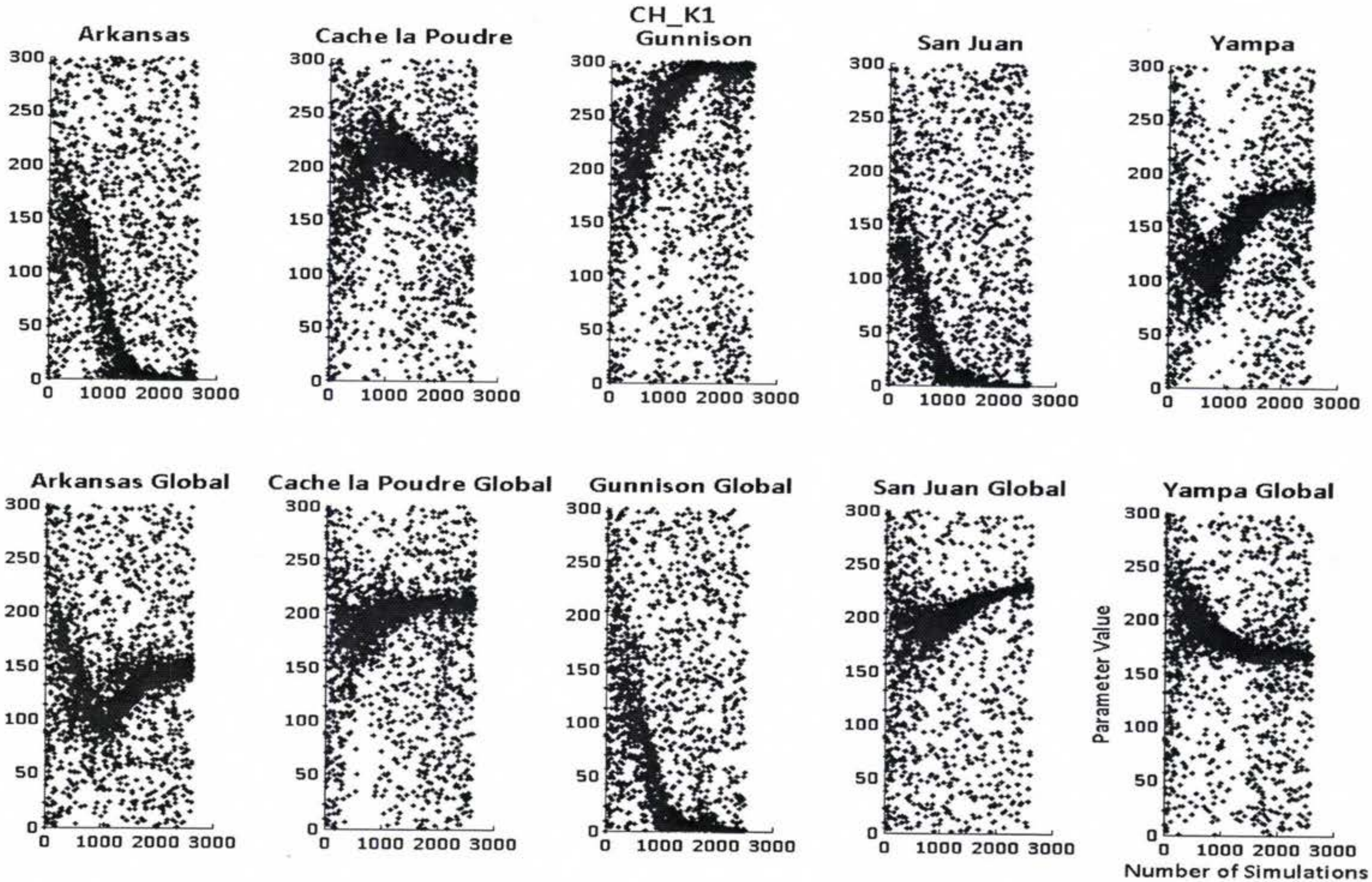

Figure A2.7. Convergence of parameter value for CH_Kl from single-site and multi-site calibration of SWAT model for the study watersheds.

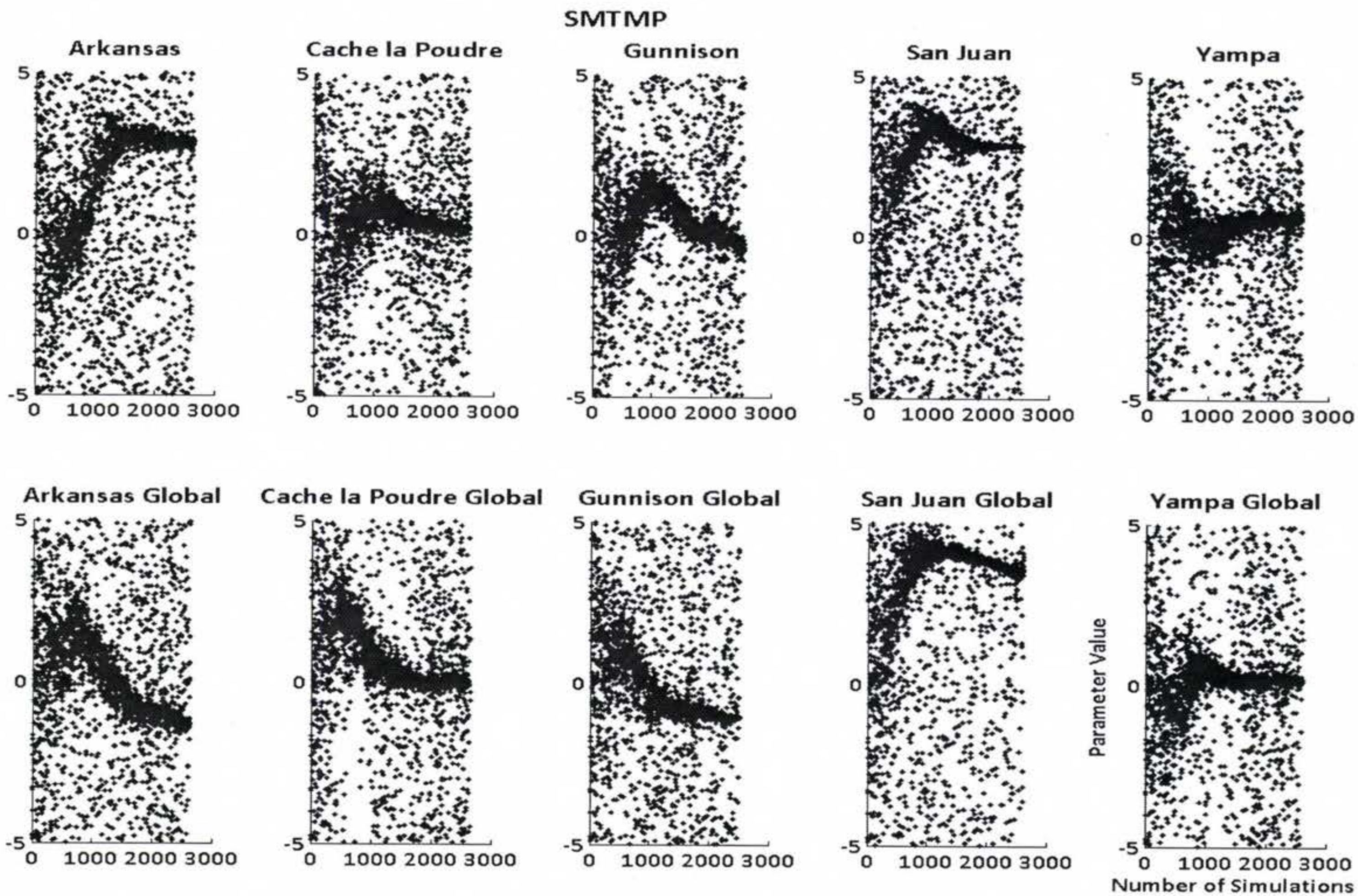

Figure A2.8. Convergence of parameter value for SMTMP from single-site and multi-site calibration of SWAT model for the study watersheds.

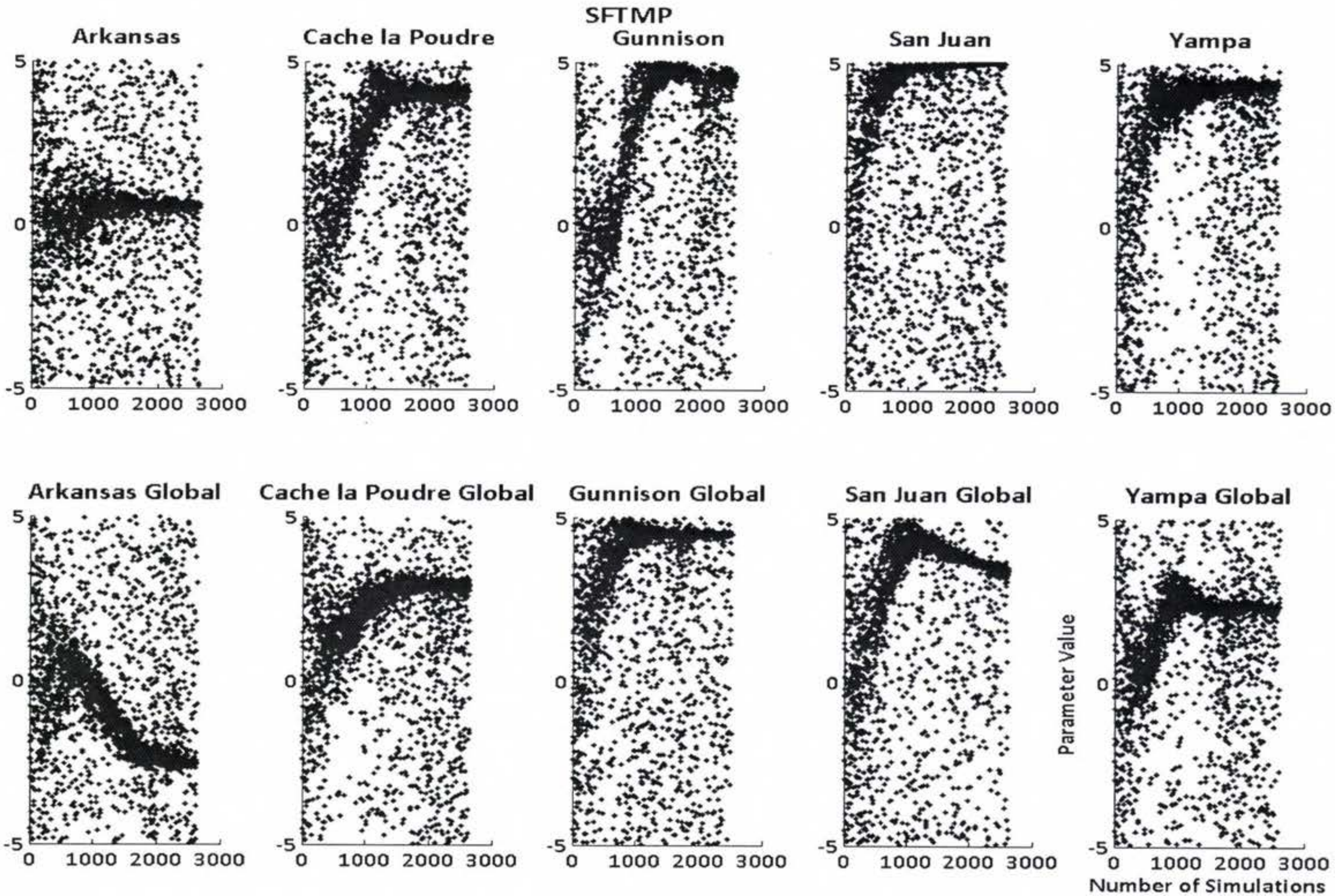

Figure A2.9. Convergence of parameter value for SFTMP from single-site and multi-site calibration of SWAT model for the study watersheds.

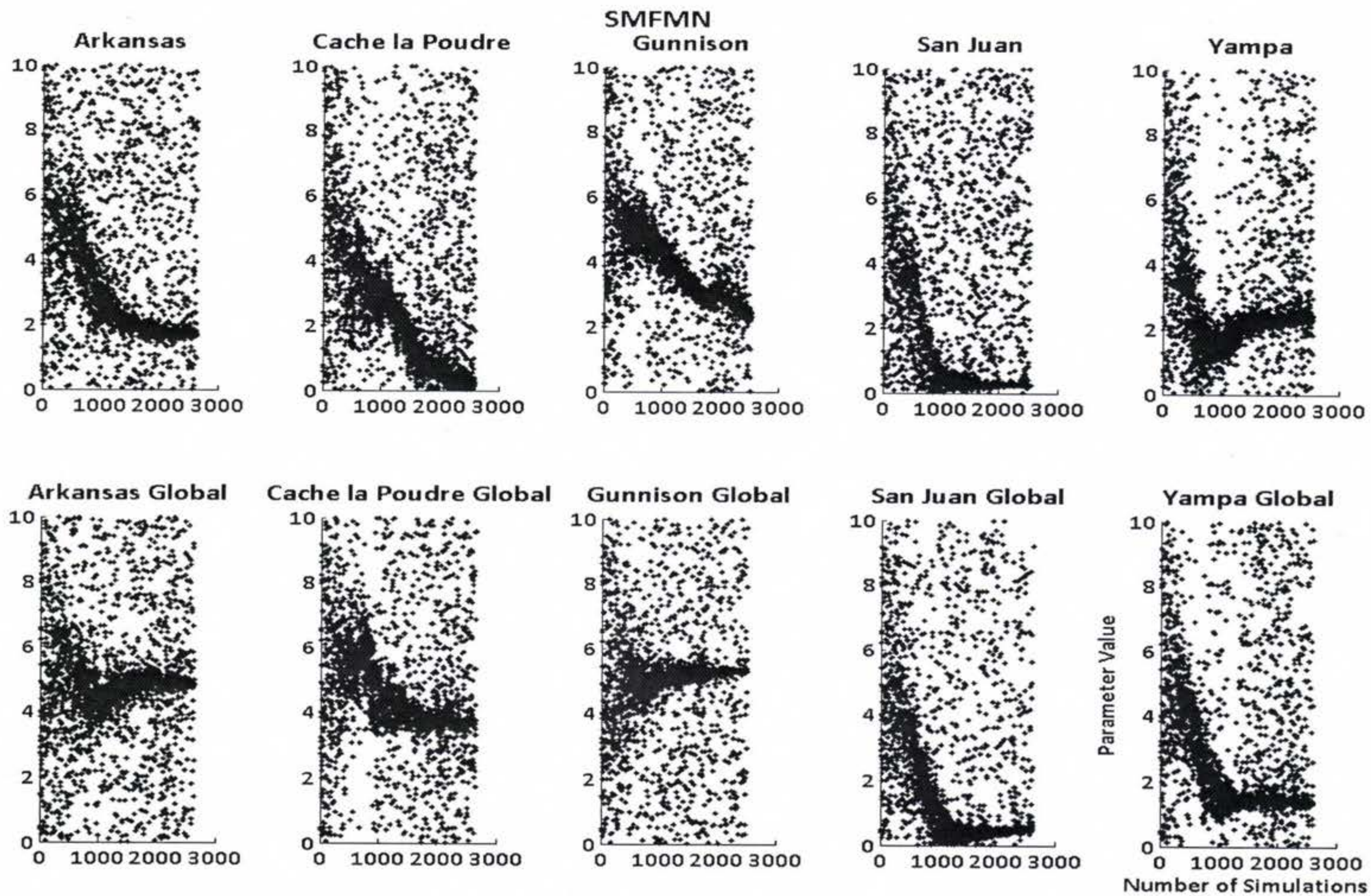

Figure A2.10. Convergence of parameter value for SMFMN from single-site and multi-site calibration of SWAT model for the study watersheds.

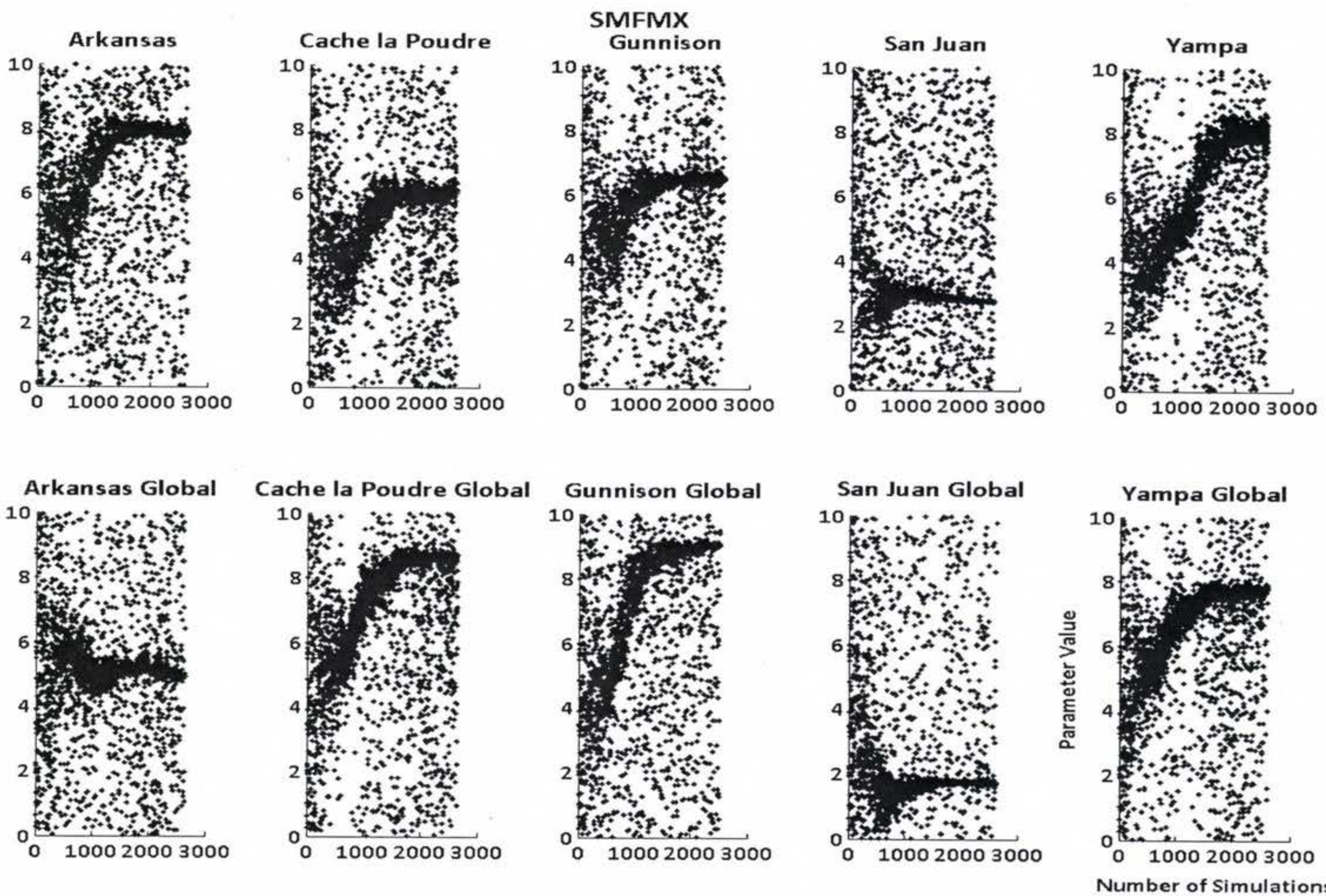

Figure A2.11. Convergence of parameter value for SMFMX from single-site and multi-site calibration of SWAT model for the study watersheds.

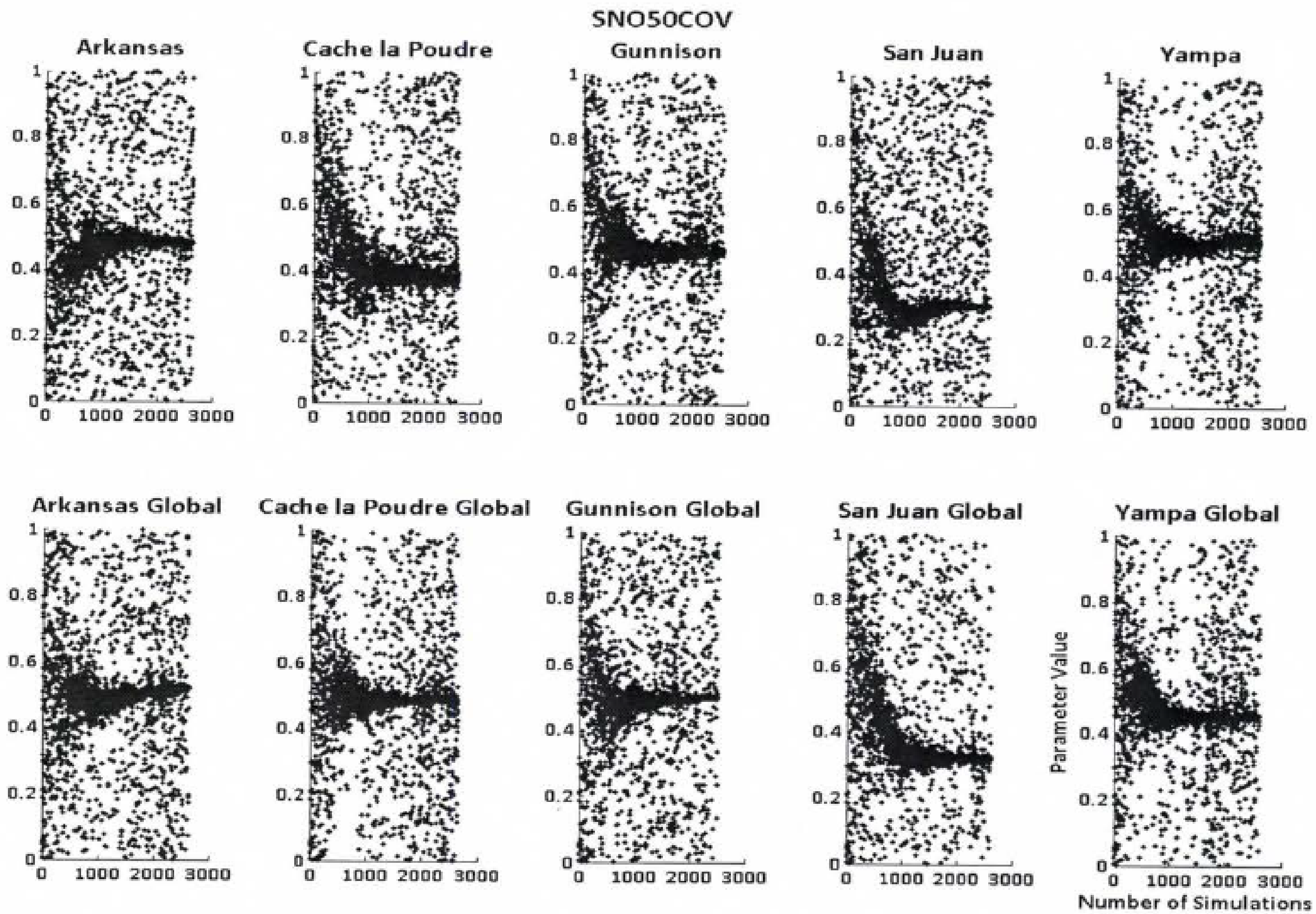

Figure A2.12. Convergence of parameter value for SNO50COV from single-site and multi-site calibration of SWAT model for the study watersheds.

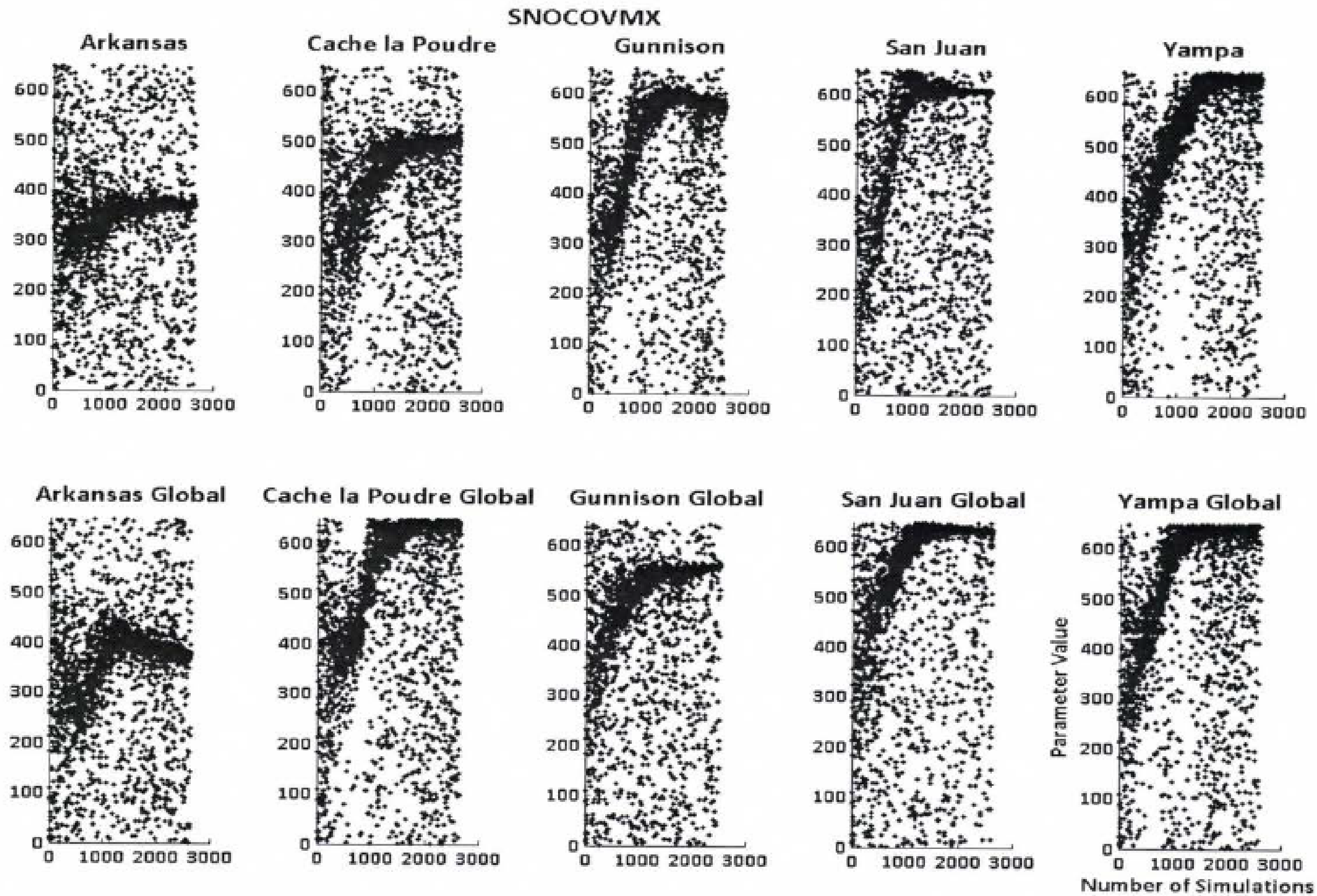

Figure A2.13. Convergence of parameter value for SNOCOVMX from single-site and multi-site calibration of SWAT model for the study watersheds.

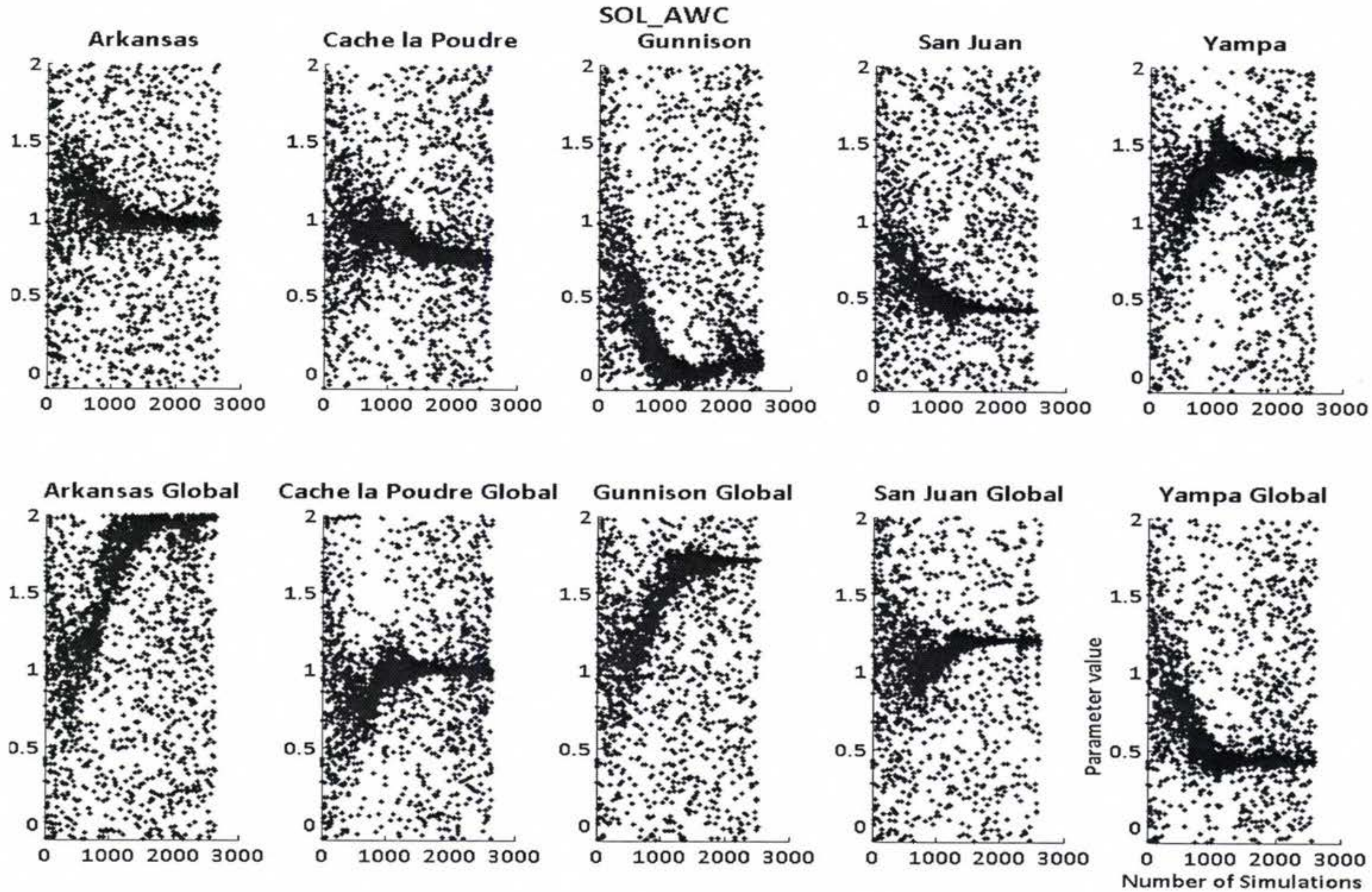

Figure A2.14. Convergence of parameter value for SOL_AWC from single-site and multi-site calibration of SWAT model for the study watersheds.

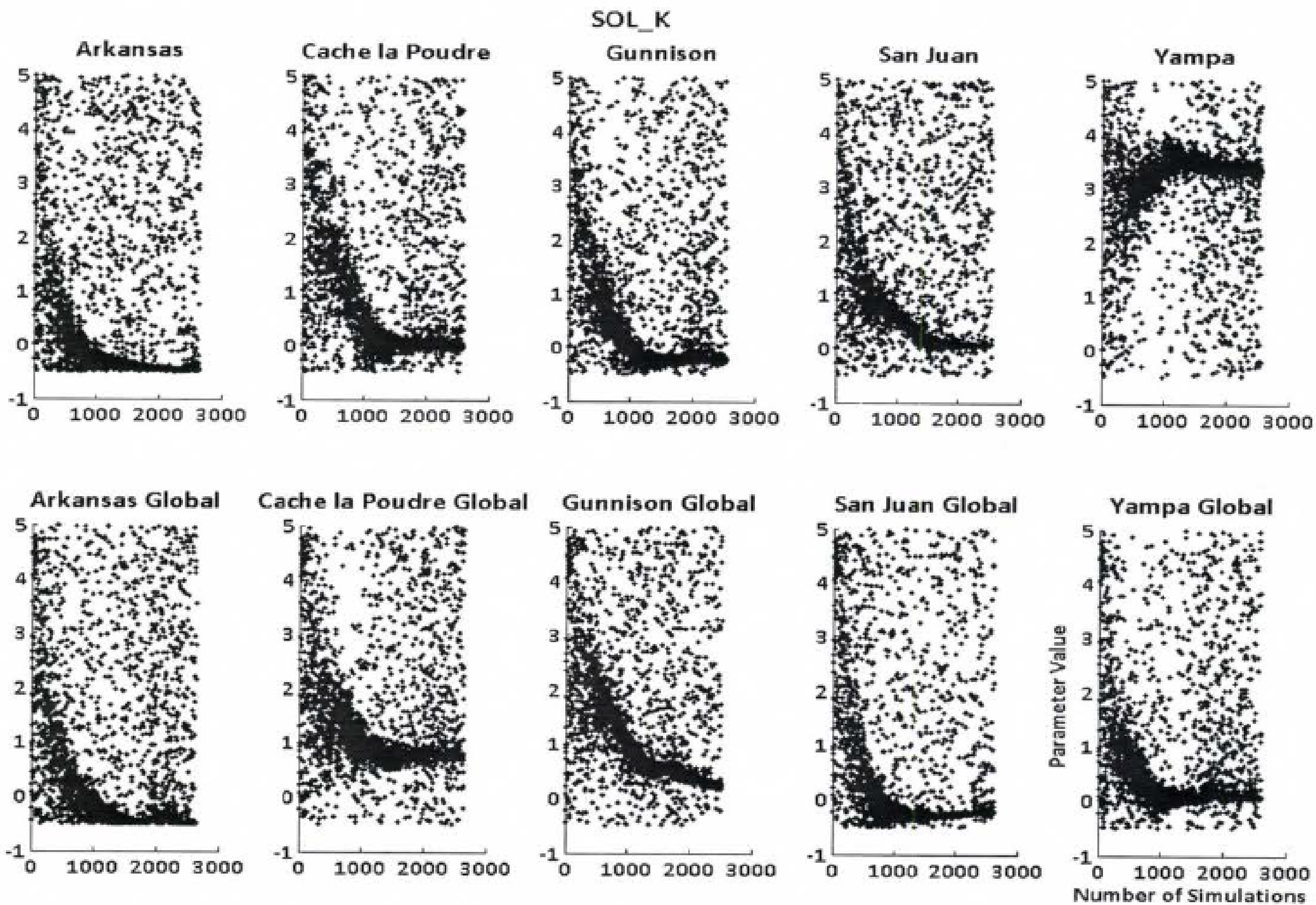

Figure A2.15. Convergence of parameter value for SOL_K from single-site and multi-site calibration of SWAT model for the study watersheds.

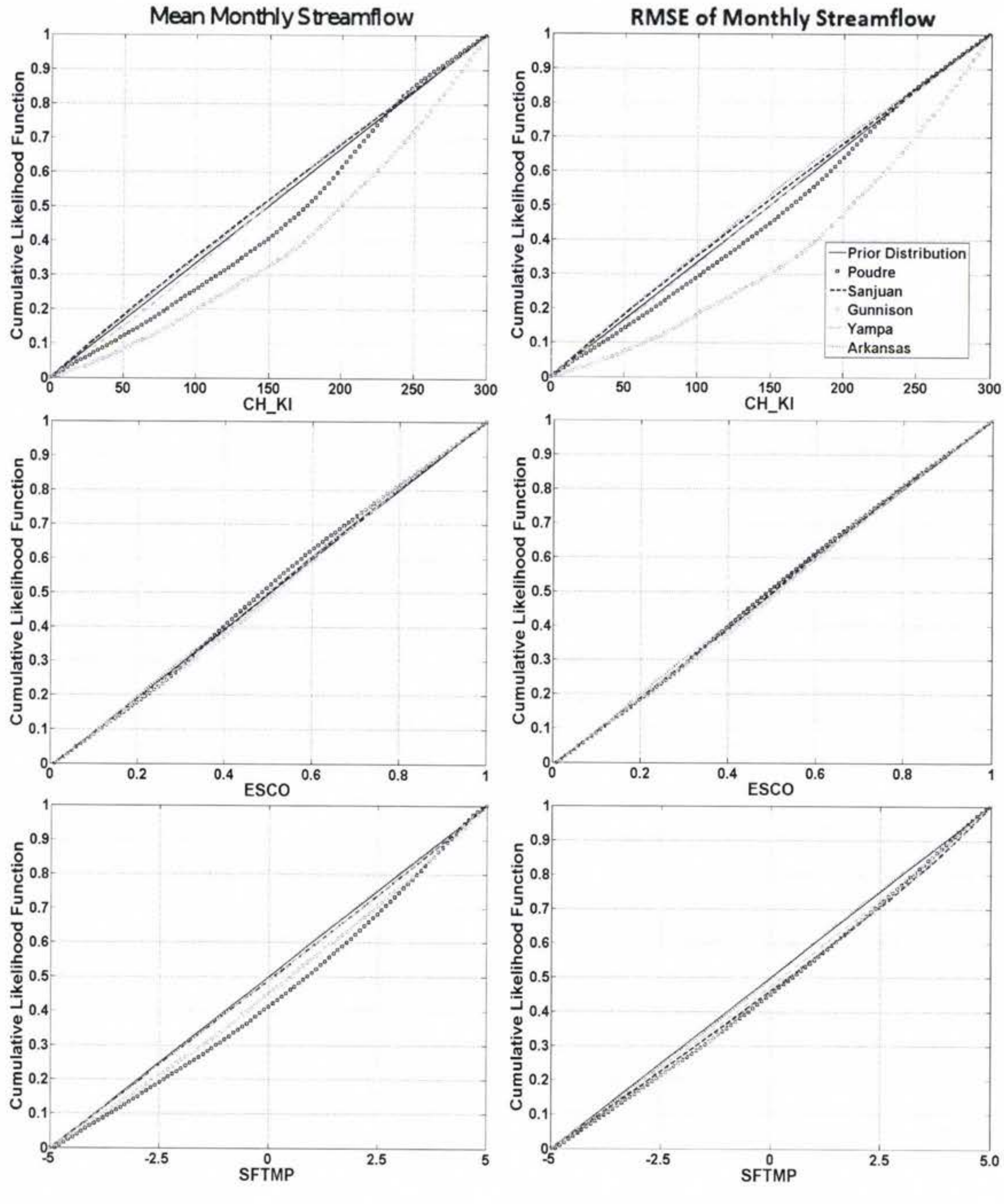

Figure A2.16. CDF's of parameters, CH_Kl, ESCO, and SFTMP using the FAST total order indices for mean monthly streamflow and corresponding RMSE.

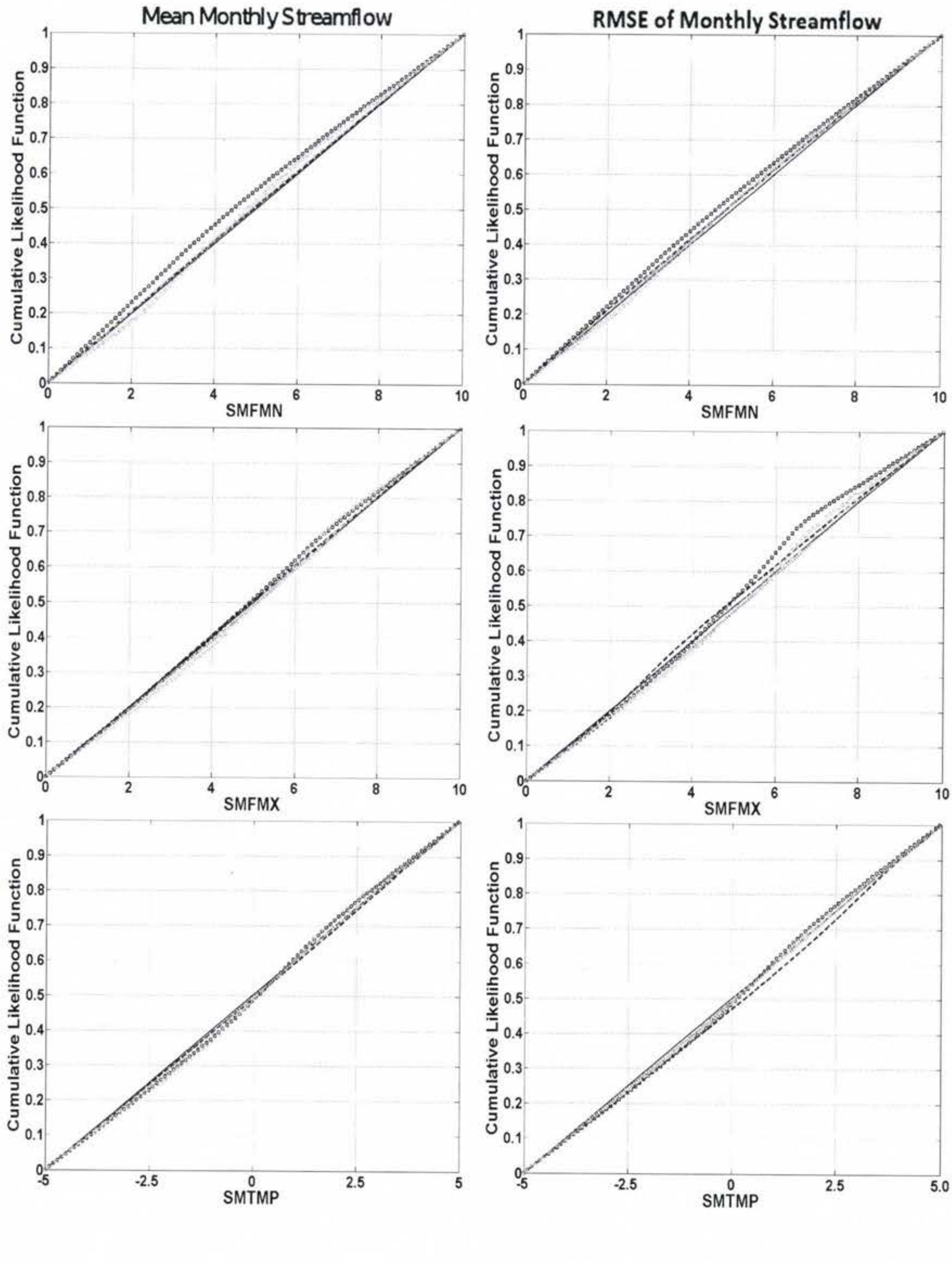

Figure A2.17. CDF's of parameters SMFMN, SMFMX, and SMTMP using the FAST total order indices for mean monthly streamflow and Corresponding RMSE

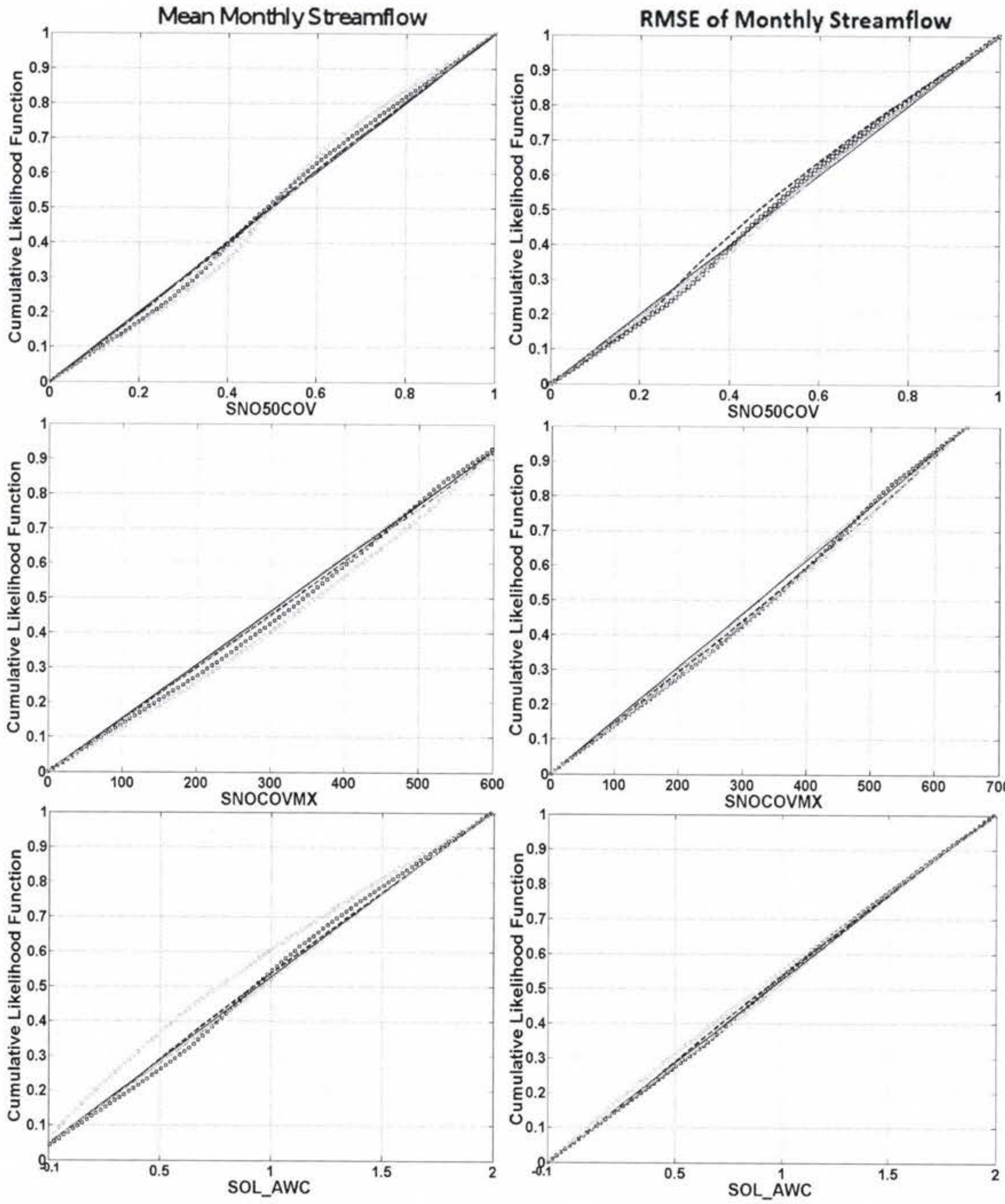

Figure A2.18. CDF's of parameters SNO50COV, SNOCOVMX, and SOL_AWC using the FAST total order indices for mean monthly streamflow and corresponding RMSE