STUDYING THE EFFECT OF SPATIAL SCALING ON HYDROLOGIC MODEL CALIBRATION USING SOIL AND WATER ASSESSMENT TOOL (SWAT)

A Thesis

Submitted to the Faculty

of

Purdue University

by

Sanjiv Kumar

In Partial Fulfillment of the

Requirements for the Degree

of

Master of Science in Civil Engineering

May 2008

Purdue University

West Lafayette, Indiana

ACKNOWLEDGMENTS

My special gratitude to my major professor, Dr. Venkatesh Merwade, for providing the support, and guidance that helped me to conduct the research presented in this thesis. I would like to thank the members of M.S. committee, Dr. Rao S. Govindaraju and Dr. Chad Jafvert, for their comments during the course of this research. I would also like to thank Dr. Carol Song, Lan Zhao, Young Moon and Hyoku Daniel Kang for their help in running calibration programs. Help received form SWAT user group at Purdue and swatuser@googlegroups.com is greatly appreciated. I am thankful to C4E4 project (Cyberinfrastructure for End to End Environmental Exploration) for providing an excellent platform to work. Finally, I would like to thank my parents and all my friends for their unlimited support and encouragement.

This material is based upon work supported by the National Science Foundation under Grant No: 0619086. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

TABLE OF CONTENTS

Page

LIST OF TABELS

LIST OF FIGURES

LIST OF SYMBOLS

A0.3 to A7.0	SJRW configurations corresponding to 0.3% CSA to 7.0 CSA with SSURGO soil data
Alpha_Bf	Baseflow recession constant
ARS	Agriculture Research Service
b_slope	Sub-basin Slope
B0.3 to B7.0	SJRW configurations corresponding to 0.3% CSA to 7.0 CSA with STATSGO soil data
Biomix	Biological mixing efficiency
Blai	Maximum potential leaf area index
BMP	Best Management Practices
BP	Best Parameter
C0.5 to C10.0	Cedar Creek configurations corresponding to 0.5% CSA to 10.0 CSA with SSURGO soil data
C4E4	Cyberinfrastructure for End-to-End Environmental Explorations
Canmx	Maximum canopy storage
CDR	Cedar Creek
Ch_K2	Effective hydraulic conductivity for the main channel
Ch_n2	Manning's "n" for main channel
ch_slope	Channel Slope
CN2	SCS Curve Number for antecedent moisture condition II
comp	component
CSA	Critical Source Area

D0.5 to D10.0	Cedar Creek configurations corresponding to 0.5% CSA to 10.0 CSA with STATSGO soil data
DD	Drainage Density
DEM	Digital Elevation Models
EPA	Environmental Protection Agency
Epco	Plant uptake compensation factor
Esco	Soil evaporation compensation factor
GIS	Geographic Information System
GOC	Global Optimization Criterion
Gw_delay	Groundwater delay
Gw_revap	Revap Coefficient
Gwqmn	Threshold water level in shallow aquifer for baseflow
HRU	Hydrologic Response Unit
HUC	Hydrologic Cataloging Unit
LB	Lower Bound
LH	Latin Hypercube
Lp	longest flow path
LU SWAT	SWAT land Use class
LULC	Land Use Land cover
m	meter
MA	Manually Adjusted
MAX	Maximum
Mbias	Model bias
MIN	Minimum
mm	millimeter
MRLC	Multi-Resolution Land Characteristics Consortium

MUSLE	Modified Universal Soil Loss Equation
NAD83	North American Datum 1983
NED	Nation Elevation Dataset
NE-SW	North East- South West
Net CDF	Network Common Data Form
NEXRAD	Next Generation Weather Radar
NHD	National Hydrographic Dataset
NLCD	National Land Cover Dataset
NOAA	National Oceanic and Atmospheric Administration
NRCS	Natural Resource Conservation Services
OAT	One-factor-At-a-Time
OF	Objective Function
P10	10th Percentile
P50	50th Percentile
P90	90th Percentile
pcp	precipitation
R2NS	Nash-Sutcliff efficiency coefficient
Rchrg_dp	Deep Aquifer Percolation coefficient
revap	ravaporation
Revapmn	Revap threshold
SCE-UA	Shuffled Complex Evolution- University of Arizona
SCS	Soil Conservation Service
SEA	SSURGO Extension Tool for AVSWATX
sftmp	snow fall temperature
SJRW	St. Joseph River Watershed
SJRWI	St. Joseph River Watershed Initiative

Slsubbsn	sub basin slope length
Smfmn	snow melt minimum rate
Smfmx	snow melt maximum rate
Smtmp	Snow melt threshold temperature
Smtmp	Snow fall threshold temperature
Sol_awc	Soil available water capacity
Sol_k	Soil Saturated hydraulic conductivity
Sol_z	depth of individual soil layer
SSE	Sum of Square of Errors
SSE*	minimum SSE
SSET	threshold SSE
SSURGO	The Soil Survey and Geographic
STATSGO	The State Soil and Geographic
surlag	Surface runoff lag
SWAT	Soil and Water Assessment Tool
SWM	Stanford Watershed Model
TDML	Total Daily Maximum Load
Timp	Snow pack temperature lag factor
tmp	temperature
UB	Upper Bound
UC	Uncertainty score
USDA	United States Department of Agriculture
USGS	United Sates Geological Survey
USLE_K	soil erodibility factor
UTM	Universal Transverse Mercator
WYLD	Water Yield

ABSTRACT

Student, Sanjiv Kumar, Purdue University, May 2008. Studying the effect of spatial scaling on hydrologic model calibration using Soil and Water Assessment Tool (SWAT). Major Professor: Dr. Venkatesh Merwade.

Calibration of model parameters is a critical step in any successful watershed modeling project. The calibrated values of model parameters, however, are influenced by sub-watershed divisions and resolution of input data. The objective of this research is to study the effects of sub watershed divisions and scale of soil data on calibration of the SWAT model (Soil and Water Assessment Tool) for the St. Joseph River Watershed (SJRW). Two sets of SJRW models one with SSURGO data (1:24,000 scale) and other with STATSGO data (1:250,000 scale), each set having six different level of sub-watershed division varying from 12 sub-watersheds to 97 sub-watersheds, are independently calibrated using shuffled complex evolution algorithm for daily streamflow output at the watershed outlet. To further study issues of spatial scale, similar experiments are repeated for one of the major sub watersheds of SJRW, namely Cedar Creek. For Cedar Creek, two sets of watershed models are created with each set having 8 different levels of watershed sub divisions. Twenty eight independently calibrated model results showed no significant difference in terms of model performance, however parameter uncertainty ranges were found to be dependent on sensitivity of individual parameters. Sensitive parameters showed very small uncertainty range compared to less sensitive parameters.

CHAPTER 1 INTRODUCTION

1.1 Background

Environmental modeling provides a tool to study impacts of human intervention in natural processes. As available landscape is being increasingly altered in the form of agricultural practices, fertilizer and pesticide application, urbanization, and industrial development to meet societal needs, the impact of these alterations on local and global environment has become a major concern. Water quality and air quality are the two major issues that are being addressed by researchers in various disciplines. Better understanding of natural processes and prudent management of natural resources can aid in reducing adverse impacts of human interventions. Improvement in Great lakes water quality over the last 30 years through continued research and implementation of mitigation strategies is one such success story (State of Great Lakes, 2007).

In agriculture-dominated mid-west region of the U.S., sediment, nutrient and pesticide coming out of agricultural fields are major non-point sources of pollution affecting stream water-quality in watersheds (Bernot et al. 2006, Yu et al. 2004). An understanding of source area and flow path of pollutants can greatly improve watershed management. Stream water quality is a complex function of natural variables and human induced changes in a catchment area. Natural variables include climate, topography, and soil characteristics, whereas human induced changes include point and non-point sources of pollution, land use changes and flow regulations. Changes in natural and human induced variables occur at different spatial and temporal scale. For example, under similar climatic conditions, land use pattern in a region changes within a range of few miles. Similarly, low flow conditions in summer and fall can make stream water quality an alarming issue, whereas high flow conditions in winter and spring can dilute pollutants to such an extent where water quality is of no concern. Variability in spatial and temporal scale poses considerable challenges in data collection, archival, and analysis. In addition, integration of multi-scale, heterogeneous datasets to create prediction models pose more challenges.

Lack of an integrated source for relevant data and suitable modeling tools has been a major stumbling block for conducting interdisciplinary environmental research. To fill this gap, a group of researchers at Purdue University is working on development of a web portal that will allow researchers to conduct a broad spectrum of environmental research at the watershed scale. This NSF sponsored project (Grant number 0619086) titled ‘Cyberinfrastructure for End-to-End Environmental Explorations (C4E4)’ aims to combine heterogeneous datasets with sate-of-the-art modeling and visualization tools through a web portal. The web portal will allow users to query or retrieve different datasets, run appropriate models, and analyze and visualize results to make decisions.

1.2 Problem Statement and Objectives

The first step in developing the C4E4 portal is to have a calibrated watershed model that will allow researchers and watershed managers to evaluate effects of different Best Management Practices (BMPs) on stream water quality. A well-calibrated hydrologic model is a prerequisite to simulate other watershed processes (sediment, nutrient and pesticide), but model representation and parameters depend on several factors such as spatial resolution of input data (digital elevation model, soil data, land use data) and threshold area for stream generation (number of sub watersheds). A calibrated model is just one realization out of several other possible realizations in which watershed hydrology can be represented and simulated. One may get a different model and associated set of parameters if model spatial scale is changed. Therefore, to develop a robust base model for the C4E4 portal, it is necessary to understand sensitivity of model parameters to different spatial scales.

With the broader aim of creating a robust base model for C4E4 portal, this thesis has the following objectives:

a. To study effects of watershed sub-division (spatial scale) on model representation (watershed attributes).
b. To study effects of watershed sub-division (spatial scale) on model calibration and validation (model performance).
c. To study effects of STATSGO (1:250,000 scale) and SSURGO (1: 24,000 scale) soil data on model results.
d. To study sensitivity of calibrated parameters to model spatial scale and soil data.

1.3 Approach

The objectives of this research are accomplished by creating a set of watershed configurations representing different spatial scale for a study area, and studying the effects of these configurations on calibrated parameters and model output. A brief description of the study area, model, and overall approach is provided below.

Watershed: The St. Joseph River Watershed (SJRW) located at the intersection of Michigan, Ohio and Indiana States is used as a test bed for this study. SJRW is a source water protective watershed with many environmental groups monitoring water quality in the watershed. St. Joseph River is the main source of drinking water for 200,000 people in Fort Wayne, Indiana. Peak level of Atrazine (an herbicide) higher than 3 ppb, (EPA drinking water standard) was reported in the watershed between 1995 and 1998 (Amabile et al., 2006). More details on SJRW are provided in Section 3.1.

Model**:** A comprehensive model is required for this research that can (a) continuously simulate watershed hydrology and its response to different management scenarios over long time periods, (b) incorporate physical variability in the watershed, and (c) track flow path of pesticide and nutrients in the watershed. Considering these requirements, Soil and Water Assessment Tool (SWAT) is selected as a candidate model for this study (Arnold et al., 1998; Neitsch et al., 2005; Gassman et al., 2007). More details on SWAT model are provided in Section 3.3.

Methodology**:** Seven SJRW watershed configurations are created by using different critical source areas (CSAs) for stream generation ranging from 0.3% to 7.0 % of total watershed area, thus creating SWAT models representing different spatial scale. The effect of soil data resolution is incorporated by using two types of soil data (SSURGO and STATSGO) for each configuration, thus creating 14 (2*7) model sets. All models are independently calibrated for flow output at the watershed outlet to study effects of spatial scale and soil data on model calibration. Finally, to gain more insight with regard to spatial scaling, similar exercise is repeated for one of SJRW's major sub watershed, namely Cedar Creek ($1/4^{th}$ of SJRW size).

1.4 Thesis organization

The thesis is organized in six chapters. Chapter Two provides a literature review of the research work related to effects of data resolution and watershed sub division on model outputs, model calibration, and parameter uncertainty in hydrologic modeling. Chapter Three presents description of study area, data and model used in this study. Effects of watershed sub division on model attributes are described in Chapter Four. Model calibration and validation, and parameter uncertainty, procedure, and results are presented in Chapter Five. Conclusions of this research are summarized in Chapter Six. Appendix A outlines procedure for processing of SSURGO data. SWAT hydrologic parameters from theoretical perspective are described in Appendix B. Control parameters for model calibration are documented in Appendix C.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

A watershed is a complex system consisting of various hydrologic processes such as precipitation, interception, surface runoff, infiltration, groundwater percolation and evapotranspiration that occur at different spatial and temporal scales. The interaction or interplay among all watershed components is collectively represented by watershed response in the form of runoff hydrograph. Watershed response depends upon watershed topography (shape, size, slope, and orientation), land use pattern, soil types, magnitude and timing of rainfall events, and human interventions. For example, when land surface is parched after summer, even intense precipitation in fall season may not produce high runoff, but during winter or spring, such precipitation can cause flooding because soils are either saturated or frozen to convert most of precipitation to surface runoff. Similarly, an ill-managed agricultural farm can cause excessive erosion from fields, and contribute nutrients and pesticides to streams, creating water quality problems in a watershed.

A hydrologic model represents a complex hydrologic system in simple and readily comprehensible manner to permit hydrologic simulation and prediction by establishing relationships between different watershed components (Black, 1991). Watershed models have come a long way since their inception in 1960's from lumped rainfall-runoff model such as Stanford Watershed Model (SWM) (Crawford and Linsley, 1966), to more process based semi-distributed models such as SWAT that is capable of simulating runoff, sediment, nutrient and pesticide at various points in a watershed (Arnold et al., 1998). In addition, advances in computing resources and Geographic Information System (GIS) have played a significant role in development of recent hydrologic models. Today hydrologic models are used as a decision support tool for TDML (Total Daily Maximum Load) program and BMP (Best Management Practices) evaluation programs to alleviate water quality issues in watersheds (Santhi et al., 2003; Arabi et al., 2006). Therefore, it has become increasingly important to understand various steps involved in hydrologic modeling process and interpretation of model results with respect to input uncertainty and model constrains. Various steps involved in hydrologic modeling can be grouped under four broad categories: (1) Organization of input data, (2) Data preprocessing, (3) Watershed delineation and discretization, and (4) Model calibration and validation.

Input data consist of static data (kept constant throughout modeling process in a model) such as Digital Elevation Models (DEM), land use and soil maps. If any of the data are not available in digital format, they can be generated from using legacy data such as paper maps or other sources (remote sensing images). For example DEM can be generated from contour maps, land use data can be extracted from remote sensing data (Landsat 5 and 7), soil data can be developed from field soil survey maps. Watershed characteristics such as area, slope, and basin curve number are determined based on information contained in static data. Another group of input data required is dynamic input such as daily time series of temperature and precipitation, and crop management information.

Data preprocessing step includes projection of GIS data, filling of sinks in DEM, and formatting of dynamic data into model specified format. With the availability of weather data in different formats such as ASCII format, Net CDF (Network Common Data Form) format, and XMRG format, preprocessing of weather data takes considerable time.

Step 3 includes delineating of watershed by generating a stream network based on user defined threshold area for stream origination called Critical Source Area (CSA). Higher CSA results into less number of sub watersheds and low density of drainage network (total channel length/total watershed area) and vice-versa. In a semi distributed model such as SWAT each sub watershed is further divided into basic calculation units called HRUs (Hydrologic Response Units) based on minimum thresholds area of land use and soil type. Since model does all calculation for individual HRUs, appropriate representation of watershed variability in HRUs are necessary.

After delineating watershed boundary and defining calculation units (HRUs), the next step is to calibrate model parameters to reproduce observed watershed response (hydrograph, sediment yield, chemograph). Calibrated parameters are then validated by producing watershed response for another set of dynamic input data that are not included in calibration process. Once a model is calibrated and validated, it is used for watershed management planning and decision. The objective of this chapter is to describe related work on effect of input data and watershed sub division on hydrologic modeling process, model calibration and uncertainty in hydrologic modeling.

2.2 Input data

2.2.1 Digital Elevation Model (DEM)

Different resolution DEMs (10, 30, 90 m) are available to users to create a watershed model. Di Luzio et al. (2005) found that selection of DEM data is critical for delineating 21.3 km^2 Goodwin Creek watershed in Mississippi- a watershed delineation using 90 m DEM was incorrect. An incorrectly generated watershed from 90 m DEM resulted in 11 to 13% less watershed area compared to 30 m DEM. Incorrect geomorphologic parameters, reduced annual runoff, soil erosion and sediment yield. In a similar study, Chaubey et al. (2005) compared SWAT model output produced by using DEM ranging from 30 m to 1000 m for 18.9 km^2 Moores Creek watershed in Arkansas. Although coarser DEM reduced streamflow and NO_3-N (nitrate nitrogen), total P (Phosphorous) prediction did not always decrease with coarser DEM. Chaubey et al. concluded that effect of DEM resolution depends on model output variable of interest. DEM resolutions ranging from 100 m to 200 m produced streamflow, NO3-N, and total P within a relative error of $\pm$10%.

Chaplot (2005) studied the effect of DEM resolution (20 to 500 m) on SWAT model output, and recommended an upper limit of 50 m on DEM resolution to simulate watershed loads. Contrary to previous research, Chaplot found that SWAT runoff prediction was accurate across all DEM resolution, but beyond 50 m DEM resolution, sediment and NO3-N load were significantly decreased. The insensitivity of runoff prediction on DEM resolution is due to the SCS Curve Number method used in runoff calculation. In SCS Curve Number method (Soil Conservation Service, 1972), topography is given low importance in calculating surface storage, interception infiltration and retention. Therefore, runoff calculation is not affected by changing topography from different DEM resolutions. In the case of MUSLE equation (Modified Universal Soil Loss Equation) for sediment and NO3-N simulation, channel slope and length play a significant role, and get substantially affected (decreased) by smoothening of landscape at coarser DEMs, thus affecting respective outputs.

2.2.2 Land Use data

Land Use data along with soil hydrologic group are critical when SCS Curve Number method is used to determine curve number distribution in a watershed. However, fewer studies are available on the effect of spatial scale of land use data in hydrologic modeling. This may be due to non availability of different resolution land use data in public domain.

Di Luzio et al. (2005) analyzed the effect of three land use data sets: LULC (Land Use Land cover USGS map 1:250,000 scale), LNSL (land use land cover map derived from Landsat 5 Thematic Mapper 1987, 30 m resolution) and NLCD-1992 (National Land Cover data 1992, 30 m resolution) on SWAT model output. Difference in model output (runoff and sediment yield) was mainly attributed to inherent discrepancy in land cover classification in the original datasets. For example, coarser resolution LULC included pasture class into agricultural class resulting in higher curve number and hence higher runoff. In addition, coarser resolution land cover map resulted in limited number of HRUs, thus preventing more precise management practice strategy in a small watershed.

Cotter et al. (2003) analyzed the effect of land cover data of varying resolution ranging from 30 m to 1000 m on hydrologic model output. Compared to 30 m resolution land use data, 1000 m resolution land use data overestimated forest cover (23%) by combining forest cover with pasture (16%) and urban land cover (7%). Increased forest cover resulted in reduced curve number for the watershed, which in turn produced reduced runoff (7%), sediment (19%) and nutrient output (NO3-N:11%, total P:41%) from the model.

2.2.3 Soil data

With the availability of high resolution 1:24,000 scale SSURGO (The Soil Survey and Geographic) soil data, there is a growing interest in comparing the effect of SSURGO on model simulation with respect to earlier available coarser resolution 1:250,000 scale STATSGO (The State Soil and Geographic) soil data. By analyzing the effect of STATSGO and SSURGO soil data on SWAT model streamflow output in the snow melt dominated Elm River watershed, North Dakota, Wang and Melesse (2006) found that overall SSURGO model showed slightly better performance in predicting monthly, seasonal, and annual mean discharge. During validation period, STATSGO model predicted consistently higher mean discharge compared to SSURGO model. The difference between STATSGO and SSURGO model was more pronounced in upstream part of the watershed because of dominant overland hydrologic process compared to channel processes in the downstream part of the watershed.

Di Luzio et al. (2005) presented a detailed analysis of SNSL (equivalent to SSURGO soil map) and STATGO soil data for Goodwin Creek watershed, Mississippi, and found that soil parameter differed significantly between these two soil datasets. Higher resolution SNSL soil data resulted in higher curve number for the watershed (a 4-6 range) compared to STATSGO soil data. Saturated hydraulic conductivity for top most soil layer was nearly double in the case of SNSL soil map compared to STATSGO, but soil available water capacity (*sol_awc)* and soil erodibility factor (*USLE_K*) remained unchanged between the two datasets. The combined effect was higher annual streamflow prediction (5-10%) in the case of SNSL soil data, but sediment output remained unchanged.

Chaplot (2005) compared effects of three soil datasets: 1:25,000 SSURGO, 1:250,000 STATSGO, and 1:500,000 soil data derived from STATSGO, on SWAT model output for Walnut Creek watershed in central Iowa. The result showed that the mean monthly value of runoff prediction was not significantly affected by soil data, but nitrogen and sediment load were significantly reduced for coarser scale soil data. Sediment and nitrogen load were underestimated by 40% and 25% for STATSGO and 1:500,000 scale soil data, respectively compared to load prediction from SSURGO soil data.

2.2.4 Weather Input (precipitation and temperature)

Precipitation and temperature data are used as the source input to simulate hydrologic process at watershed scale (at regional and global scale temperature drives hydrologic cycle), and therefore, representative distribution of weather input is required to create a hydrologic model. Generally hydrologic models are calibrated against observed streamflow at the watershed outlet in response to rainfall distribution in the watershed, but rainfall distribution used in the model is based on point measurement at few gauging stations in the watershed, which may or may not represent the actual rainfall distribution. Therefore, uncertainty associated with rainfall distribution in the model, and subsequent error transmitted to model result is a major area of research in hydrology.

Chaplot et al. (2005) used 51 km^2 Walnut Creek (WC) in Iowa with 15 rain gauging stations and 918 km^2 Bosque River watershed (BUR) in Texas with 14 rain gauging stations to study effect of number of rain gauging stations on prediction of runoff and nitrogen flux. Watershed conditions in WC and BUR were simulated by considering a range of rain gauging stations, including climatic data from nearest National Weather Service station. Result showed that mean monthly runoff and nitrogen fluxes varied only slightly with decreasing rain gauges. However, statistical parameters such as root mean standard difference (RMSD) indicated that model errors were higher and more skewed when the number of rain gauging stations reduced to half or below. Based on findings Chaplot et al. recommended use of highest available number of rain gauges for watershed modeling.

Kalin and Hantush (2006) compared SWAT model output (streamflow, baseflow and surface runoff) for 120 km^2 Pocono Creek watershed in Pennsylvania by using precipitation input from rain gauging stations and from 4 x 4 km resolution NEXRAD (Next Generation Weather Radar) data. NEXRAD precipitation matched well ($R^2 \sim 0.90$) with rain gauging station measurement on daily and monthly basis. Hydrographs generated from both rain gauging stations and NEXRAD data were similar and matched well with observed data on daily and monthly basis. Although NEXRAD data did not show any improvement in model results compared to rain gauging stations, it was suggested that simulation at sub watershed level may shed more light on advantages of using spatially distributed NEXRAD data.

2.3 Watershed sub divisions

Watershed sub division is another major area which has been researched extensively to study the effects of spatial scale on hydrologic modeling. Model parameters are aggregated at user defined spatial scale through watershed sub division, and model results are found to be highly sensitive to this aggregation. Often attempts have been made by various researchers (Bingner et al., 1997; Jha et al., 2004; Arabi et al., 2006) to define optimum sub-watershed division level for different model outputs, but no standard set of framework exists for watershed sub division.

Mammilaplli (1998) suggested existence of a basin dependent threshold configuration beyond which there is no or minimal increase in model efficiency.

Mammilaplli also suggested that land use and soil type combination (represented by the number of HRUs) have more impact on the streamflow output than the topography of the basin (represented by the number of sub watersheds) because of the use of curve number method for runoff calculation. Bingner et al. (1997) did not find annual runoff to be sensitive to the sub watershed division in 21 km^2 Goodwin Creek watershed (GCW) in Mississippi, but annual sediment yield was sensitive to the level of watershed sub divisions. Increase in sediment yield at finer resolution watershed division was attributed to two factors: (1) increase in overland slope (topography), and (2) representation of land use distribution in HRUs. At coarser resolution, most erosive land use type (crop land) had very little coverage, which increased with finer resolution of watershed sub division, and became constant after a threshold resolution.

Jha et al. (2005) found that optimum value of watershed sub division is dependent upon the output of interest and suggested 3%, 2%, and 5% (of total watershed area) as minimum threshold sub watershed size for sediment, nitrate, and inorganic phosphorous prediction, respectively. Jha et al. attributed the difference in sediment yield to channel process (deposition and degradation) due to change in drainage density and slope, and not to the overland slope as suggested by Bingner et al. (1997). Findings of Jha et al. seem more logical because overland slope is calculated based on DEM data resolution and therefore sub watershed division level is not expected to have any significant effect on overland slope. Drainage density and channel slope on the other hand are dependent upon sub watershed division level, and therefore can affect sediment yield.

FitzHugh and Mackay (2000) also found that sediment prediction was very sensitive to size of sub watersheds. Effect on sediment yield was due to the sensitivity of runoff component in MUSLE (Modified Universal Soil Loss Equation) equation. FitzHugh and Mackay also emphasized the importance of channel time of concentration in MUSLE equation, and recommended further research to determine model behavior for watersheds larger than the one considered (48 km^2) in their study. Both Jha et al. and

FitzHugh and Mackay did not find streamflow output to be sensitive to sub watershed divisions.

Arabi et al. (2006) found that BMP simulations (sediment and nutrient load) to be very sensitive to sub watershed division in SWAT. They suggested that a threshold average sub watershed size of 4% of total watershed area is required to model BMP effectiveness in 6.2 km^2 Dreisbach watershed in Indiana and 7.3 km^2 Smith Fry watershed in Indiana. Consistent with previous findings by Jha et al. and FitzHugh and Mackay, channel slope and sediment generation from upland area were cited as critical factors affecting model results.

2.4 Parameter estimation

Distributed watershed models are highly parameterized – SWAT, for example, has twenty six parameters for flow components, six for sediment, and nine for water quality, and many of these parameters can have different values for each basic calculation unit (HRUs) in the model. Model results can be in acceptable range for one set of parameter values, but can become totally unacceptable for another set of parameter values for the same given input. Therefore determining acceptable set of parameters is critical in creating a successful watershed model. However, it is not feasible to determine these parameters from experiments because of several reasons such as cost involved in experimental setup, physical variability present in the watershed, interaction among different parameters and scale issues. Consequently, parameter values are determined by calibration process within the modeling framework (Eckhardt and Arnold 2001, Rouhani et al. 2007).

There are two calibration approaches: manual and automatic calibration. Manual calibration for SWAT model is explained in detail by Santhi et al. (2001), but this process is time consuming and subjective depending on modeler preference and expertise. Therefore, manual calibration is not a preferable option when large numbers of parameters are involved (Eckhardt and Arnold 2001, Eckhardt et al. 2005).

Duan et al. (1992) suggested Shuffled Complex Evolution- University of Arizona (SCE-UA) algorithm for automatic model calibration that has been extensively used in hydrologic model calibration (Sorooshian et al. 1993, Eckhardt and Arnold 2001, Van Griensven et al. 2002, Eckhardt et al. 2005). SCE-UA is a global search algorithm belonging to the family of genetic algorithms. It samples population (parameter set) from entire feasible space (upper and lower bound specified by user) and based on evolutionary steps, entire population converges towards the neighborhood of global optimum. Eckhardt and Arnold (2001) used SCE-UA algorithm for calibrating 18 parameters of SWAT-G model, and concluded that automatic calibration can be successfully used for calibration of complex distributed hydrologic models.

Van Griensven et al. (2002) employed auto calibration preceded by sensitivity analysis with multi objective and multi site criterion for river water quality modeling in Belgium using ESWAT (Extended SWAT). Total seventeen objective functions (OFs) were defined at three sites (representing flow, Dissolve Oxygen, Biological Oxygen Demand, Ammonia, Nitrate, and Phosphate at three sites) in Dender River watershed, and they were normalized to form Global Optimization Criterion (GOC). SCE-UA algorithm was used to minimize GOC for 32 parameters selected during sensitivity analysis. Because streamflow and water quality are related, using multi-objective calibration (instead of doing step by step calibration i.e. first flow then water quality) put more constraints on many parameters and improves their indentifiability. Results showed that GOC also correspond to optimum for individual OFs with few exceptions, and simulated results were in good agreement with measured observations for streamflow and water quality. Because of its wide range of applicability, SCE-UA algorithm has been incorporated in SWAT-2005 as auto calibration tool along with sensitivity analysis tool (van Griensven et al. 2006).

Regardless of calibration procedures used in estimating model parameters, it is not possible to find parameter values that represent the true parameter set. Because of inherent assumptions and simplifications in model structure, and errors associated with input and observed datasets, there can be several parameter sets that can produce similar model response for a given input. This concept of non-unique parameter sets is called '*equifinality'* (Beven, 1993). Identification of uncertainty associated with different stages in modeling process such as input data uncertainty, parameter uncertainty and model output uncertainty, is a major area of research in hydrologic modeling.

Many studies exist where model output uncertainty have been documented (Muleta and Nicklow 2005, Arabi et al. 2007 (a)), but these studies are based on one model configuration (spatial scale). As explained in previous sections (Sections 2.2 and 2.3) model spatial scale itself can be a major factor affecting model output, but little information is available on how model spatial scale affects calibrated model parameters and results. Therefore the focus of present research is to study the effect of model spatial scale on model calibration and parameter uncertainty.

2.5 Summary

Previous works related to effect of input data resolution and watershed sub division on hydrologic modeling are summarized in this chapter. Resolution of input data in combination with watershed sub division determines model spatial scale. Effect of model spatial scale depends on output of interest, and in general, coarser resolution model resulted in erroneous results compared to finer resolution model. Apart from model spatial scale, work related to calibration of semi distributed hydrologic model is also covered in this chapter. Because of large number of parameters associated with semi distributed model such as SWAT, manual calibration is very difficult if not impossible. Shuffled Complex Evolution algorithm (SCE-UA) developed by Duan et al. (1992) has been extensively used as auto calibration tool in hydrologic studies. Further, work related to non uniqueness of model parameter set is presented.

CHAPTER 3 STUDY AREA, DATA AND MODEL DESCRIPTION

3.1 Study Area

St. Joseph River watershed located at intersection of Michigan, Ohio and Indiana states (Figure 3.1 (a)) is used as test bed for research in this study. SJRW is an 8-digit HUC (Hydrologic Cataloging Unit) watershed with HUC number: 04100003. The 100 mile St. Joseph River originates at the Hillsdale County in Michigan and flows in NE-SW direction through south central Michigan, northwest Ohio and northeast Indiana covering 8 counties (Figure 3.1 (b)). St. Joseph River meets St Mary River near the city of Fort Wayne in Indiana to form river Maumee, which flows to Lake Erie, one of the Great Lakes. Indiana covers major portion (56%) of 280,000 ha SJRW, whereas Ohio and Michigan cover 22% each. SJRW has varied topography, starting from rolling hills in upstream part to level plain downstream.

Located in the heart of mid-west, SJRW is an agriculture-dominated watershed (53.6%) with major crops being corn and soybeans (Amabile et al., 2006). Other dominant land use types are hay (17.4%), deciduous forest (10.8%), and urban land (7.4%). St. Joseph River is the main source of drinking water for 200,000 people in the city of Fort Wayne. Peak level of Atrazine (an herbicide) higher than 3 ppb (EPA drinking water standard) was reported in this watershed between 1995 and 1998 (Amabile et al., 2006).

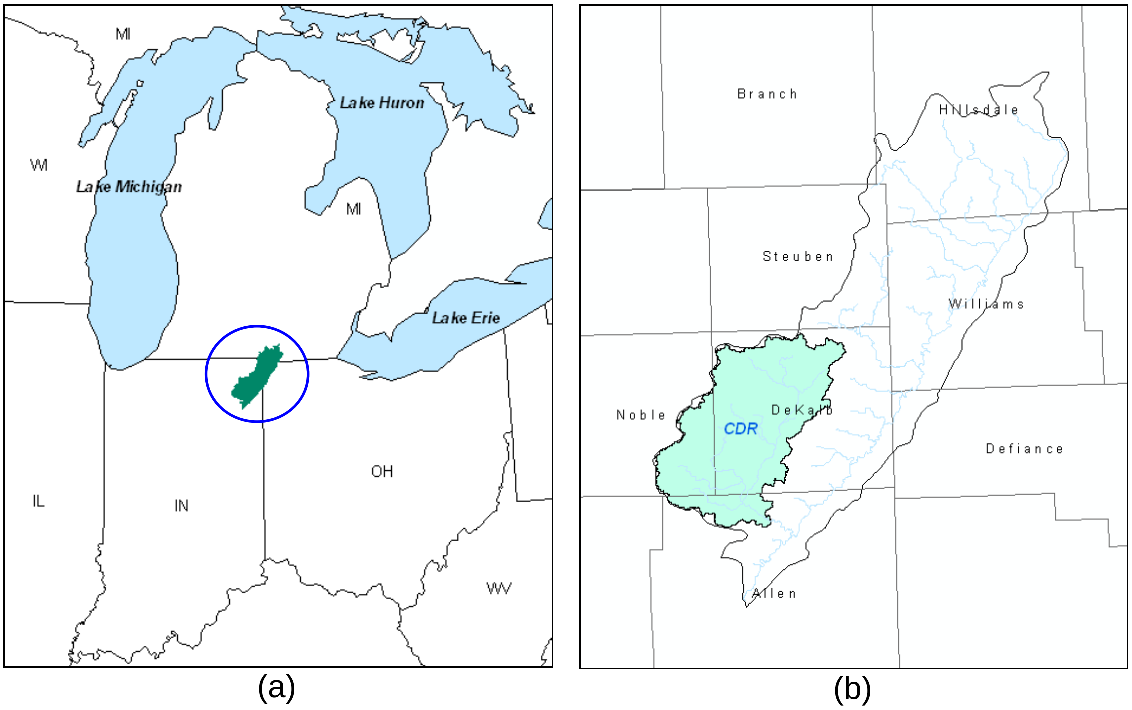


Figure 3.1 SJRW (a) in Great Lakes region, USA (b) with counties and Cedar Creek (CDR)

St. Joseph River Watershed Initiative (SJRWI), which is one of the several environmental groups working towards improving water quality of St. Joseph River through environmental friendly land use management practices (http://www.sjrwi.org/) has been monitoring water quality in SJRW since 1996. In 2005, SJRWI had 25 water quality sampling stations in the watershed, and reported decreasing trend in the atrazine concentration, but found elevated concentration of metolachlor concentration (another herbicide). SJRWI identified sediment loading as one of the major concerns in several areas of SJRW. USDA ARS (United States Department of Agriculture Agriculture Research Service) National Soil Erosion Research Laboratory (West Lafayette, Indiana) is also working in SJRW to study agricultural chemicals concentration in drinking water source and effect of Best Management Practices (Flanagan et al., 2003; Amabile et al., 2006).

Besides SJRW, Cedar Creek, one of the major sub watersheds within SJRW is also used in this study. Cedar Creek (Figure 3.1 (b)) has total drainage area of 70731 hectares, covering part of Allen, De-Kalb and Nobel counties in Indiana. Cedar creek is included in Indiana's State Natural, Scenic and Recreational River System, which protects this sub-watershed from any major human alteration or interference (SJRWI, 2006).

3.2 Data

Selection of appropriate data to build a model is a vital part of hydrologic modeling process. Resolution of input data determines the extent to which physical variability can be incorporated in the model. Although one may want to incorporate maximum watershed variability in a model, there are constraints in terms of resolution of available data and model's computational efficiency. The overall approach in creating a hydrologic model is to achieve a good compromise among model's realizations of actual hydrologic system, data availability, and computational efficiency. This section provides a brief description of data used to create SJRW model based on literature review and modeling objectives.

3.2.1 Digital Elevation Model (DEM)

One arc second (30m resolution) Nation Elevation Dataset (NED) DEM available from USGS is used in this study. The DEM is downloaded from http://seamless.usgs.gov/ and projected to Universal Transverse Mercator (UTM) NAD83 (North American Datum 1983), Zone 16 (Figure 3.2 (a)).

3.2.2 National Hydrographic Dataset (NHD)

High (1:24,000 scale) and medium resolution (1:100,000 scale) NHD are downloaded from http://nhdgeo.usgs.gov/ and projected to NAD 1983, UTM Zone 16 (Figure 3.2 (b)). NHD sub watershed feature is used to define the extent for data pre-processing and high resolution NHD flow line features are used to burn stream line into the DEM during watershed delineation process.

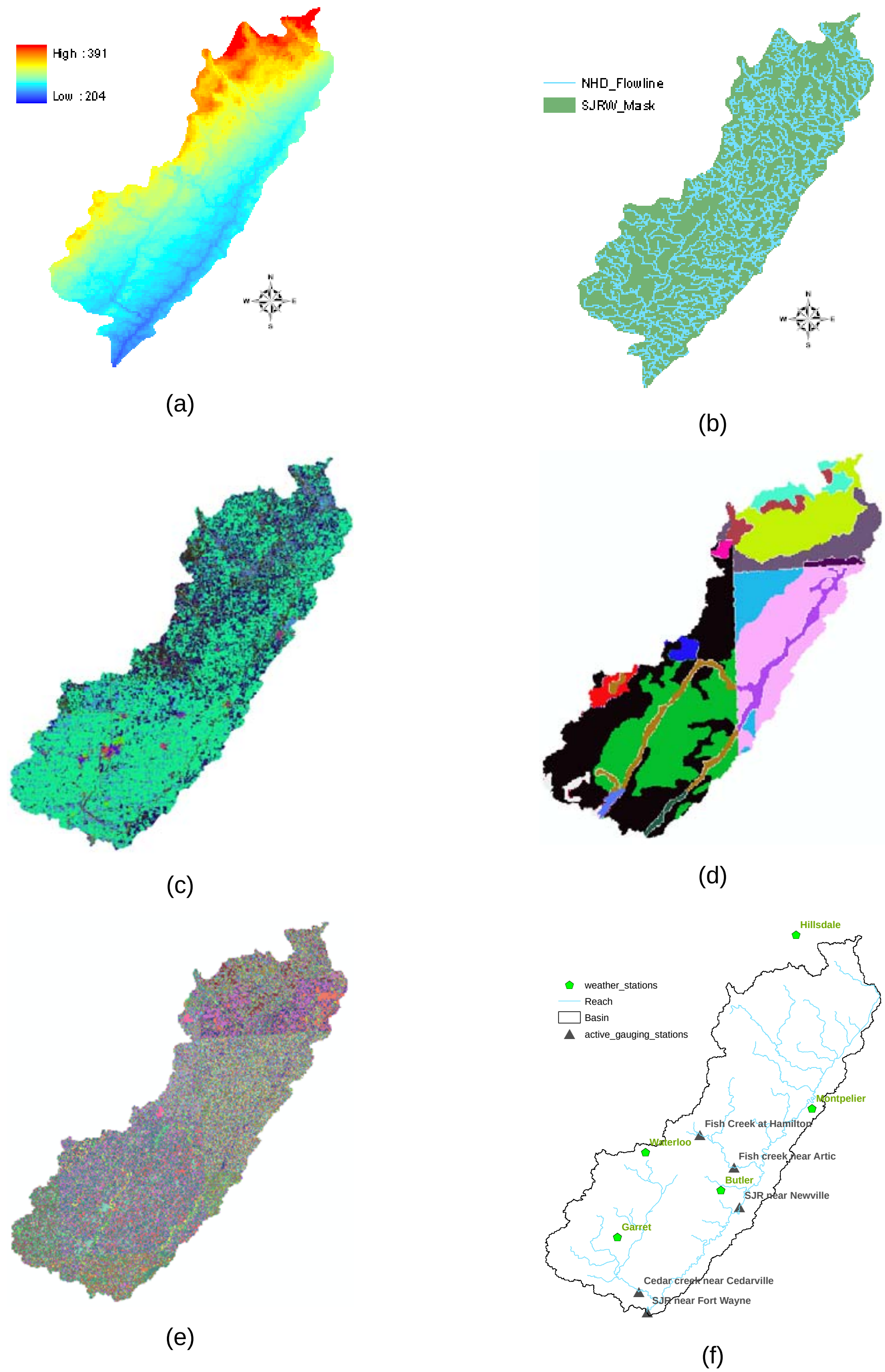


Figure 3.2 (a) DEM (b) NHD sub watershed and flowline (c) NLCD 2001 land cover data (d) STATSGO soil data (e) SSURGO soil data (f) Weather and Stream gauging stations for SJRW

3.2.3 Land Cover

National Land Cover Dataset (NLCD) 2001 is obtained form USGS website (http://seamless.usgs.gov/). NLCD-2001 is developed by Multi-Resolution Land Characteristics Consortium (MRLC) and has 16 land cover classes over conterminous U.S.A. Land cover data are generated from standardized set of data layers consisting of multi-season Landsat 5, Landsat 7 imagery, and DEM and its derivatives (slope, aspect, positional index) collected during year 2001 (Homer et al., 2007). In addition to land cover classes, it has separate data layers for tree canopy percentage and urban imperviousness percentage. For the SWAT model, only land cover data are used because SWAT does not have the provision to incorporate other NLCD layers in the model. Land cover data for SJRW is shown in Figure 3.2 (c). Table 3.1 describes mapping of NLCD 2001 land cover classes to SWAT land Use class (LU SWAT). Brief definitions of the major land cover classes in the watershed are given below (http://www.mrlc.gov/nlcd_definitions.asp).

Cultivated Crops - Area used for annual crop production including orchards and vineyards. Crop vegetation accounts for more than 20 % of total vegetation cover.

Pasture/Hay - Area planted for livestock grazing such as grass and legumes, or for the production of seeds and hay crops. Pasture/Hay vegetation are more that 20 % of the total vegetation cover.

Deciduous Forest - More than 20% of the vegetation cover are dominated by trees taller than 5 meters. 75% or more trees shed foliage simultaneously in response to seasonal changes.

Woody Wetland – More than 20% of the vegetation cover is forest or shrub-land. Soil or substrate is periodically saturated or covered with water.

Developed, Open Space – Mixture of some constructed or paved surfaces (less than 20%), but mostly vegetation in the form of lawn grasses such as parks and golf courses.

Developed, Low Intensity – Mixture of constructed or paved surfaces (20-49%) and vegetation such as single-family housing units.

Open Water– All area of open water, vegetation and soil cover less than 25%.

Developed, Medium Intensity – Impervious surface 50-79%, remaining area is covered by vegetation.

Developed High Intensity – Highly developed residential/commercial/industrial area, impervious surface 80 to 100%.

Table 3.1 Land Use classes in the St. Joseph River Watershed

LU SWAT	NLCD-2001 Land Cover Class	% Area
AGRR	Cultivated Crops	53.64
HAY	Pasture/Hay	17.37
FRSD	Deciduous Forest	10.79
WETF	Woody Wetland	7.17
URLD	Developed, Open Space	5.16
URMD	Developed, Low Intensity	2.2
WATR	Open Water	1.16
RNGB	Shrub/ Scrub	0.59
RNGE	Grassland/ Herbaceous	0.59
URHD	Developed, Medium Intensity	0.46
WETN	Emergent Herbaceous Wetland	0.37
UIDU	Developed, High Intensity	0.2
FRSE	Evergreen Forest	0.19
FRST	Mixed Forest	0.06
SWRN	Barren Land (Rock, Sand, Clay)	0.05

3.2.4 Soil Data

STATSGO (The Sate Soil and Geographic) and SSURGO (The Soil Survey and Geographic) soil data available from USDA NRCS (United Sates Department of Agriculture Natural Resource Conservation Services) are used in this study. Brief descriptions of these datasets are provided below.

STATSGO data set

The 1:250,000 scale Sate Soil and Geographic (STATSGO) data has map units that have a minimum area of 1544 acres or larger. Unlike land use data that are generated using satellite data (Landsat 5 and 7), soil data are developed based on field soil surveys. Field survey maps are used to create soil data in spatial and tabular format that can be combined to form a GIS layer. STATSGO data set, which is also known as U.S. General Soil Map Coverage, can be downloaded from the soil data mart (http://soildatamart.nrcs.usda.gov/). SJRW has total 17 STATSGO soil types (Figure 3.2 (d)). Because of its coarser resolution, STATSGO is not suitable for modeling at county level or below. Major soil hydrologic group (75%) present in SJRW is Class C.

SSURGO data set

The 1:24,000 scale Soil Survey Geographic (SSURGO) data are available county wise from USDA NRCS website (http://soildatamart.nrcs.usda.gov/) and contain most detailed information about soil types. Minimum single unit size in SSURGO data varies between 1.5 to 40 acres. SSURGO data cannot be used directly in ArcSWAT, and the procedure used to incorporate SSURGO data into SWAT is described in Appendix A of this thesis. SSURGO data has 433 soil types as shown in Figure 3.2 (e). Major soil hydrologic group (90%) present in SJRW is Class C.

3.2.5 Weather Data

SJRW has five NCDC (National Climatic Data Center) weather stations as shown in Figure 3.2 (f) and Table 3.2. Daily precipitation (pcp) and temperature (maximum and minimum) data for these stations are available from NOAA (National Oceanic and Atmospheric Administration) website (http://www.ncdc.noaa.gov/oa/ncdc.html). Annual average precipitation for study period (1990-2003) is 955 mm. January is the coldest month with a daily average maximum temperature of 0.1 degree C and minimum of -8.4 degree C. July is the warmest month with daily average maximum temperature of 28.5 degree C and minimum of 15.9 degree C. SWAT uses inbuilt weather generator function to generate solar radiation, relative humidity and wind speed data based on long term monthly average values available in the model.

3.2.6 Streamflow data

SJRW has five active stream gauging stations as shown in Figure 3.2 (f) and Table 3.3. Annual average streamflow at Fort Wayne stream gauging station, which is considered as outlet for SJRW, is 29.10 m^3/s for simulation period (1993-2003). Annual variability in precipitation and streamflow for study period is shown in Figure 3.3. Annual minimum and maximum values for precipitation are 757.7 mm (1994) to 1113.6 mm (2003), respectively, and for streamflow are 231.4 mm (1995) and 467.0 mm (1997), respectively. To incorporate dry and wet years daily streamflow data from 1993 to 1999 (7 years) are used for calibration and data from 2000 to 2003 (4 years) are used for validation. Three years from 1990 to 1992 as are taken as warm-up period for the model.

Table 3.2 Weather gauging stations in the SJRW

Sl. No.	Stations	COOPID	Available Data
1	Butler 1 SE, IN	121187	01 Sept. 1999 to present (only pcp)
2	Garrett 1 S, IN	123207	23 Jan. 1989 to Present
3	Hillsdale, MI	203823	01 Jan. 1948 to Present
4	Montpelier, OH	335438	01 Jan. 1948 to Present
5	Waterloo 2 NW, IN	129271	01 Dec. 1939 to 14 Dec. 2003 (only pcp)

3.3 Model Description

Soil and Water Assessment tool (SWAT) is a process based semi-distributed watershed model (Neitsch et al., 2005) developed by the United States Department of Agriculture (USDA) to study impact of land management practices on water, sediment and agricultural chemical yields in large ungaged basins. SWAT operates on daily time step, and is intended for long-term simulation (up to 50-100 years) (Arnold et al. 1998).

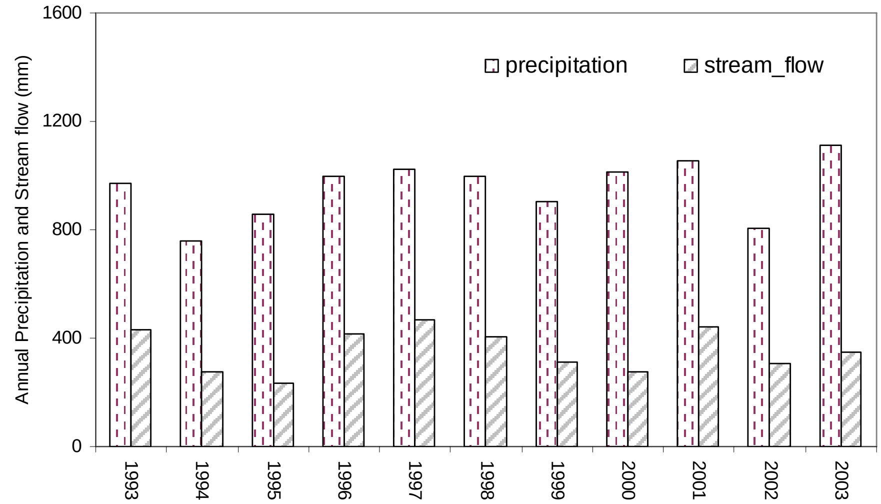


Figure 3.3: Annual Precipitation (basin average) and Streamflow at Fort Wayne

Table 3.3 Stream gauging stations in SJRW

Sl. No.	Stations	Station Number	Available Data
1	St. Joseph River near Fort Wayne, IN	4180500	08 Aug 1941 to present
2	Cedar creek near Cedarville, IN	4180000	30 Oct. 1946 to present
3	St. Joseph River near Newville, IN	4178000	21 Nov. 1946 to present
4	Fish Creek near Artic, IN	4177810	08 April 1998 to Present
5	Fish Creek Near Hamilton, IN.	4177720	01 Oct. 1969 to Present

In SWAT, a watershed is divided into a number of sub units at two levels. First a watershed is divided into sub watersheds and then each sub watershed is further sub divided into basic calculation units called Hydrologic Response Units (HRUs). A watershed is divided into sub watersheds by providing minimum source area for stream generation (Critical Source Area, CSA) during watershed delineation. HRUs are generated by fixing threshold values for land use and soil type as percentages of sub watershed area. Land use and soil type having area below specified thresholds are not considered in the model and those areas are proportionally assigned to the land use and soil types having higher percentage area in respective sub watersheds. Therefore HRU is an unique combination of land use and soil type in a sub watershed. All calculations in SWAT are performed at HRUs level. Major components of SWAT include surface runoff, percolation, groundwater, evapotranspiration, channel routing, plant growth, fertilizer and pesticide application, pond and reservoir storage, and water transfer. A brief description of SWAT hydrologic component is provided in the following section. Sediment and water quality components are not described and, one may refer to SWAT Theoretical Documentation (Neitsch et al., 2005) for complete model description.

3.3.1 Hydrology

Hydrologic component in SWAT works on water balance equation for soil water content in the root zone (Figure 3.4) as given in Equation 3.1.

$$SW_t = SW_0 + \sum_{t=1}^{t} (R_i - Q_{surf\,i} - ET_i - P_i - QL_i) \qquad 3.1$$

Where SW_t is final soil water content (mm water), SW_o is initial soil water content (mm water), t is time (days), R_i is precipitation, $Q_{surf\,i}$ is surface runoff, P_i is percolation and QL_i is lateral flow on day i (mm water). Percolation becomes a part of groundwater and a portion of groundwater appears as baseflow in the stream, whereas lateral flow (QL_i) directly contributes to streamflow in the basin.

Surface Runoff

SWAT uses two methods for surface runoff calculation: (1) SCS curve number method, and (2) Green -Ampt infiltration method (Green and Ampt, 1911). It is reported in literature that SCS curve number performs better than Green-Ampt method (Ponce and Hawkins 1996, Kannan et al. 2007). In addition, Green-Ampt infiltration method requires hourly precipitation data, and flow routing at hourly time step which makes the model computationally demanding for long-term simulations. Therefore SCS Curve Number method is used in this study. Curve Number for antecedent moisture condition II (*CN2*) are adjusted for sub watershed slope in the model, and these values are updated on daily time step based on soil moisture conditions in the root zone.

Percolation

Soil is divided into several layers and water is assumed to percolate through these layers to reach shallow aquifer depending upon moisture condition in each layer. When soil moisture present in a layer is more than field capacity (water content corresponding to 1/3 bar suction pressure), water can travel to another layer below. Percolation rate is maximum (saturated hydraulic conductivity) at saturation and decreases to zero at field capacity. Storage routing technique combined with crack flow is used to model flow through each soil layer. When the soil is dry and cracked, water can just drain through the cracked layer without affecting its water content. Temperature also affects the percolation rate, which drops to zero when soil temperature is below zero degree C. Water that percolate through all layers becomes part of groundwater, thus partly contributing baseflow to a stream.

Lateral flow

Soil water above saturation flows laterally to streams. A kinematic storage model (Sloan et al., 1983) is used to model lateral flow through each soil layer. Lateral flow volume depends upon soil layer properties (saturated hydraulic conductivity and porosity), terrain slope, and flow length.

Groundwater flow

Groundwater component in SWAT is modeled as two aquifer system consisting of shallow (unconfined) and deep aquifer (confined) (Figure 3.4). Recharge to shallow aquifer from percolation is divided into two parts: one part goes into deep aquifer and never returns to the stream, while the remaining part in shallow aquifer contributes to the stream as baseflow besides satisfying a portion of evaporative demand in the root zone (*revap*).

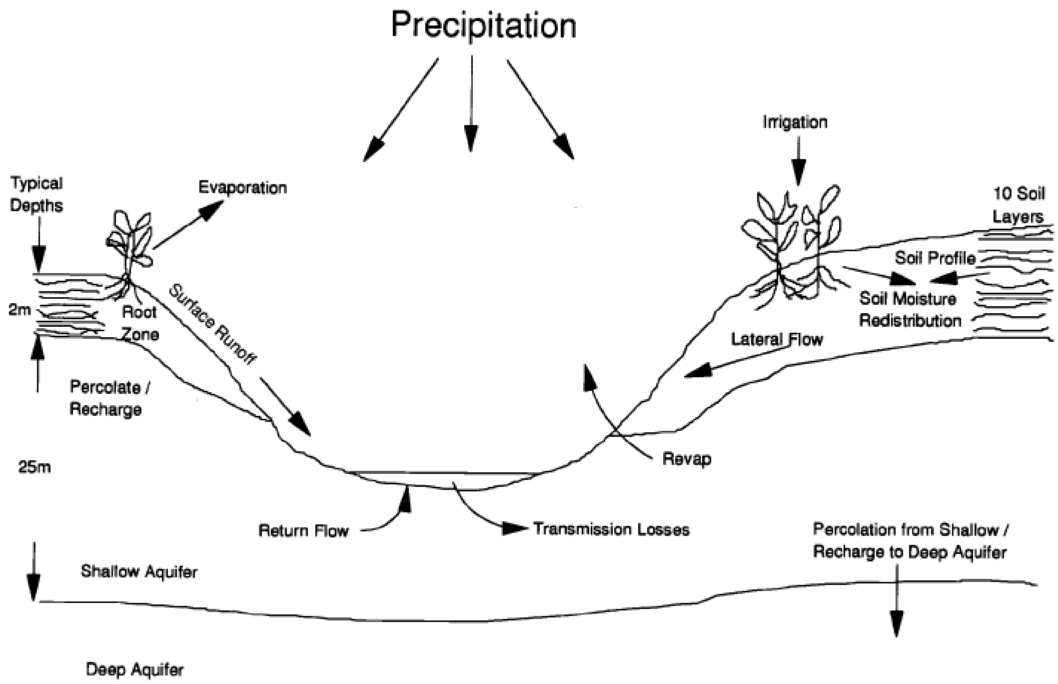


Figure 3.4 Hydrologic components in a HRU (adopted from Arnold et al. 1998)

The time for water leaving the root zone and reaching shallow aquifer is modeled through groundwater delay factor (*Gw_dealy*) as proposed by Venetis (1969). A user defined fraction (*deep aquifer percolation coefficient*) is used divide total recharge into deep aquifer recharge and shallow aquifer recharge. If water in shallow aquifer is more than user defined threshold value (*Gwqmn*), then it will contribute to stream as baseflow. Water table fluctuations are modeled as change in baseflow rate from shallow aquifer to the stream using a constant factor defined as baseflow recession constant (α_{bf}). If soil profile is not able to meet its evaporative demand, then a portion of the evaporative demand (defined by *revap coefficient*) is met by shallow aquifer if it has more water than the specified threshold value (*revap threshold*).

Evapotranspiration

SWAT has three options to calculate potential evapotranspiration: Hargreaves (Hargreaves and Samani, 1985), Priestley-Taylor (Priestley and Taylor, 1972) and

Penman-Monteith (Monteith, 1965). Hargreaves method requires only daily air temperature, Priestley-Taylor requires solar radiation and air temperature, whereas Penman-Monteith method requires solar radiation, air-temperature, wind-speed, and relative humidity as inputs. Kannan et al. (2007) found that Hargreaves method performs as good as more complex energy based Penman-Monteith method.

Potential evapotranspiration is the maximum amount of evapotranspiration that can take place in a HRU. Actual evapotranspiration in SWAT is calculated based on availability of water in different storage volume such as canopy storage and soil moisture. Actual evapotraspiration may or may not match potential evapotranspiration. Evaporative demand is met in a sequential order i.e., at any stage in the sequence if potential evapotranspiration demand is met, no further demand will be there from the stages below. First all canopy water is removed, and then remaining evaporative demand is met by plant transpiration and soil moisture evaporation. If ground is covered with snow then soil evaporation demand is first met by sublimation of snow. During the period of high plant use, evaporative demand from soil layer decreases.

Transmission loss

When a channel runs through a semi arid region, it looses water when water table is at lower level compared to the channel bottom. SWAT calculates transmission loss using Lane's method (USDA, 1983) as a function of channel width, length and flow duration.

Snow Hydrology

Input daily time series of precipitation is partitioned into rainfall and snow based on threshold value of average daily temperature. If average daily temperature is less than the threshold temperature (*Sftmp*) then precipitation is classified as snow. Snow melt occurs when the average of snow pack temperature (T_{snow}) and daily maximum air temperature (T_{max}) is more that base temperature required for snow melt to occur

(*Smtmp*). Snow melt factor (b_{mlt}, mm water/day-degree C) varies for different days of the year, it is maximum for June 21 and minimum for December 21. Snow melt factor also varies for different land use types. For example, in urban areas snow melt rate can be higher (3 to 8 mm water/day-degree C) because of high vehicular and pedestrian traffic, but in rural area it can be lower (1.4 to 6.9 mm water/day-degree C). Snow melt is treated same as rainfall for surface runoff and percolation calculation except that rainfall energy is set to zero (no erosion) and peak runoff rate is estimated by assuming uniformly distributed rainfall for 24 hour duration.

3.3.2 Flow Routing

Volume of water to be routed (surface runoff + lateral flow + baseflow– transmission loss) are calculated for each HRU and then added to find out total volume of water to be routed from a sub watershed. Channel length in each sub watershed is computed using stream network, and channel dimension are provided by user (bank full width, depth and side slope). Cross sectional area for flow is calculated by dividing volume of flow to be routed by length of the channel. Manning's equation (manning's n is provided by user) for uniform flow is used to determine flow rate and velocity.

In SWAT, water can be routed though channel network by using either the variable storage method (Williams, 1969) or Muskingum River routing method using daily time step. In addition to transmission loss, channel also looses water through evapotranspiration, which is a function of water surface area in the channel. Evaporation loss in each reach (channel segment) is subtracted from total volume before routing the flow through next reach.

3.4 Summary

A brief description of study area, data and model used for the study are provided in this chapter. Agricultural dominated SJRW located at intersection of Indiana Ohio and Michigan states is used as test bed in this study. Datasets used for modeling SJRW are

DEM, NHD flow line and sub watershed feature, NLCD 2001 land cover data, SSURGO and STATGO soil data, daily temperature and precipitation data from five National Weather Service stations, and daily streamflow data from two USGS gauging stations. Soil and Water Assessment Tool (SWAT) is used as modeling tool in the study.

CHAPTER 4 WATERSHED DISCRETIZATION AND ATTRIBUTES

4.1 Introduction

Discretization of a watershed into smaller units or sub divisions plays an important role in representing physical variability of the watershed in a hydrologic model. Discretization essentially represents the scale of integration of input information in the model. Finding an optimum level of discretization that can maintain hydrologically significant variability in the model without affecting computational efficiency for calibration and long term prediction is a critical step in creating a hydrologic model. The objective of this chapter is to study the effect of watershed discretization on watershed attributes such as number of sub watersheds and HRUs, drainage density (DD), Curve Number (*CN2)*, sub watershed and channel slope, and soil characteristics. First SJRW was discretized and then one of SJRW's sub watershed, Cedar Creek was discretized to see how discretization affects watershed attributes for larger and smaller watersheds.

4.2 SJRW configurations

Seven SJRW model configurations are created corresponding to CSA of 0.3%, 0.5%, 1.0%, 2.0%, 3.0%, 5.0% and 7.0% of the total watershed area. Each configuration resulted into different stream network, and the watershed is delineated for stream gauging station at Fort Wayne (station number: 4180500) as the watershed outlet (Figure 3.2 (f)). Because same DEM and watershed outlet are used for creating different watershed configurations, the delineated watershed area (257990 ha) is unchanged for all watershed configurations. Each configuration is further divided into HRU's using 10% threshold for land use (NLCD-2001 land use data) and 5% threshold for two different soil types (STATSGO and SSURGO), thus creating 14 configurations (7 for STATSGO and 7 for

SSURGO). SJRW configurations with SSURGO data are referred as AX, and SJRW configurations with STATSGO data are referred as BX wherever necessary, where X is %CSA for the configuration. For example A1.0 stands for SJRW configuration with 1.0% CSA and SSURGO soil data, and B1.0 stands for SJRW configuration with 1% CSA and STATSGO soil data. Watershed attributes corresponding to each configuration are discussed in following section.

4.3 Watershed Attributes for SJRW

4.3.1 Sub watersheds

Number of sub-watersheds decreased from 180 for 0.3% CSA to 10 for 7.0% CSA (Table 4.1, Figure 4.1). Sub watershed size affects further discretization of watersheds into HRUs. Larger sub watershed size will eliminate many minor land use and soil type having area below the threshold specified for land use (10%) and soil type (5%). Eliminated land use and soil type area are assigned to dominant land use and soil types (having area higher than the specified threshold) thus making the model biased towards dominant land use and soil types. One such example for soil hydrologic group is discussed in section 4.3.7.

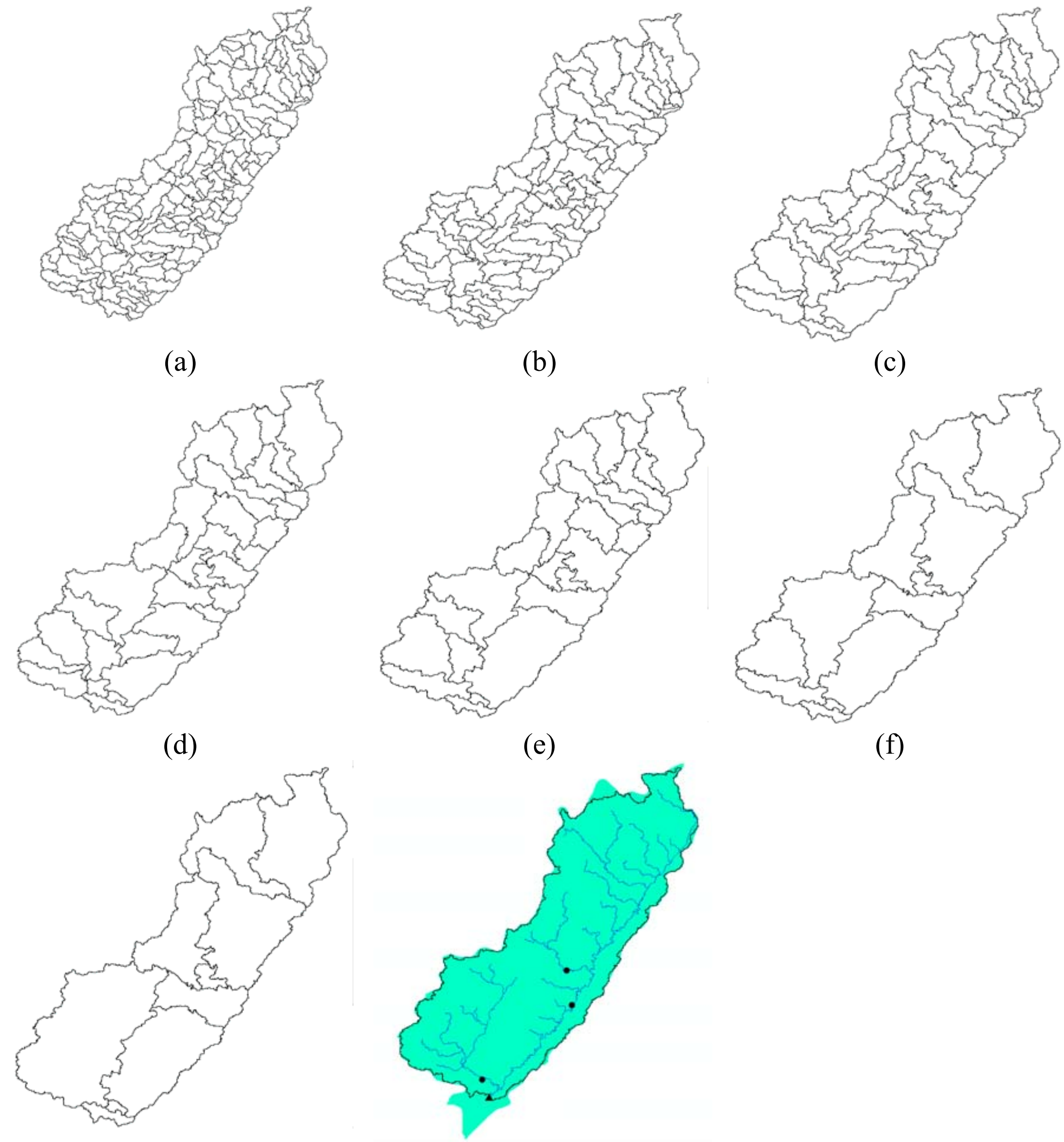
4.3.2 Drainage Density (*DD*)

Drainage density (DD) is ratio of the total channel length to total watershed area (km/km^2). DD decreased from 0.33 km/km^2 for 0.3% CSA to 0.08 km/km^2 for 7.0% CSA (Table 4.1, Figure 4.2, and 4.3 (a)). DD for medium resolution (1:100,000 scale) NHD flow line is 0.65 km/km^2. DD can affect instream processes such as transmission losses, flow rate and velocity, channel bed erosion, and deposition.

Table 4.1 Watershed attributes for SJRW configurations

Model	CSA (%)	# Sub watersheds	DD (km/km^2)	*Ch_slope* (%)	*B_slope* (%)	*Lp* (km)	# of HRUs SSURGO	# of HRUs STATSGO	Average CN2 SSURGO	Average CN2 STATSGO
SJRW	0.3	180	0.33	0.14	2.21	12	2283	903	78.86	78.19
	0.5	97	0.27	0.13	2.21	18	1209	558	79.34	78.28
	1.0	58	0.21	0.11	2.21	23	750	401	79.66	78.3
	2.0	36	0.15	0.09	2.21	30	391	273	80.04	78.29
	3.0	24	0.12	0.07	2.21	37	320	209	80.04	78.43
	5.0	12	0.09	0.05	2.21	54	145	110	80.48	78.7
	7.0	10	0.08	0.05	2.21	58	124	97	80.52	78.92
	NHD flow line (stream/river)		0.65	0.27	Not Applicable					
	NHD flow line (All)		0.76	0.28	Not Applicable					

CSA: Critical Source Area as % of total watershed area, DD: Drainage density, Ch_slope: Average channel slope, B_slope: Average basin slope, Lp: Average longest path in sub basin, NHD flow line (All) includes artificial path, canal, ditch, connector and stream/ river



(a) (b) (c)

(d) (e) (f)

(g) (h)

Figure 4.1 Sub watersheds of SJRW for (a) 0.3% CSA, (b) 0.5% CSA, (c) 1.0% CSA (d) 2.0% CSA (e) 3.0% CSA, (f) 5.0% CSA, and (g) 7.0% CSA, and (h) NHD HUC-04100003 sub watershed feature and delineated watershed boundary

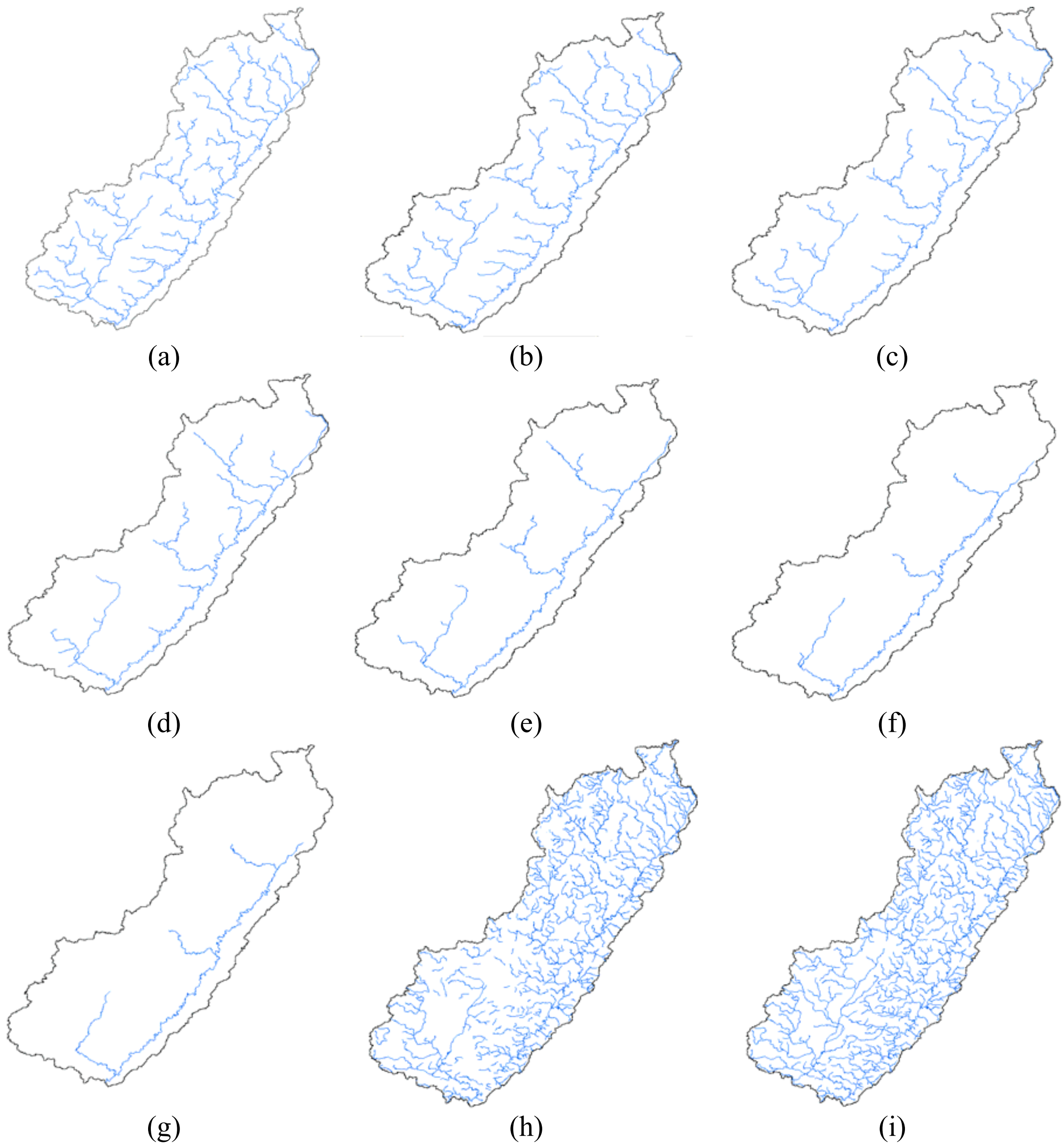
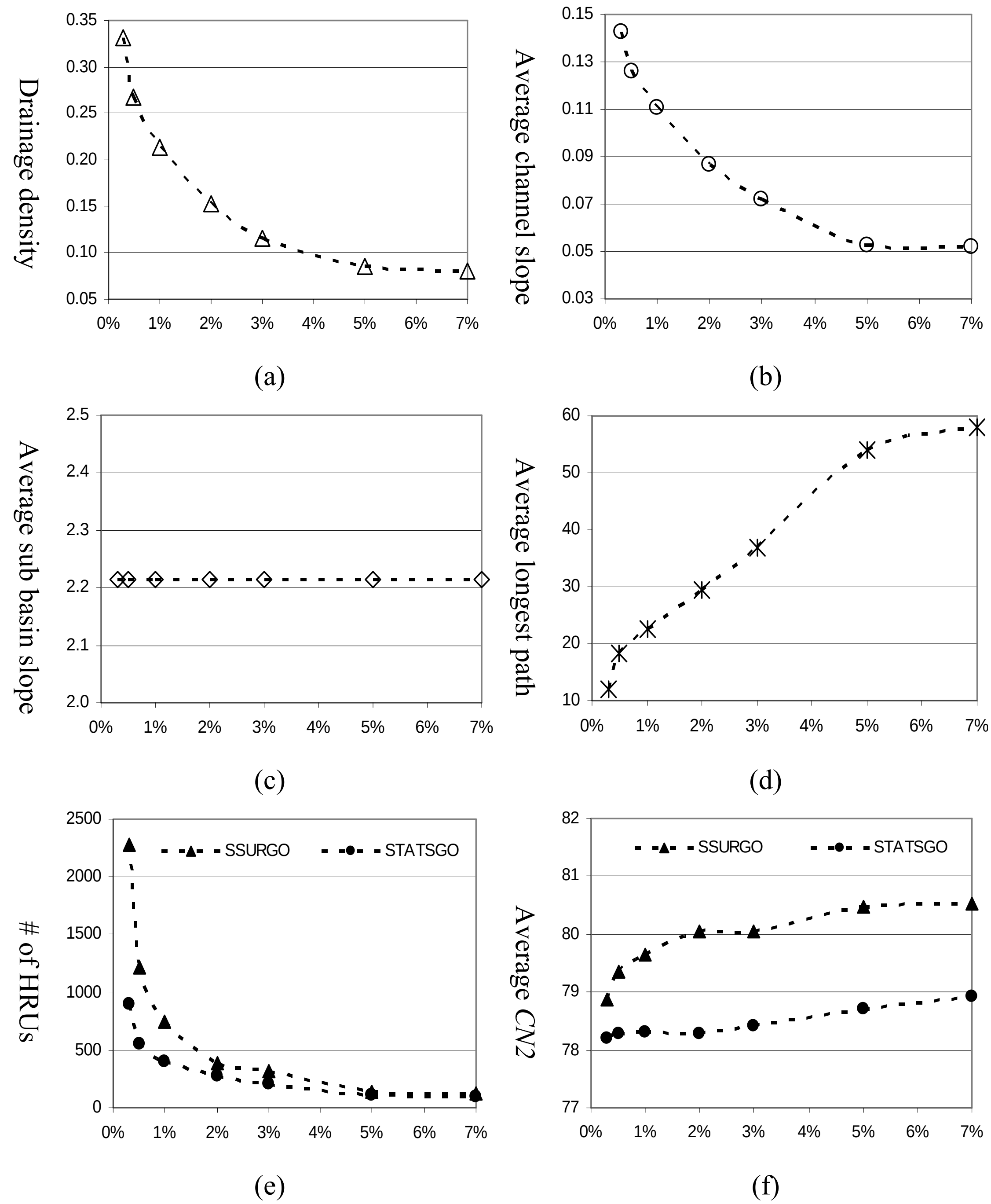


Figure 4.2 Drainage Density of SJRW configurations for (a) 0.3% CSA, (b) 0.5% CSA, (c) 1.0% CSA (d) 2.0% CSA (e) 3.0% CSA, (f) 5.0% CSA, and (g) 7.0% CSA (h) NHD flow line density (Stream and River), and (i) NHD flow line density (all)



X axis represent %CSA area of SJRW

Figure 4.3 Watershed attributes for SJRW configurations (a) Drainage density (km/km2), (b) Average channel slope (%), (c) Average sub basin slope (%) (d) Average longest flow path in a sub basin (km), (e) # of HRUs, and (f) Average CN2

4.3.3 Channel Slope (*ch_slope*)

Average channel slope decreased from 0.14% for 0.3 % CSA to 0.05% for 7% CSA (Table 4.1, and Figure 4.3 (b)). The average slope for medium resolution NHD flow line is 0.27%. Channel slope affects flow velocity (manning's equation) which in turn affects sediment load transport capacity of the channel. Increased slope can lead to higher peak velocities and higher transport capacities of the channel.

4.3.4 Sub-basin Slope (*b_slope*) and longest flow path (L_p) in the sub basin

Average sub-basin slope remained constant (2.2%) for all CSAs (Table 4.1, and Figure 4.3 (c)). Longest flow path in a sub-basin is the path traveled by water from farthest point in the sub-basin to the sub-basin outlet (named as tributary channel in SWAT). L_p increased from 12 km for 0.3% CSA to 58 km for 7% CSA (Table 4.1, and Figure 4.3 (d)). L_p has greater impact on channel time of concentration and after a certain threshold it becomes a dominant factor in reducing sediment generation from sub basins.

4.3.5 Hydrologic Response Unit (HRUs)

HRUs are the basic calculation unit in SWAT model. Any physical feature to be represented in SWAT model should have at least one HRU. Because SSURGO has total 433 soil types compared to 17 soil types in STATSGO, use of SSURGO data resulted in a higher number of HRUs compared to STATGO data. The difference in the number of HRUs is more accentuated at lower CSA values. The total number of HRUs for 0.3% CSA using SSURGO and STATGO are 2383 and 903, respectively; whereas for 7% CSA, total number of HRUs decreased to 124 and 97 for SSURGO and STATSGO, respectively (Table 4.1, and Figure 4.3(e)). To incorporate small field level details such as land management practices and differential fertilizer or pesticide application rate in the model, SSURGO data is a better option. For example, in the case of 1% CSA, average HRU area for SSURGO model is 344 ha, whereas for STATGO model, it is 643 ha.

4.3.6 Average *CN2*

Average *CN2* for SJRW show slight increase with the increasing CSA (Table 4.1, Figure 4.3 (f)). The increase in *CN2* from 0.3% CSA to 7% CSA is 2% in the case of SSURGO, and 1% in the case of STASGO. Watershed configurations with SSURGO have slightly higher average *CN2* compared to that from STATSGO. Because SCS Curve number method is used to calculate surface runoff, *CN2* value becomes an important factor in determining surface runoff.

4.3.7 Soil Hydrologic Group

Soil hydrologic group distribution for SSURGO and STATSGO data are given in Table 4.2. Major soil hydrologic group (Group C) area increased from 82.3% for 0.3% CSA to 94.7% for 7.0% CSA in the case of SSURGO, and from 74.3% for 0.3% CSA to 77.2% for 7.0% CSA in the case of STATGO. Group B soil area decreased from 13.5% for 0.3% CSA to 3.5% for 7.0% CSA in the case of SSURGO, and from 22.7% for 0.3% CSA to 21.0% for 7.0% CSA in the case of STATSGO.

4.3.8 Average Soil Available Water capacity (*sol_awc*)

Soil available water capacity is the difference between water content at the field capacity and the water content at wilting point. SWAT calculates field capacity of a soil layer based on the available water capacity of the layer. Water is allowed to percolate through a layer if water content in the layer exceeds field capacity. Higher *sol_awc* leads to higher field capacity of the soil layer. Average *Sol_Awc* remained constant across all CSA in SSURGO and STATGO configurations. However, SSURGO *sol_awc* is 25% lower than STATSGO *sol_awc* (Table 4.3). Figure 4.4 (a) and (b) show cumulative distribution of *Sol_Awc* for two extreme watershed configurations (0.3% and 7.0% CSA) for SSURGO and STATSGO data, respectively.

Table 4.2 Soil Hydrologic Group distribution for SJRW

Model	CSA	Soil Hydrologic Group (% of watershed area)							
		SSURGO				STATSGO			
		A	B	C	D	A	B	C	D
SJRW	0.3	3.9	13.5	82.3	0.4	3.1	22.7	74.3	0.0
	0.5	3.1	10.6	86.1	0.2	3.0	22.7	74.4	0.0
	1.0	2.2	9.0	88.6	0.2	3.0	23.2	74.8	0.0
	2.0	2.3	4.5	93.2	0.0	3.0	22.0	75.3	0.0
	3.0	2.3	5.0	92.7	0.0	2.8	22.0	75.2	0.0
	5.0	1.8	3.9	94.3	0.0	2.6	22.0	75.5	0.0
	7.0	1.8	3.5	94.7	0.0	1.8	21.0	77.2	0.0

Table 4.3 Average *sol_awc* and *sol_k* for SJRW

Model	CSA	sol_awc*		sol_k*	
		SSURGO	STATSGO	SSURGO	STATSGO
SJRW	0.3	0.118	0.154	26.64	21.07
	0.5	0.118	0.154	20.95	20.46
	1.0	0.115	0.154	17.20	19.97
	2.0	0.114	0.155	12.72	19.46
	3.0	0.113	0.154	12.72	19.31
	5.0	0.111	0.154	11.64	18.40
	7.0	0.110	0.153	11.42	16.97

**Sol_awc*: mm water/mm soil, *sol_k* mm/hr; these values are depth across a soil profile

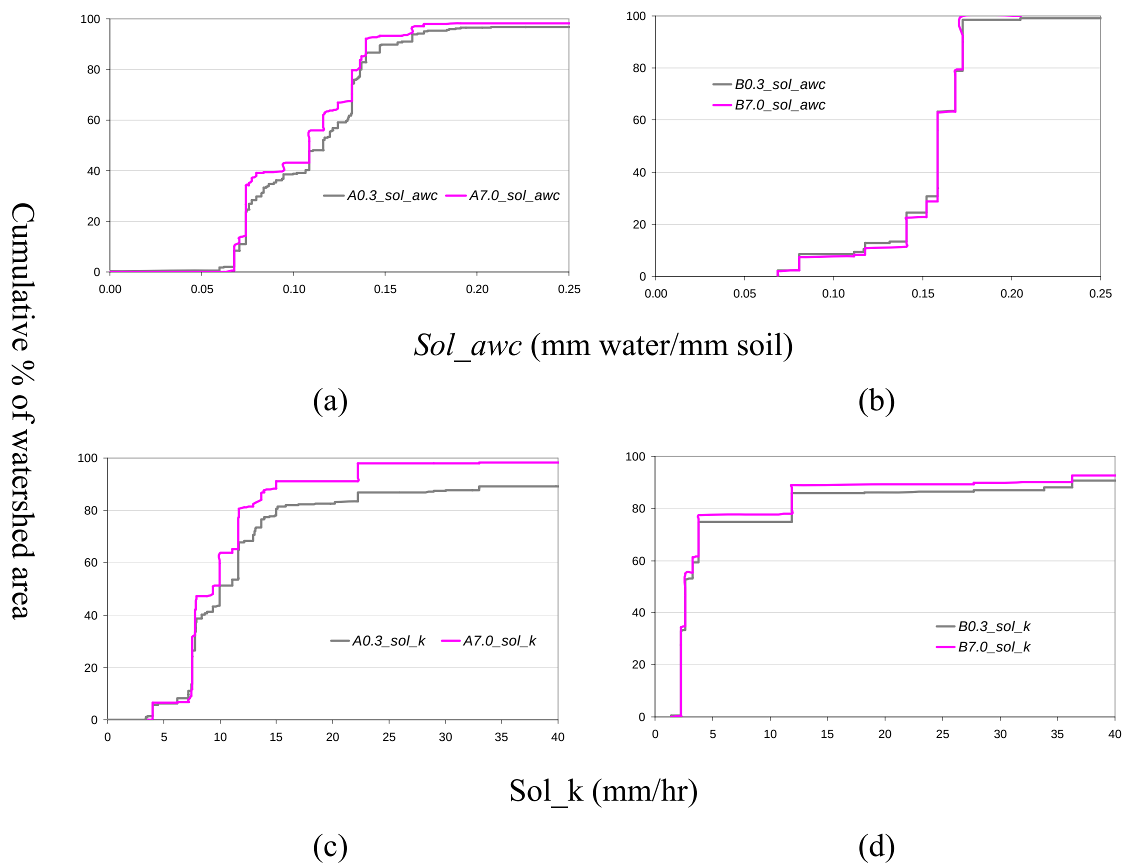


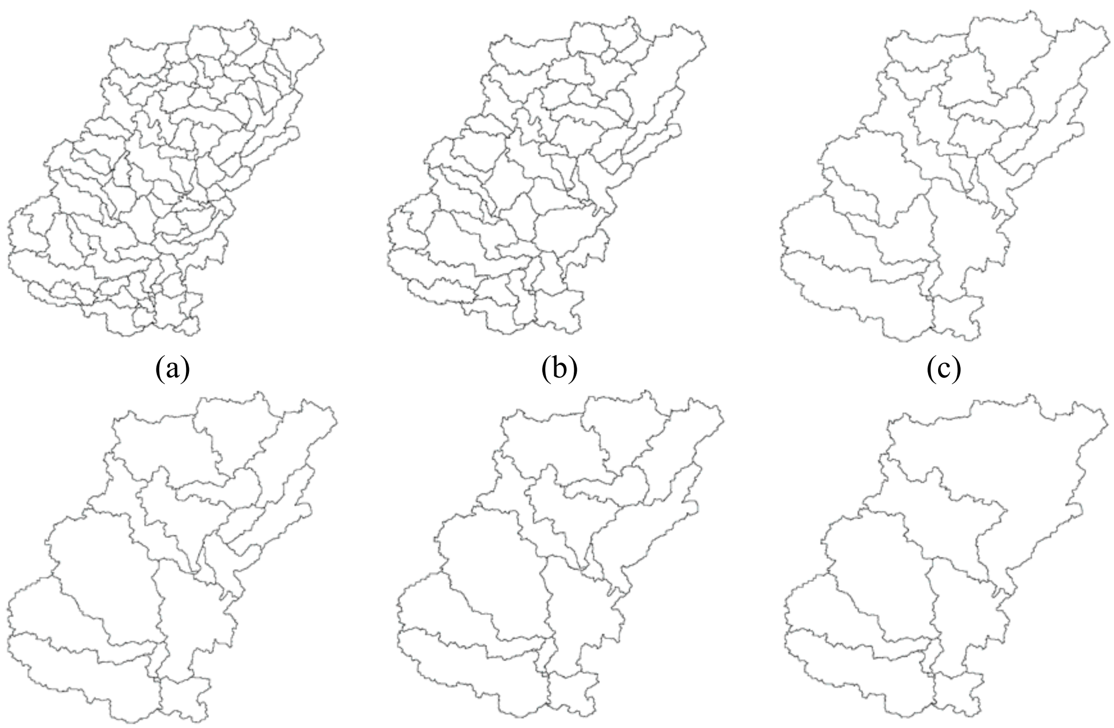
Figure 4.4 Cumulative distribution (a) sol_awc with SSURGO data (b) sol_awc with STATSGO data (c) sol_k with SSURGO data (d) sol_k with STATSGO data for SJRW configurations

4.3.9 Average Soil Saturated Hydraulic Conductivity (*sol_k*)

Saturated hydraulic conductivity determines the rate of percolation in each soil layer. Average *sol_k* decreased from 26.64 mm/hr for 0.3% CSA to 11.42 mm/hr for 7.0% CSA in the case of SSURGO, and from 21.07 mm/hr for 0.3% CSA to 16.97 mm/hr in the case of STATGO (Table 4.3). Figure 4.4 (c) and (d) show cumulative distribution of *sol_k* for two extreme watershed configurations (0.3% and 7.0% CSA) for SSURGO and STATSGO data, respectively.

4.4 Cedar Creek

To look into the issue of spatial scale in more detail, and also to compare the findings of this research with other related work (Fitzhugh and Mackay, 2000; Muleta et al. 2007), one of the major sub watersheds of SJRW, Cedar Creek (25% of SJRW area) was discretized using different CSAs and soil data (STATGO and SSURGO). Cedar Creek watershed is delineated using stream gauging station at Cedarville (station number: 4180000, Figure 3.2 (f)) as the watershed outlet. CSA values for Cedar creek ranged from 0.5% to 10%, and land use and soil type threshold for HRU delineation are 5% each. Findings from discretization of Cedar Creek are similar to that from SJRW and are presented in Table 4.4, and Figures 4.5, 4.6, and 4.7.



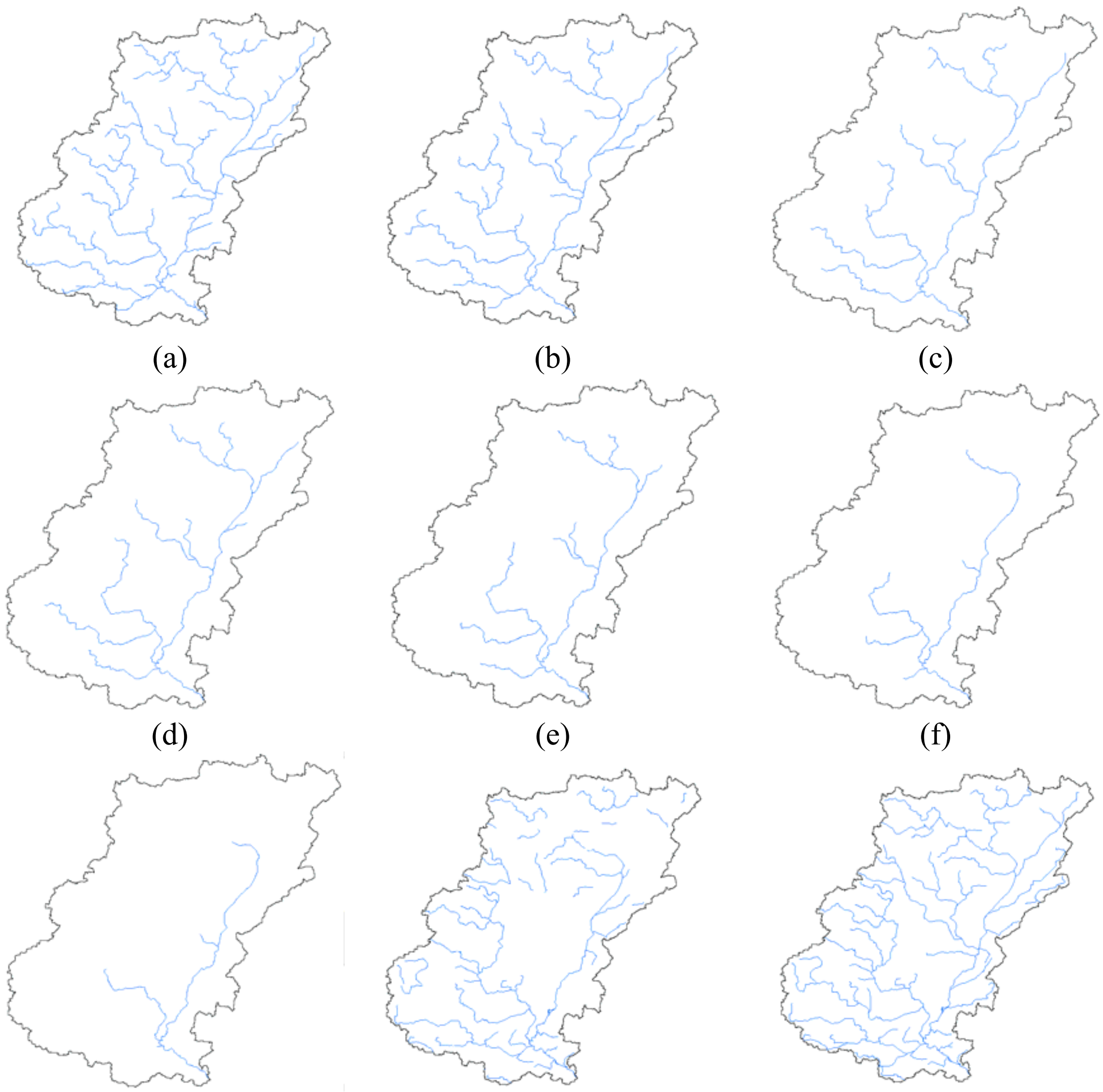
(a) (b) (c) (d) (e) (f)

Figure 4.5 Sub watersheds of Cedar Creek configurations for (a) 0.5% CSA (b) 1.0% CSA (c) 2.0% CSA, (d) 3.0% CSA, (e) 5.0% CSA, and (f) 7.0% CSA

Table 4.4 Watershed attributes for Cedar Creek configurations

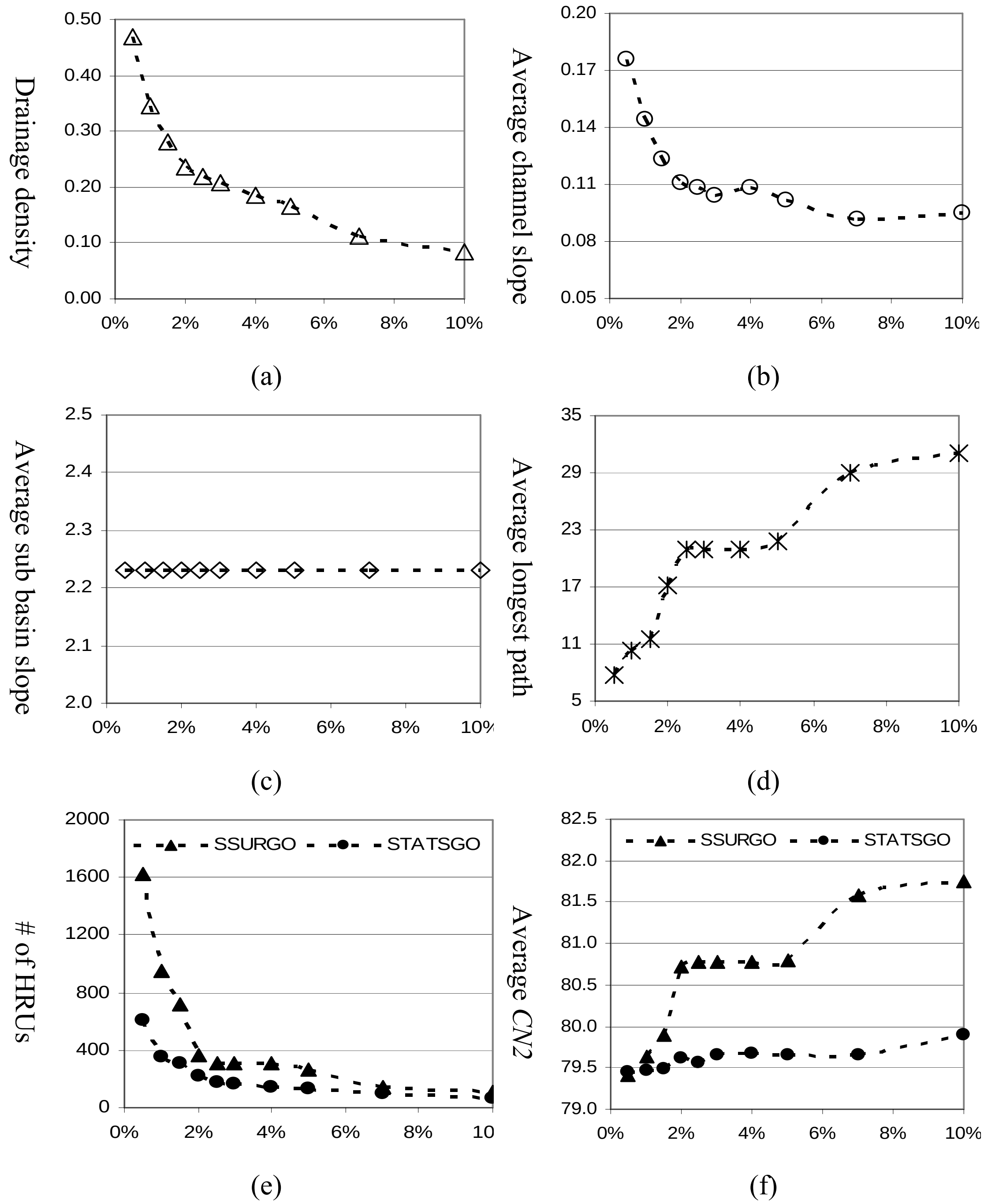
Model	CSA (%)	# Sub-watersheds	DD (km/km^2)	*Ch_slope* (%)	*B_slope* (%)	*Lp* (km)	# of HRUs		Average *CN2*	
							SSURGO	STATSGO	SSURGO	STATSGO
Cedar Creek	0.5	97	0.47	0.18	2.23	7.8	1624	607	79.41	79.45
	1.0	53	0.35	0.14	2.23	12.2	951	356	79.64	79.47
	1.5	41	0.28	0.12	2.23	11.6	722	310	79.89	79.49
	2.0	23	0.24	0.11	2.23	17.2	365	216	80.73	79.62
	2.5	17	0.22	0.11	2.23	21	305	174	80.78	79.56
	3.0	17	0.21	0.1	2.23	21	305	164	80.78	79.66
	4.0	17	0.19	0.11	2.23	21	305	145	80.78	79.68
	5.0	15	0.17	0.1	2.23	21.7	266	133	80.79	79.66
	7.0	9	0.11	0.09	2.23	29	139	98	81.59	79.66
	10.0	7	0.08	0.09	2.23	31	107	62	81.76	79.89
	NHD flow line (stream/river)		0.43	0.2	Not Applicable					
	NHD flow line (All)		0.62	0.22						

CSA: Critical Source Area as % of total watershed area, DD: Drainage density, Ch_slope: Average channel slope, B_slope: Average basin slope, Lp: Average longest path in sub basin, NHD flow line (All) includes artificial path, canal, ditch, connector and stream/ river



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure 4.6 Drainage Density of Cedar Creek configurations for (a) 0.5% CSA, (b) 1.0% CSA, (c) 2.0% CSA (d) 3.0% CSA (e) 5.0% CSA, (f) 7.0% CSA, (g) 10.0% CSA (h) NHD flow line density (Stream and River), and (i) NHD flow line density (all)



X axis represent %CSA area of Cedar Creek

Figure 4.7 Watershed attributes for Cedar Creek configurations (a) Drainage density (km/km2), (b) Average channel slope (%), (c) sub basin slope (%), (d) Average longest flow path in a sub basin (km), (e) # of HRUs, and (f) Average CN2

Cedar Creek configurations with SSURGO data are referred as CX, and Cedar Creek configurations with STATSGO data are referred as DX wherever necessary, where X is %CSA for the configuration. For example C1.0 stands for Cedar Creek configuration with 1.0% CSA and SSURGO soil data, and D1.0 stands for Cedar Creek configuration with 1.0% CSA and STATSGO data.

4.5 Summary

Watershed attributes of SJRW and Cedar Creek models corresponding to different watershed configurations are discussed in this chapter. Many watershed attributes are found to be sensitive to different levels of watershed discretization. In general, areal characteristics such as total watershed area, average *CN2*, average *sol_awc*, and sub basin slope are found to be insensitive to level of watershed discretization; whereas channel characteristics such as drainage density, channel slope and longest flow path changed significantly. However average *CN2*, average *sol_awc*, average *sol_k* are different for two soil datasets. Effects of different discretization on model calibration and validation are discussed in Chapter 5.

CHAPTER 5 MODEL CALIBRATION AND VALIDATION

5.1 Introduction

Semi-distributed nature of SWAT makes the model calibration process computationally intensive because of representation of HRUs and parameters associated with each HRU. For example, if there are 100 HRUs and 10 model parameters, model calibration essentially involves tuning of 10 x 100 = 1000 parameters, thus requiring an auto-calibration procedure. The auto calibration procedure incorporated in SWAT (van Griensven et al. 2006) is based on SCE-UA (Shuffled Complex Evolution-University of Arizona, Duan et al., 1992) algorithm is used in this study. An upper and lower bound are provided for each parameter based on literature and available data to keep parameters in acceptable range. The SWAT model has twenty six parameters for flow, six parameters for sediment and nine parameters for water quality, but only the flow component is considered in this study. To evaluate whether all twenty six parameters related to flow should be included or a sub-set can be included, sensitivity analysis is performed as the first step to pick sensitive parameters for calibration. After sensitivity analysis, the model is calibrated for daily streamflow from 1993- 1999, and validated form 2000-2003. The process of calibration-validation (C-V) is repeated for all SJRW and Cedar Creek watershed configurations. Results from all configurations are presented in this chapter.

5.2 Sensitivity Analysis and Parameter Selection

Sensitivity analysis tool in SWAT 2005 (Van Griensven, 2005) uses Latin Hypercube (LH, McKay et al. 1979, McKay 1988) sampling method combined with One-factor-At-a-Time (OAT, Morris 1991) to study the effect of change in individual parameters on model output. Sum of square of error (*SSE*) as defined in Equation 5.1 is used as objective function for sensitivity analysis.

$$SSE = \sum_{i=1}^{n} (x_{i,observed} - x_{i,\mathrm{mod}\,el})^2 \qquad 5.1$$

where $x_{i,observed}$ is observed daily streamflow and $x_{i,\mathrm{mod}\,el}$ is the daily model streamflow. The output from the sensitive analysis is a ranked set of parameters with highest rank assigned to the most sensitive parameter and other parameters are ranked in descending order. A sample output from sensitivity analysis for A1.0 model is shown in Table 5.1. *CN2* is found to be the most sensitive parameter followed by *Alpha_Bf*, *Surlag*, *Esco*, and *Ch_k2* in top five. Most sensitive parameters are related to surface runoff, followed by parameters related to groundwater flow and snow. Similar results as shown in Table 5.1 are found for other SJRW and Cedar Creek configurations.

It should be noted that results obtained from sensitivity analysis depend upon the objective function selected for the analysis, which may or may not capture all watershed responses equally well (Rao and Han, 1987). For example, the objective function used in this study (*SSE*) is found to be biased towards peak flow (Muleta and Nicklow, 2005), thus underestimating groundwater contribution in overall flow results. Sensitivity analysis results can also be affected by parameter ranges provided (default parameter ranges provided by model developers were used in this study) and the Latin Hypercube sampling method (limited number of sampling, 10 in this case). Considering these factors, and related work in the literature, a total of 19 parameters for SJRW (Table 5.2) and 14 parameters for Cedar Creek (Table 5.3) are selected for calibration. Although most parameters selected for calibration ranked high in sensitivity analysis result (Table 5.1), some parameters that are not highly ranked such as *Gwqmn, Gw_revap,* and *Gw_delay* are also included because they are reported to be very important for calibration of baseflow component in the model (Neitsch et al., 2002). Parameters that are physically based or estimated from available data such as *Sol_z* (depth of individual soil layer), *Slope* (channel slope) and *Slsubbsn* (sub basin slope length) are not included in calibration process.

Table 5.1 Parameter sensitivity for A1.0 configuration

Parameter	Rank	Related hydrologic process
CN2	1	Surface runoff
Alpha_Bf	2	baseflow recession constant
Surlag	3	Surface runoff lag in a sub-basin/reach
Esco	4	Evapotranspiration from soil
Ch_K2	5	transmission loss in channel
Blai	6	maximum leaf area index, initial abstraction
Sol_Z	7	root zone hydrologic process
Ch_n	8	flow rate and velocity
Timp	9	snow pack temperature
Sol_Awc	10	root zone water movement and evapotranspiration
Canmx	11	Initial abstraction/evapotranspiration
Biomix	12	soil erosion
Epco	13	evapotranspiration
Gw_Revap	14	groundwater for evapotranspiration
Smtmp	15	snow melt
Sol_K	16	root zone water movement
Slsubbsn	17	soil erosion in a sub-basin
Sol_Alb	18	evapotranspiration
Slope	19	flow rate and velocity
Gw_Delay	20	water movement from vadose zone to unconfined aquifer
Revapmin	21	groundwater for evapotranspiration
Gwqmn	27	groundwater for baseflow
Smfmx	27	snow melt maximum rate
Smfmn	27	snow melt minimum rate
Sftmp	27	snow fall temperature
Tlpas	27	temperature lapse rate

Three options are available to change parameters during auto calibration. These are (1) change by value, (2) change by addition to initial value, and (3) change by percentage of initial value. Options 2 and 3 change parameter values relative to initially assigned values, whereas option (1) assigns new absolute value to the parameter in each model run. Change options used for selected parameters are given in Tables 5.2 and 5.3 for SJRW and Cedar Creek, respectively. Default parameters ranges provided by model developers are used for Cedar Creek model calibration. For SJRW models, some of these ranges are changed to more stringent criteria for parameters whose initial distributions are known. For example *CN2* and sol_*awc* are allowed to change within ± 25 % of their initial value instead of default range of ±50 % so that calibrated values are closer to available data.

Table 5.2 Parameters for SJRW model calibrations

Sl. No.	Parameter	Rank	Default value	Lower bound	Upper bound	Unit
1	*Alpha_Bf* (1)	1	0.048	0	1	days
2	*Cn2* (3)	2	mgt file	-25	25	na
3	*Surlag* (1)	3	4.000	0	10	days
4	*Ch_N* (1)	4	0.050	0	1	na
5	*Esco* (1)	5	0.000	0	1	na
6	*Ch_K2* (1)	6	0.000	0	150	mm/hr
7	*Blai* (3)	7	crop data	-25	25	na
8	*Timp* (1)	8	1.000	0	1	na
9	*Sol_Awc* (3)	9	soil data	-25	25	mm H2O/mm soil
10	*Canmx* (1)	11	0.000	0	10	mm
11	*Biomix* (1)	12	0.200	0	1	na
12	*Epco* (1)	13	0.000	0	1	na
13	*Smtmp* (3)	14	0.500	-25	25	degree C
14	*Gw_Revap* (2)	17	0.020	-0.036	0.036	na
15	*Sol_Alb* (3)	18	soil data	-25	25	na
16	*Sol_K* (3)	19	soil data	-25	25	mm/hr
17	*Gw_Delay* (2)	20	31.000	-10	10	days
18	*Revapmin* (1)	21	1.000	0	500	mm
19	*Gwqmn* (1)	27	0.000	0	5000	mm

Number in parenthesis next to parameter represent the option used for changing parameter values during calibration. (1) change by value, (2) change by addition to new value, and (3) change by percentage of initial value. na: Not applicable

Table 5.3 Parameters for Cedar Creek Model Calibrations

Sl. No.	Parameter	Rank	Default value	Lower bound	Upper bound	Unit
1	*CN2* (3)	1	mgt file	-50	50	na
2	*Ch_k2* (1)	2	0.00	0	150	mm/hr
3	*Surlag* (1)	3	4.00	0	10	days
4	*Alpha_bf* (1)	4	0.05	0	1	days
5	*Esco* (1)	9	0.00	0	1	na
6	*Sol_awc* (3)	11	soil type	-50	50	mm H2O/mm soil
7	*Canmx* (1)	13	0.00	0	10	mm
8	*ch_n* (3)	13	0.05	-20	20	na
9	*Gwqmn* (1)	15	0.00	0	5000	mm
10	*rchrg_dp* (1)	17	0.05	0	1	na
11	*Epco* (1)	22	0.00	0	1	na
12	*Gw_revap* (1)	23	0.02	0.02	0.2	na
13	*Gw_dealy* (1)	24	31.00	0	100	days
14	*Revapmn* (1)	25	1.00	0	500	mm
	Other value changed manualy before auto calibration					
				Changed value		
15	*Timp*	5	1.0	0.74		na
16	*Sftmp*	8	1.0	1.44		Degree C
17	*Smtmp*	7	0.5	0.56		Degree C
18	*Smfmx*	7	4.5	1.51		mm H2O/degree C-day
19	*Smfmn*		4.5	1.51		mm H2O/degree C-day

Number in parenthesis next to parameter represent the option used for changing parameter values during calibration. (1) change by value, (2) change by addition to new value, and (3) change by percentage of initial value. na: Not Applicable

First Cedar Creek configurations are calibrated with 14 parameters, and then five more parameters are added to SJRW configurations creating a set of 19 parameters for

SJRW. Numbers of parameters for SJRW are increased to evaluate the performance of SWAT auto calibration program in calibrating a larger model compared to Cedar Creek with more parameters.

5.3 Auto Calibration

Auto calibration tool in SWAT 2005 uses Shuffled Complex Evolution (SCE-UA) algorithm developed by Duan et al. (1992) to optimize the parameter values. Shuffled complex evolution method belongs to the family of genetic algorithms. As a first step, initial population (parameter space defined by its upper and lower bound) is partitioned into several communities called complexes. In each complex, different combinations of individual parameters produces offspring using simplex procedure of Nadler and Mead (1965). The probability of individual set taking part in the reproduction is proportional to its fitness. Individuals of lower fitness are replaced by their offspring to direct the search in an improvement direction. These complexes are shuffled at periodic interval and points are re-distributed among different complexes to ensure the information sharing. As search progresses, entire population converges towards the global optimum value (Duan et al., 1992).

Sum of square of error (Equation 5.1) for daily flow output at the watershed outlet is used as objective function for calibration. Similar to sensitive analysis, calibration results are also dependent upon objective function selected (Gupta et al., 1998, Sorooshian and Gupta, 1995). Model's performance is evaluated in terms of commonly used Nash-Sutcliff efficiency coefficient (R_{NS}^2, Nash and Sutcliff, 1970) and M_{bias} as defined below (Arabi et al., 2007; Eckhardt and Arnold, 2001; Santhi et al., 2001; White and Chaubey, 2005).

$$R_{NS}^2 = 1 - \frac{\sum_{i=1}^{n}(x_{i,observed} - x_{i,\mathrm{model}})^2}{\sum_{i=1}^{n}(x_{i,observed} - \bar{x}_{observed})^2} \qquad 5.2$$

$$M_{bias.} = \left(\frac{\overline{x}_{\text{model}} - \overline{x}_{observed}}{\overline{x}_{observed}} \right) * 100 \qquad 5.3$$

where $x_{i,observed}$ and $x_{i,\text{model}}$ are daily observed and model streamflow, respectively, and $\overline{x}_{observed}$ and $\overline{x}_{\text{model}}$ are averages of observed and model streamflow. A negative value of M_{bias} indicates that model is under estimating streamflow and vice versa.

All auto calibration programs are run on Purdue Tera-Grid computers. The average CPU (Central Processing Unit) runtime for individual calibration program is two weeks. Out of 34 individual calibration programs (14 configurations of SJRW and 20 configurations of Cedar Creek), 28 resulted into successful termination within provided control parameters for auto calibration (Appendix C). Results of 28 successful calibration programs are discussed in following sections.

5.3.1 Calibration and validation results for SJRW

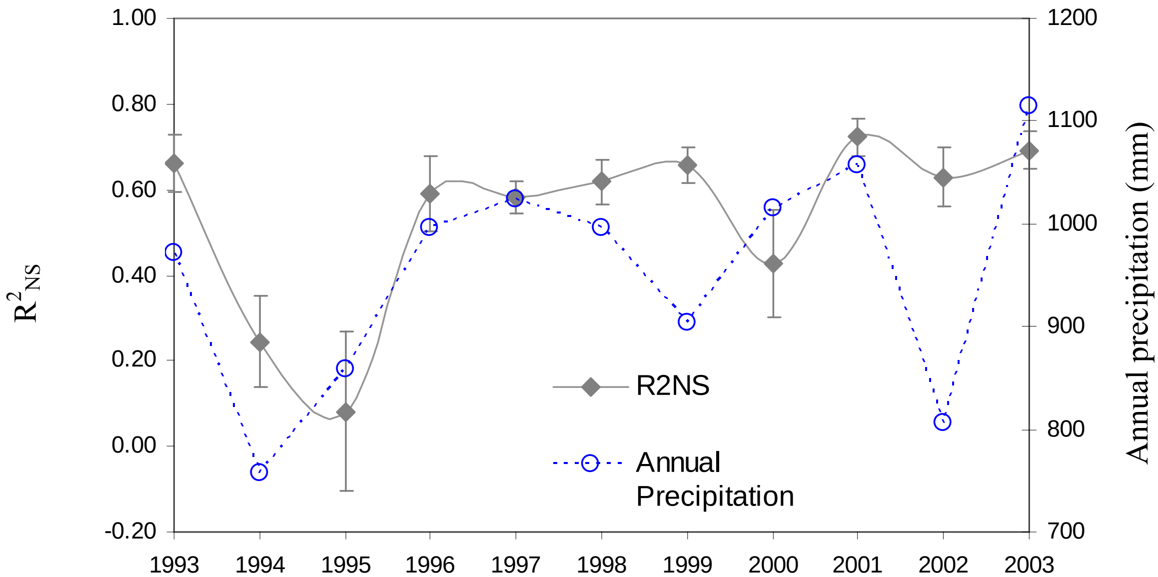
All SJRW model configurations (Table 5.4) are calibrated from 1993-1999 and validated from 2000-2003. Years 1990-1992 are used as warm up period for the model. The calibration and validation results for SJRW are presented in Table 5.4. The average R^2_{NS} for SJRW configurations with SSURGO data is 0.57 during calibration phase and 0.66 during validation phase. For STATGO data the average R^2_{NS} is 0.56 during calibration phase and 0.66 during validation phase. The average M_{bias} for SJRW configurations with SSURGO data is -19.8% during calibration phase and -4.93% during validation phase. For STATGO data, the average M_{bias} is -18.6% during calibration phase and -3.4% during validation phase. Model performances are different for different year of simulation, with 1995 being worst performing year and 2001 being best performing year. Table 5.5 and Figure 5.1 show yearly model performance in terms of R^2_{NS} for all SJRW configurations. Average R^2_{NS} are 0.10 for year 1995 and 0.72 for year 2001, for SJRW configurations. Model performance is found to be sensitive to shift in precipitation trends (Figure 5.1). If a dry year is preceded by a dry year or a wet year is preceded by a wet year, then model seems to perform well. However, if a wet year is preceded by dry year or a dry year is preceded by wet year, model performance drops. For example, in year 1995 and 2000 precipitation trend shifted from negative to positive producing an average R^2_{NS} of 0.10 and 0.14, respectively, whereas in year 1998 and 1999 precipitation trend remain unchanged producing an average R^2_{NS} of 0.62 and 0.65, respectively.

Table 5.4 Model performance (SJRW) before and after calibration

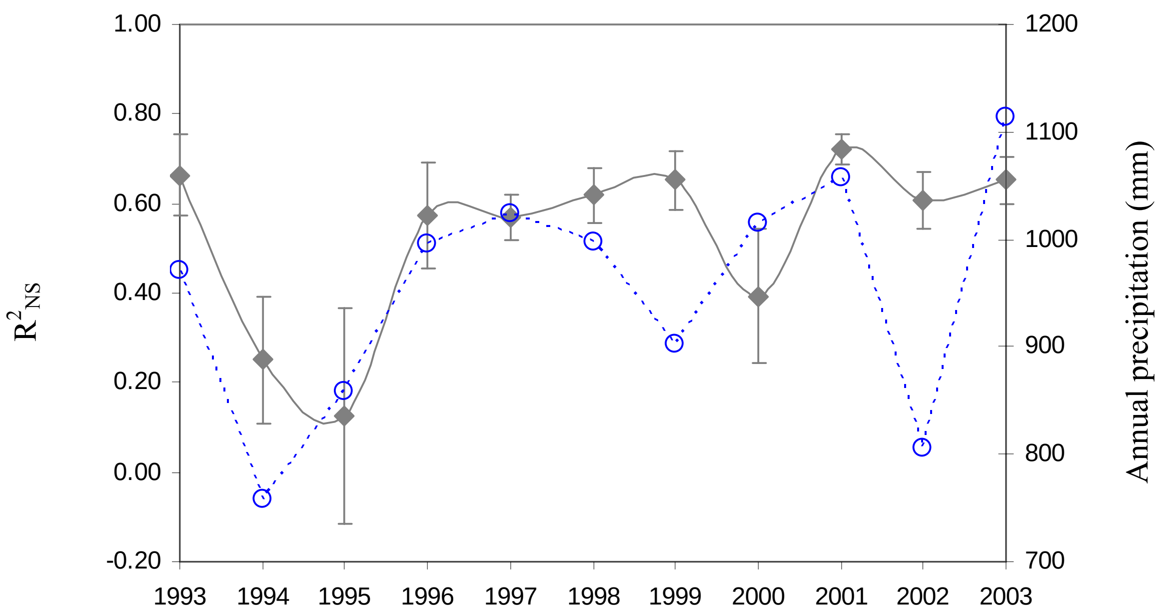
Model	Before Calibration 1993-1999		After Calibration: Calibration period 1993-1999		After Calibration: Validation Period 2000-2003	
	R^2_{NS}	M_{bias}	R^2_{NS}	M_{bias}	R^2_{NS}	M_{bias}
A0.5	0.10	-30.9	0.61	-17.8	0.68	-4.6
A1.0	0.37	-30.2	0.57	-25.0	0.67	-4.0
A2.0	0.47	-29.6	0.64	-18.6	0.68	-6.4
A3.0	0.47	-30.8	0.54	-18.4	0.65	-3.2
A5.0	0.35	-31.7	0.45	-20.5	0.62	-5.3
A7.0	0.47	-30.1	0.59	-18.7	0.66	-3.0
B0.5	0.15	-35.1	0.60	-11.0	0.62	9.8
B1.0	0.38	-34.7	0.63	-19.7	0.68	-5.9
B2.0	0.45	-34.2	0.63	-18.0	0.62	-5.4
B3.0	0.46	-36.3	0.59	-17.9	0.68	-3.4
B5.0	0.34	-37.7	0.41	-25.7	0.59	-11.7
B7.0	0.46	-35.3	0.51	-19.5	0.63	-3.9

A0.5 to A7.0 represents SJRW configurations with SSURGO data and B0.5 to B7.0 represent SJRW configurations with STATSGO data

Figures 5.2 and 5.3 show daily hydrographs for 1997 during calibration and 2001 during validation, respectively for all SJRW configurations with SSURGO data. Most model configurations exhibit similar behavior with respect to hydrograph response.



(a)



(b)

Figure 5.1 Yearly model performance for SJRW configurations with (a) SSURGO data (b) STATSGO data and annual precipitation, Error bar represent + one standard deviation

Table 5.5 Yearly model performances (R^2_{NS}) for SJRW configurations

Year	Precipitation (mm)	Model performances (R^2_{NS}) A0.5	A1.0	A2.0	A3.0	A5.0	A7.0	B5.0	B1.0	B2.0	B3.0	B5.0	B7.0
1993	971	0.69	0.65	0.75	0.68	0.55	0.66	0.69	0.73	0.75	0.70	0.54	0.56
1994	758	0.30	0.22	0.37	0.23	0.06	0.30	0.27	0.33	0.40	0.30	-0.01	0.21
1995	859	0.16	0.20	0.24	-0.02	-0.26	0.16	0.27	0.21	0.27	0.21	-0.36	0.13
1996	996	0.66	0.61	0.67	0.51	0.46	0.64	0.67	0.68	0.64	0.57	0.37	0.52
1997	1024	0.61	0.60	0.63	0.55	0.53	0.57	0.60	0.61	0.57	0.60	0.48	0.53
1998	997	0.67	0.62	0.67	0.59	0.53	0.63	0.60	0.69	0.66	0.65	0.52	0.58
1999	903	0.67	0.67	0.71	0.64	0.58	0.67	0.70	0.70	0.70	0.68	0.56	0.58
2000	1015	0.47	0.42	0.28	0.61	0.48	0.30	0.17	0.40	0.25	0.51	0.53	0.49
2001	1057	0.76	0.75	0.68	0.68	0.68	0.78	0.71	0.77	0.70	0.75	0.67	0.72
2002	806	0.63	0.63	0.76	0.59	0.55	0.62	0.67	0.64	0.62	0.65	0.50	0.56
2003	1114	0.68	0.71	0.76	0.65	0.63	0.71	0.67	0.71	0.69	0.67	0.57	0.61

A0.5 to A7.0 represent SJRW configurations with SSURGO data and B0.5 to B7.0 represent SJRW configurations with STATSGO data

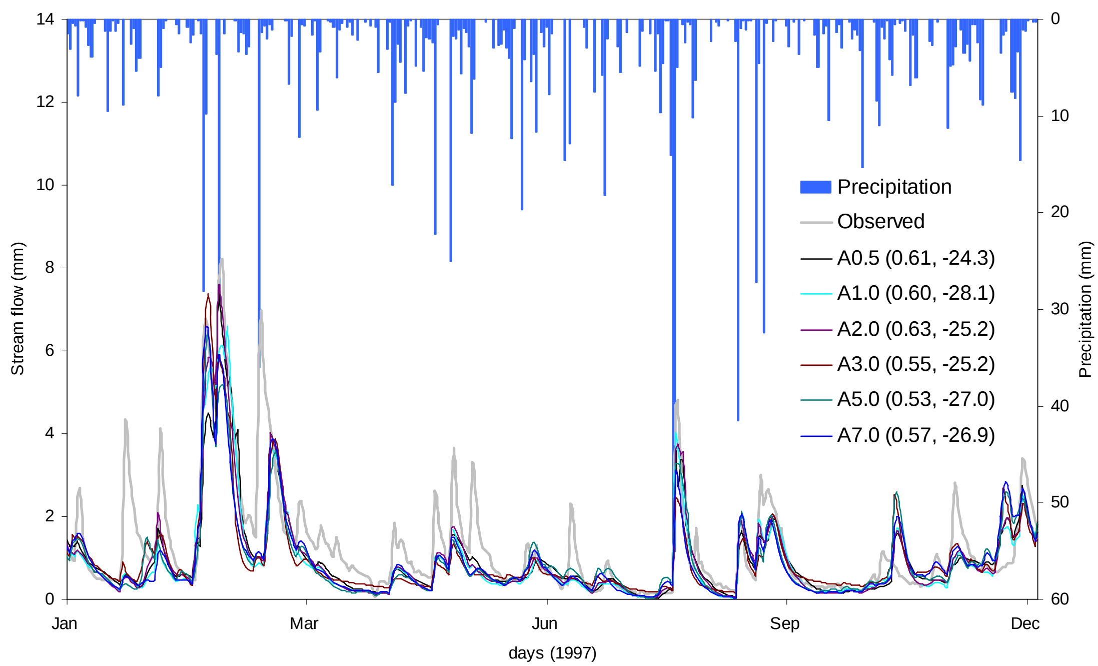


Figure 5.2 Daily hydrographs for 1997 during calibration for SJRW configurations with SSURGO data (R2NS, Mbias)

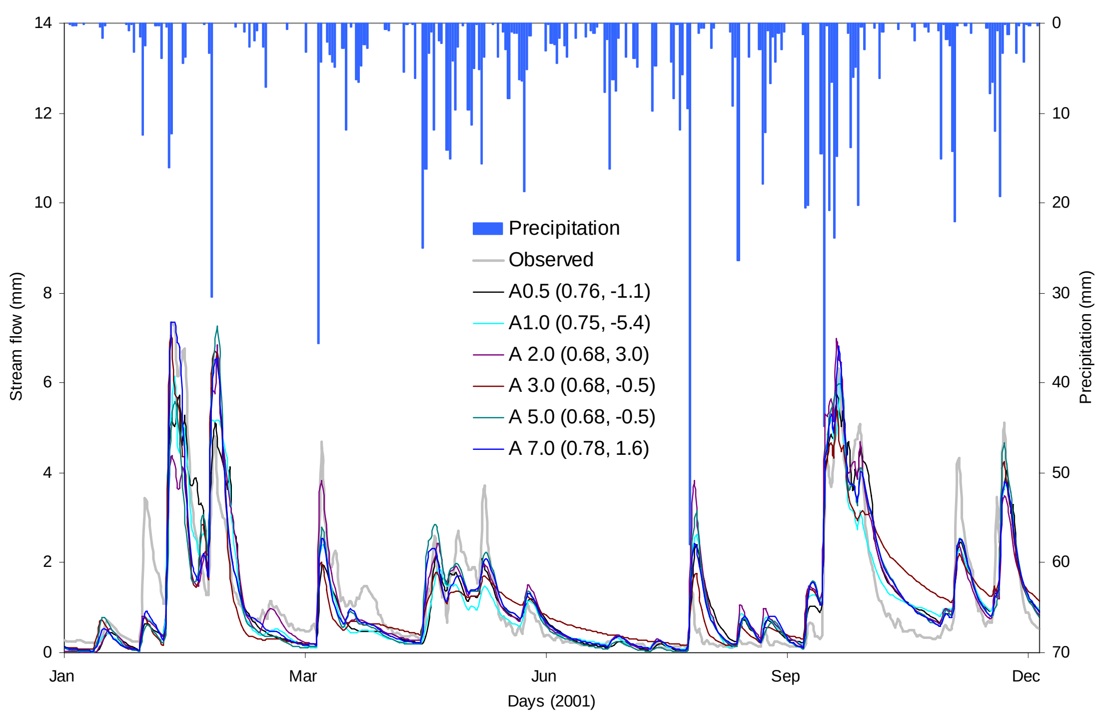


Figure 5.3 Daily hydrographs for 2001 during validation for SJRW configurations with SSURGO data (R2NS, Mbias)

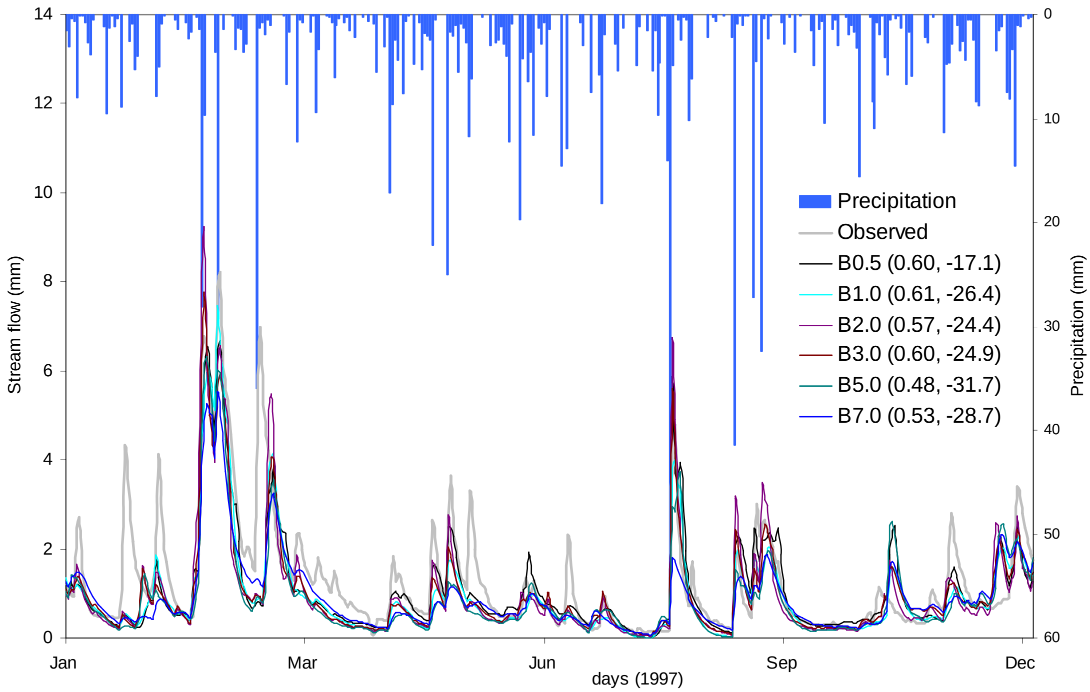


Figure 5.4 Daily hydrographs for 1997 during calibration for SJRW configurations with STATSGO data (R2NS, Mbias)

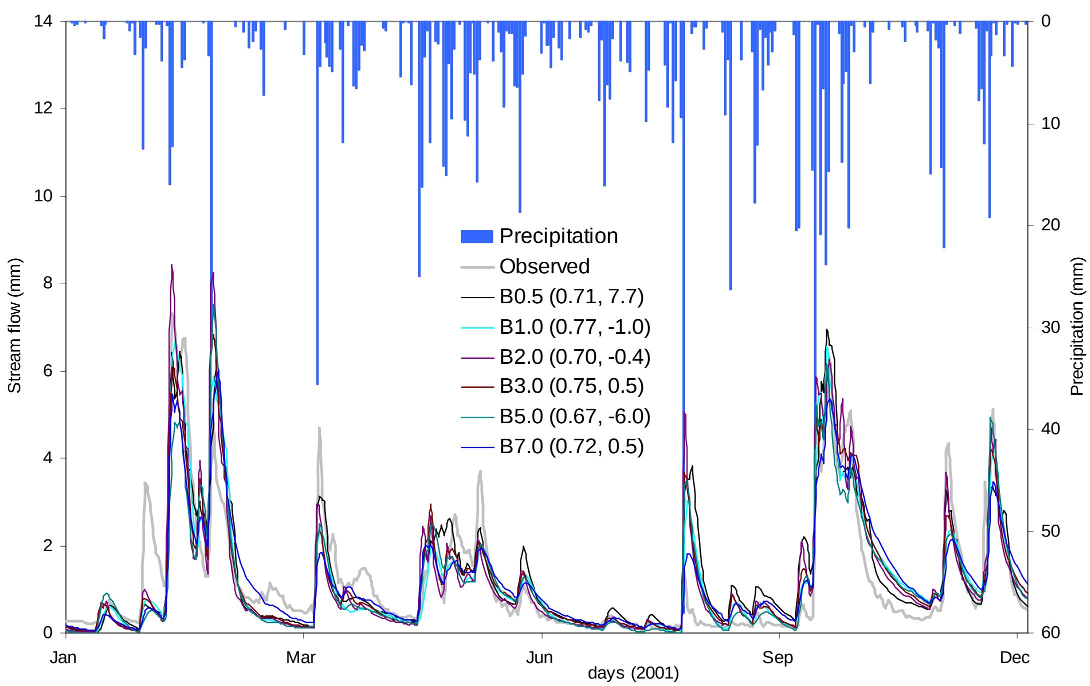


Figure 5.5 Daily hydrographs for 2001 during validation for SJRW configurations with STATSGO data (R2NS, Mbias)

Average R^2_{NS} and M_{bias} during 1997 are 0.58 and -26.1%, and those during 2001 are 0.72 and -0.5% respectively. There is a general tendency of under estimation during calibration phase, with poor simulation of mid range peaks (2-4 mm). The poor performance for low flows is due to selection of *SSE* as the objective function for model calibration, which is biased towards high flows (Dunn, 1999; Muleta and Nicklow, 2005). In year 2001, the overall performance is better for all configurations. Figure 5.4 and Figure 5.5 show daily hydrographs for 1997 during calibration and 2001 during validation, respectively for all SJRW configurations with STATSGO data. The average R^2_{NS} and M_{bias} during 1997 are 0.56 and -25.54% and those during 2001 are 0.72 and 0.2%, respectively. Hydrograph characteristics are similar as explained in the case of SSURGO data.

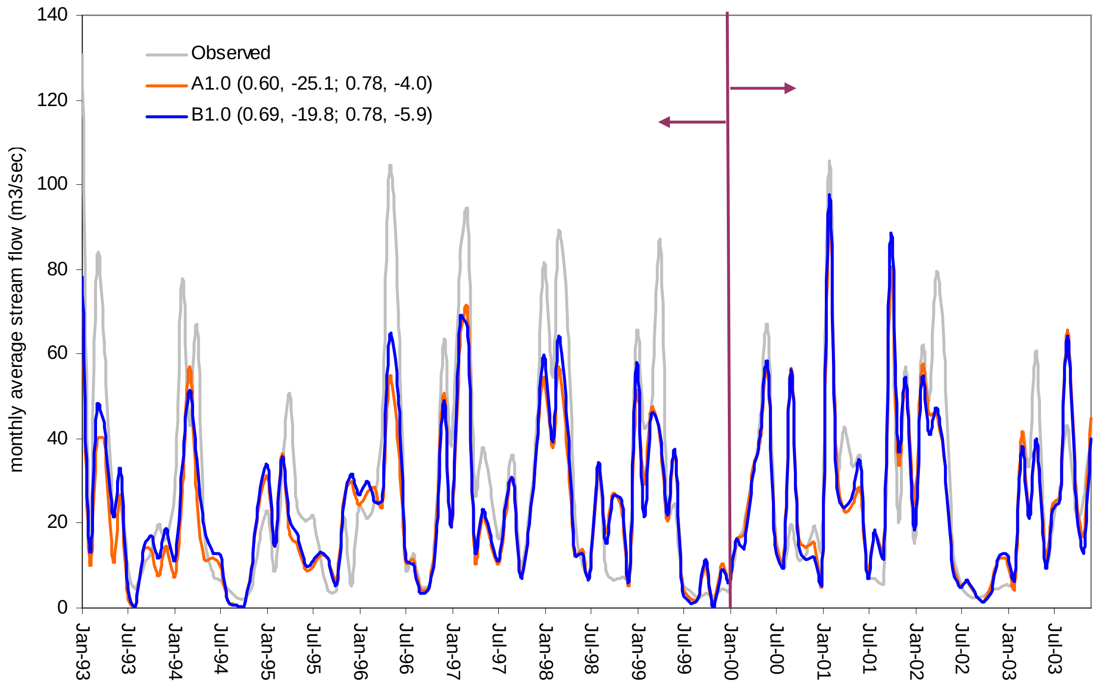


Figure 5.6 Monthly hydrograph for A1.0 and B1.0 models for entire simulation period (1993-2003), (R2NS, Mbias for calibration and validation period)

Figure 5.6 show monthly hydrograph corresponding to 1% CSA with SSURGO and STATSGO data (A1.0 and B1.0). STATSGO data performs slightly better in simulating peak flows compared to SSURGO data during calibration period, but performance during validation phase is the same. Similar to daily hydrographs, monthly hydrographs in also show underestimation of peak flows particularly during calibration period.

5.3.2 Calibration and validation results for Cedar Creek

All Cedar Creek model configurations (Table 5.6) are also calibrated from 1993-1999 and validated from 2000-2003. Years 1990-1992 are used as warm up period for the model. The calibration and validation results for Cedar Creek configurations are presented in Table 5.6. The average R_{NS}^2 for Cedar Creek configurations with SSURGO data is 0.71 during calibration phase and 0.53 during validation phase. For STATGO data, the average R_{NS}^2 is 0.75 during calibration phase and 0.61 during validation phase. The average M_{bias} for Cedar Creek configurations with SSURGO data is -14.6% during calibration phase and -25.0% during validation phase. For STATGO data, the average M_{bias} is 5.9% during calibration phase and 1.4% during validation phase.

Table 5.7 and Figure 5.7 show yearly model performance in terms of R_{NS}^2 for all Cedar Creek configurations. Highest averages R_{NS}^2 is 0.84 for year 1993, and lowest average R_{NS}^2 is 0.34 for year 2000, for Cedar configurations. Similar to SJRW configurations, yearly model performance for Cedar Creek configurations are also sensitive to precipitation trends (Figure 5.7). For example, in year 1995 and 2000 precipitation trend shifted from negative to positive producing an average R^2_{NS} of 0.47 and 0.34, respectively, whereas in year 1998 and 1999 precipitation trend remain unchanged producing an average R_{NS}^2 are 0.82 and 0.80, respectively.

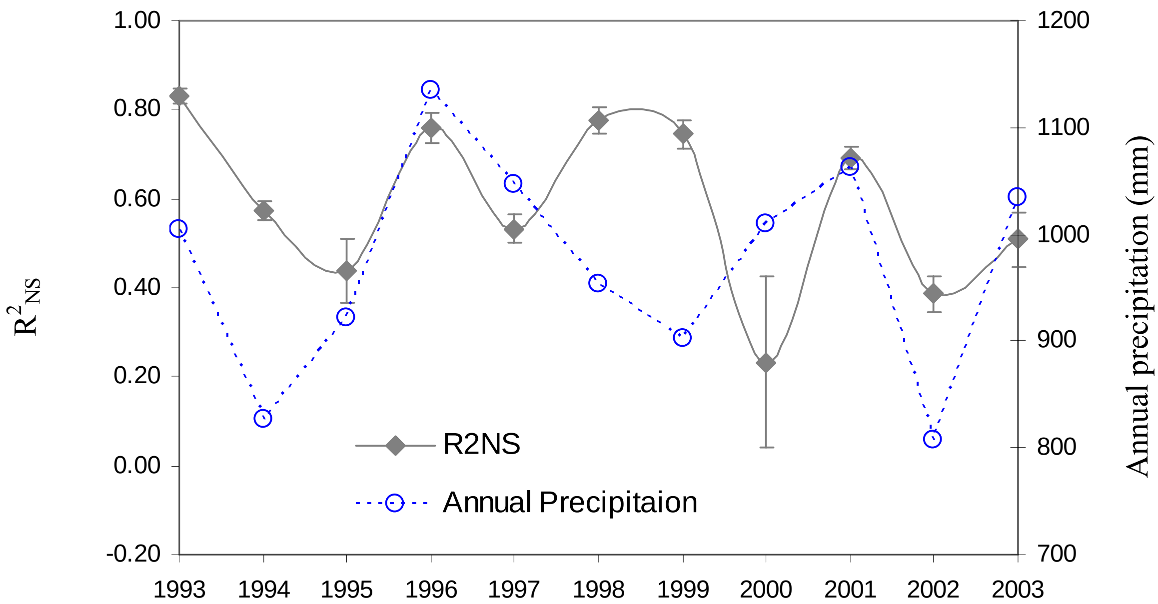
Figures 5.8 and 5.9 show daily hydrographs for 1997 during calibration and 2001 during validation, respectively for all Cedar Creek configurations with SSURGO data. Most model configurations exhibit similar behavior with respect to hydrograph response.

Average R^2_{NS} and M_{bias} during 1997 are 0.53 and -27.8%, respectively and during 2001 are 0.69 and -25.5%, respectively. The general tendency of under estimation of low flows observed for SJRW configurations continues for both calibration phase and validation phase for Cedar Creek configurations with SSURGO data.

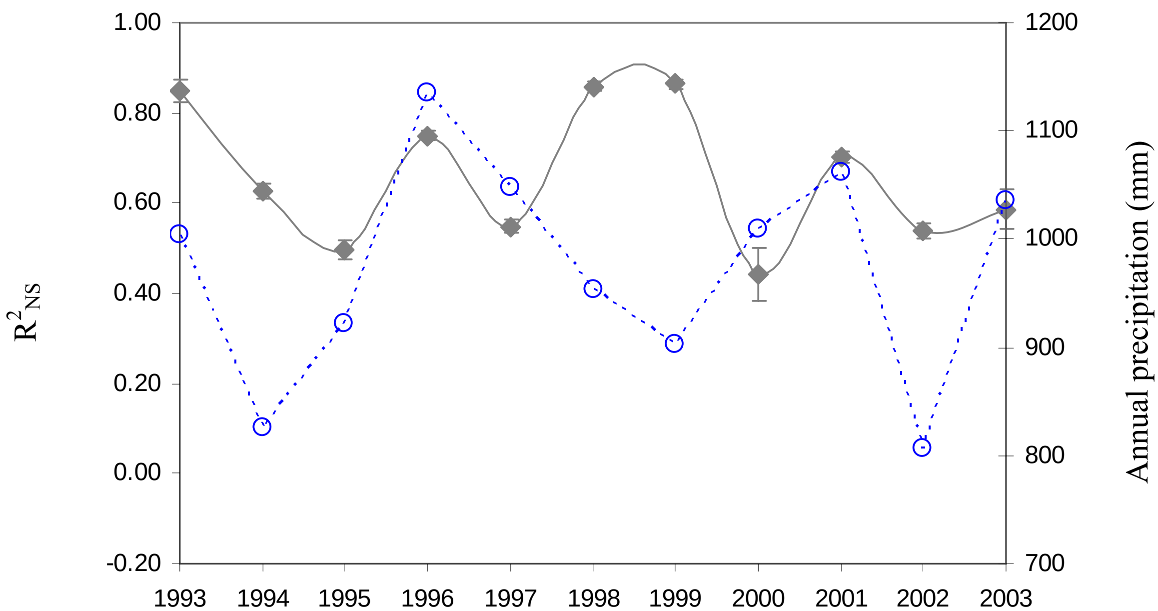
Table 5.6 Model performance (Cedar Creek) before and after calibration

Model	Before Calibration 1993-1999		After Calibration: Calibration period 1993-1999		After Calibration: Validation Period 2000-2003	
	R^2_{NS}	M_{bias}	R^2_{NS}	M_{bias}	R^2_{NS}	M_{bias}
C1.5	-0.90	-15.2	0.70	-21.7	0.52	-31.8
C2.0	-0.49	-14.8	0.71	-23.1	0.55	-28.3
C2.5	-0.46	-14.9	0.71	-28.3	0.58	-34.9
C3.0	-0.46	-14.9	0.71	-30.4	0.44	-37.7
C4.0	-0.46	-14.8	0.71	-26.0	0.51	-33.3
C5.0	-0.46	-15.2	0.71	-26.6	0.55	-33.1
C7.0	-0.23	-13.6	0.71	-20.6	0.54	-29.6
C10.0	-0.24	-13.3	0.71	-23.2	0.58	-29.5
D1.5	-1.13	48.5	0.73	-1.4	0.61	-3.0
D2.0	-1.02	47.9	0.75	7.4	0.62	2.4
D2.5	-0.79	48.0	0.75	6.5	0.62	2.2
D3.0	-0.69	48.3	0.75	7.9	0.61	3.5
D4.0	-0.66	48.2	0.75	8.5	0.61	3.7
D5.0	-0.68	48.4	0.75	6.4	0.59	0.9
D7.0	-0.64	48.1	0.74	5.9	0.60	1.3
D10.0	-0.56	48.8	0.75	5.9	0.60	0.7

C1.5 to C10.0 represents Cedar Creek configurations with SSURGO data and D1.5 to D10.0 represents Cedar Creek configurations with STATSGO data.



(a)



(b)

Figure 5.7 Yearly model performance for Cedar Creek configurations with (a) SSURGO data (b) STATSGO data and annual precipitation, Error bar represent + one standard deviation

Table 5.7 Yearly model performances (R^2_{NS}) for Cedar Creek configurations

Year	Precipitation (mm)	Model performances (R^2_{NS})															
		C1.5	C2.0	C2.5	C3.0	C4.0	C5.0	C7.0	C10.0	D1.5	D2.0	D2.5	D3.0	D.0	D5.0	D7.0	D10.0
1993	1004	0.84	0.82	0.81	0.83	0.84	0.86	0.85	0.81	0.79	0.87	0.86	0.87	0.86	0.85	0.84	0.86
1994	827	0.59	0.58	0.60	0.55	0.56	0.59	0.58	0.53	0.59	0.65	0.63	0.63	0.63	0.63	0.63	0.63
1995	922	0.39	0.48	0.58	0.34	0.41	0.40	0.45	0.45	0.53	0.48	0.50	0.49	0.50	0.52	0.46	0.50
1996	1135	0.77	0.75	0.69	0.75	0.76	0.78	0.78	0.81	0.74	0.73	0.76	0.76	0.75	0.76	0.74	0.76
1997	1047	0.53	0.54	0.49	0.49	0.53	0.54	0.56	0.58	0.52	0.54	0.57	0.54	0.56	0.56	0.54	0.56
1998	954	0.80	0.76	0.83	0.73	0.75	0.78	0.79	0.77	0.88	0.86	0.86	0.85	0.86	0.85	0.85	0.85
1999	903	0.72	0.77	0.81	0.71	0.71	0.75	0.74	0.75	0.88	0.86	0.86	0.85	0.86	0.86	0.87	0.87
2000	1009	0.20	0.24	0.47	-0.12	0.06	0.25	0.33	0.42	0.31	0.43	0.43	0.46	0.45	0.47	0.48	0.50
2001	1063	0.71	0.69	0.72	0.64	0.68	0.72	0.71	0.67	0.68	0.72	0.71	0.70	0.70	0.69	0.69	0.69
2002	808	0.42	0.39	0.40	0.31	0.36	0.38	0.43	0.38	0.51	0.54	0.55	0.56	0.55	0.54	0.53	0.53
2003	1035	0.45	0.59	0.55	0.46	0.52	0.57	0.42	0.51	0.68	0.61	0.60	0.58	0.58	0.54	0.56	0.54

C1.5 to C10.0 represent Cedar Creek configurations with SSURGO data and D1.5 to D10.0 represent Cedar Creek configurations with STATSGO data

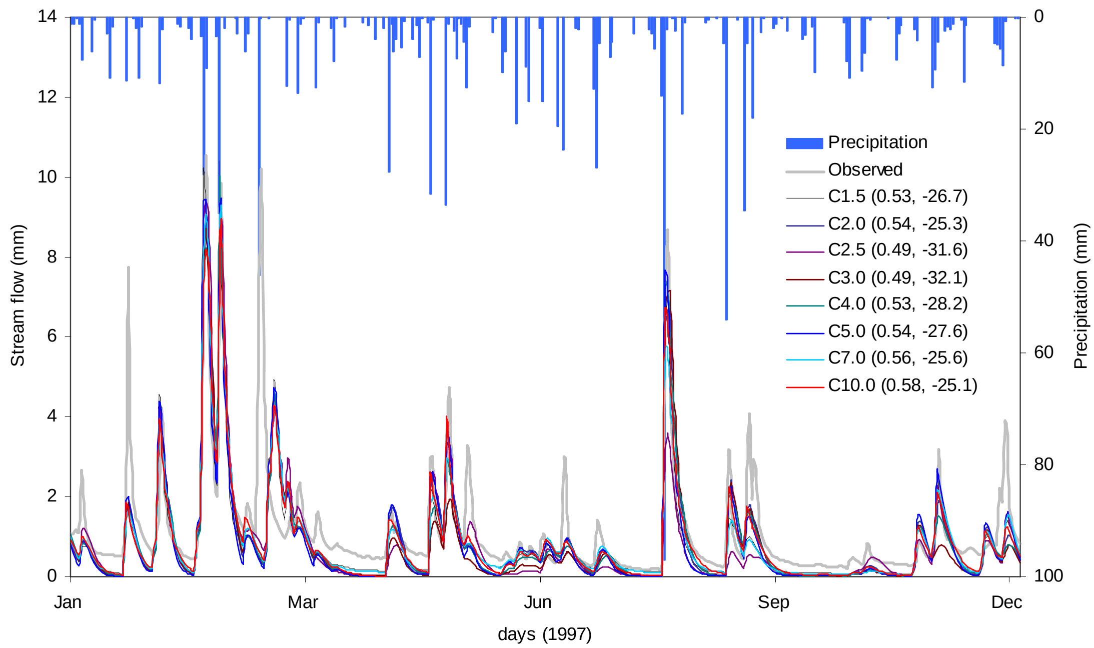


Figure 5.8 Daily hydrographs for 1997 during calibration for Cedar Creek configurations with SSURGO data (R2NS, Mbias)

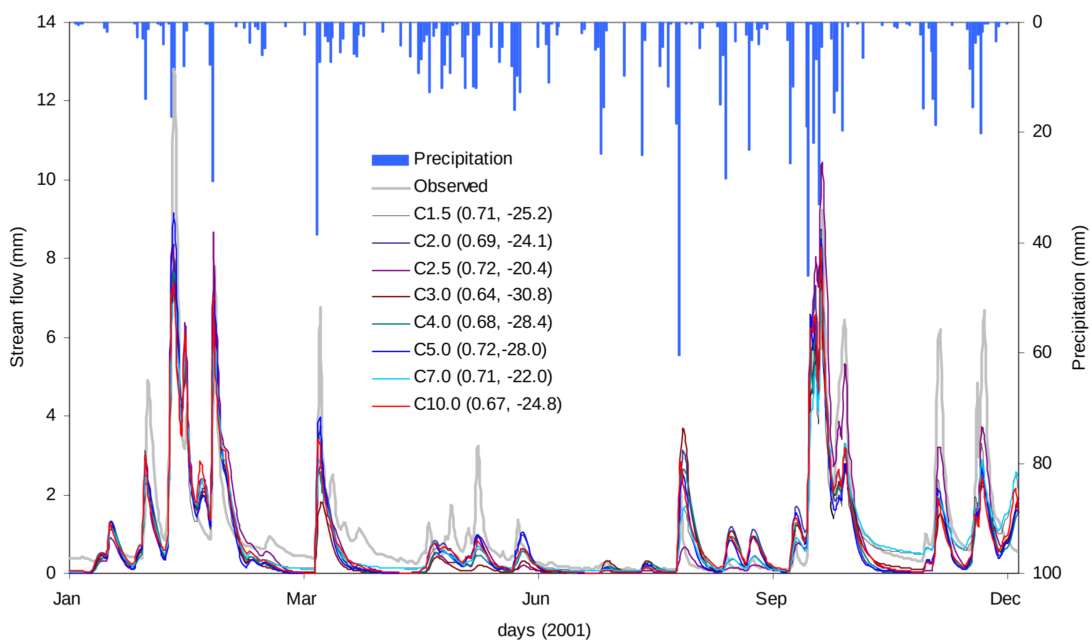


Figure 5.9 Daily hydrographs for 2001 during validation for Cedar Creek configurations with SSURGO data (R2NS, Mbias)

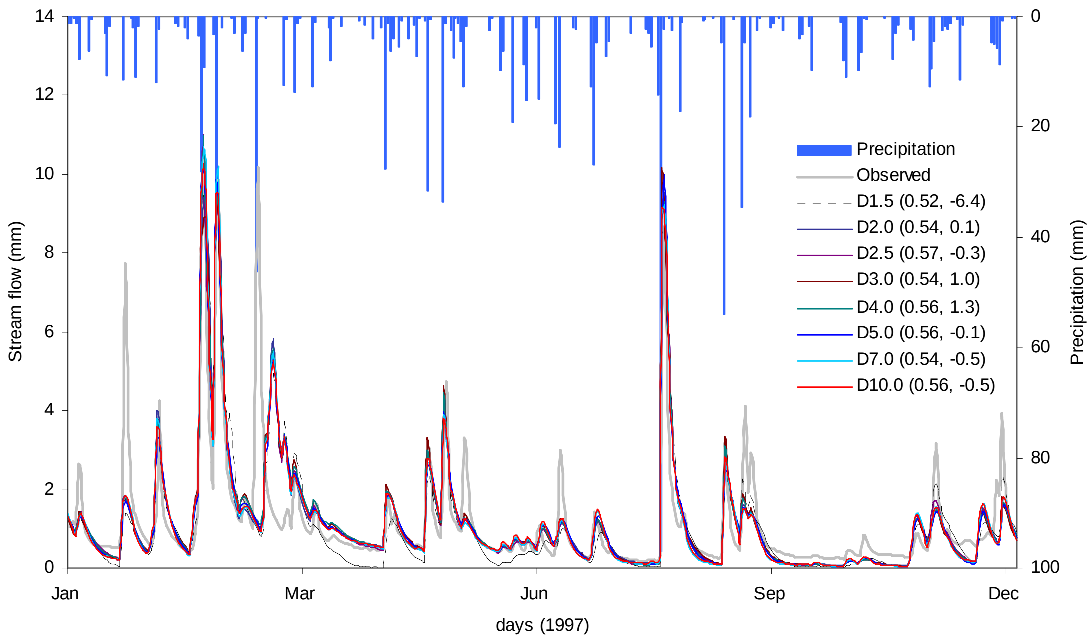


Figure 5.10 Daily hydrographs for 1997 during calibration for Cedar Creek configurations with STATSGO data (R2NS, Mbias)

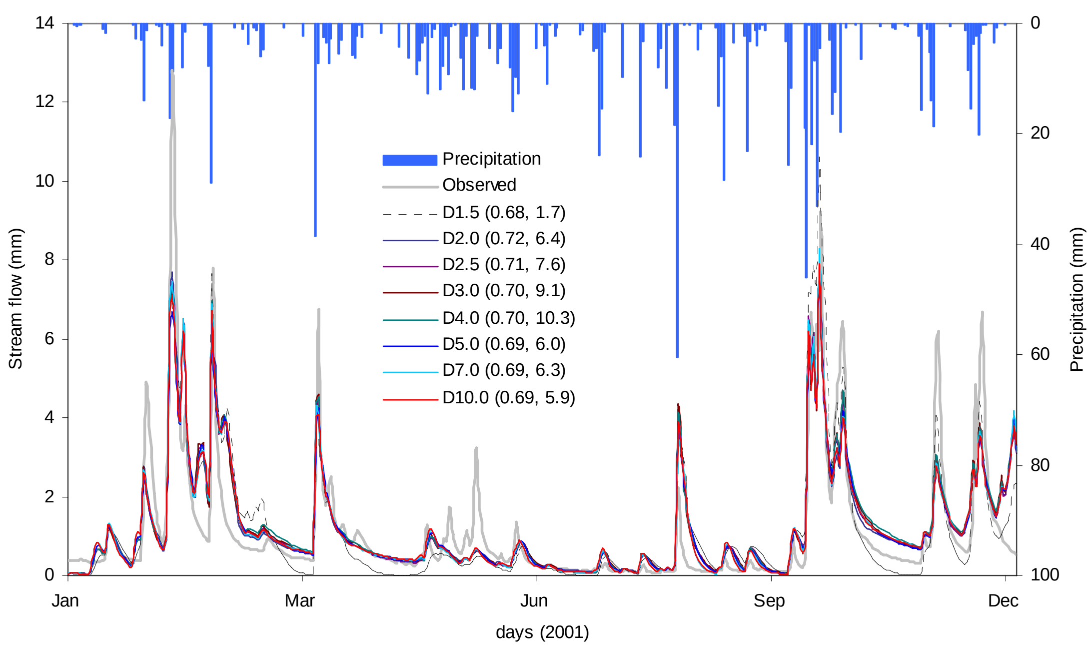


Figure 5.11 Daily hydrographs for 2001during validation for Cedar Creek configurations with STATSGO data (R2NS, Mbias)

Figure 5.10 and Figure 5.11 show daily hydrographs for 1997 during calibration phase and 2001 during validation phase, respectively for all Cedar Creek configurations with STATSGO data. Average R^2_{NS} and M_{bias} during 1997 are 0.55 and -0.8% and those during 2001 are 0.70 and 6.7%, respectively. Except for D1.5 all configurations show similar results. Cedar creek configurations with STATSGO data are performing better with respect to M_{bias} compared to configurations with SSURGO data. Better performance of STATSGO data is also visible in monthly hydrograph shown in Figure 5.12 for C5.0 and D5.0 configurations. Configuration with SSURGO data (C5.0) under estimates flows during calibration and validation phase. For the entire simulation period (1993-2003), R^2_{NS} and M_{bias} are 0.86 and 4.4%, respectively for STATSGO data, whereas for SSURGO data R^2_{NS} and M_{bias} are 0.68 and -28.9%, respectively.

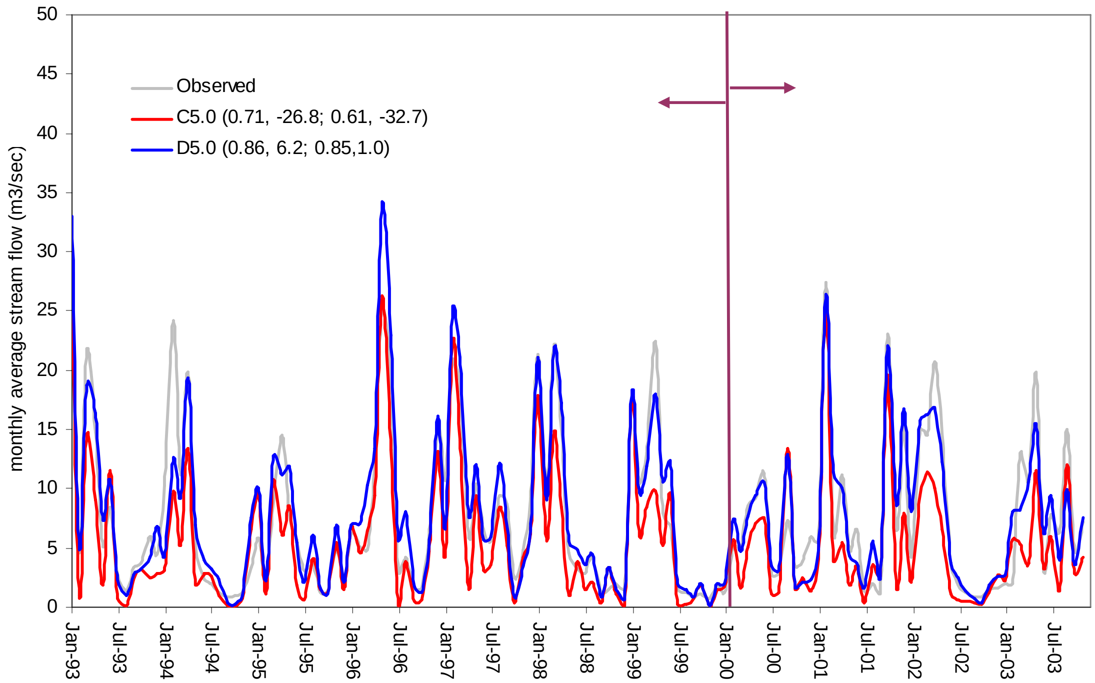


Figure 5.12 Monthly hydrograph for C5.0 and D5.0 models for entire simulation period (1993-2003), (R2NS, Mbias for calibration and validation period)

5.4 Manual adjustment of SWAT parameters

The two indicators of performance R^2_{NS} and M_{bias} show different results with R^2_{NS} showing relatively better results compared to M_{bias} for most cases. As mentioned earlier, the success of R^2_{NS} can be attributed to the bias of objective function (*SSE*) towards high flows[1]. To investigate the effect of model parameters on M_{bias}, the distribution of total precipitation among different hydrologic components of the model is explored in this section.

Table 5.8 compares the distribution of 978 mm of precipitation among different hydrologic components for two configurations C5.0 and D5.0. The overall performance of configuration D5.0 is good in terms of R^2_{NS} and M_{bias} but configuration C5.0 under estimate flows during calibration and validation phase. According to Table 5.8, while surface runoff is approximately same (~250-260 mm) for both configurations, but groundwater Q is not contributing (groundwater Q=0) to streamflow (WYLD) in the case of C5.0 configuration. In addition, percolation through soil layer is low (51 mm compared to 110 mm), and a major portion of that (39 mm out of 51 mm) is going into deep aquifer without contributing to streamflow. As a result, the baseflow component of C5.0 configuration is very low, thus underestimating low flow (Figure 5.13) and eventually affecting M_{bias}. Less volume of percolation is compensated by higher volume of evapotranspiration in C5.0 configuration.

To improve the performance of C5.0 configuration, parameters that affect groundwater contribution to stream (*Gwqmn* and *Rechrge_dp*) are manually adjusted to increase baseflow contribution to streamflow. Similarly some other parameters such as *sol_awc* are adjusted (lowered) to increase percolation though soil profile and to decrease evapotranspiration. These changes resulted in significant improvement in M_{bais} performance during calibration and validation phase for C5.0 configuration as shown in

[1] Please note that R^2_{NS} is normalized value of *SSE*, so in effect both are representing the same quantity on different scale

Table 5.9 and Figure 5.14. Because R^2_{NS} is biased towards high flows, no significant change in R^2_{NS} is observed as a result of manual adjustment.

Table 5.8 Major water balance components (yearly average value, 1993-2003) and model performances for C5.0 and D5.0 configurations

		Value (mm)	
Sl. No.	Component	C5.0	D5.0
1	Precipitation	978	978
2	Snow Fall	113	118
4	snow melt	105	116
3	Sublimation	6	0
4	Surface Runoff	250	268
5	Lateral Q	7	2
6	Groundwater Q	0	93
7	Revap	1	1
8	Deep Aq Recharge	39	17
9	Percolation through soil	51	110
10	WYLD	252	356
11	Evapotranspiration	671	598
12	Transmission loss	5	7
Model performance			
Calibration (1993-1999)	R^2_{NS}	0.71	0.75
	M_{bais}	-26.6%	6.4%
Validation (2000-2003)	R^2_{NS}	0.55	0.59
	M_{bais}	-33.1%	0.9%

Similar adjustments are made for other Cedar Creek configurations with SSURGO data and SJRW configurations with SSURGO and STATSGO data and results are presented in Table 5.10. Main parameters changed during manual adjustment are *sol_awc* and *Gwqmn* (values lowered). As result of manual adjustments, M_{bais} show significant improvement without any effect on R^2_{NS} compared to model performances shown in Table 5.4 and 5.6.

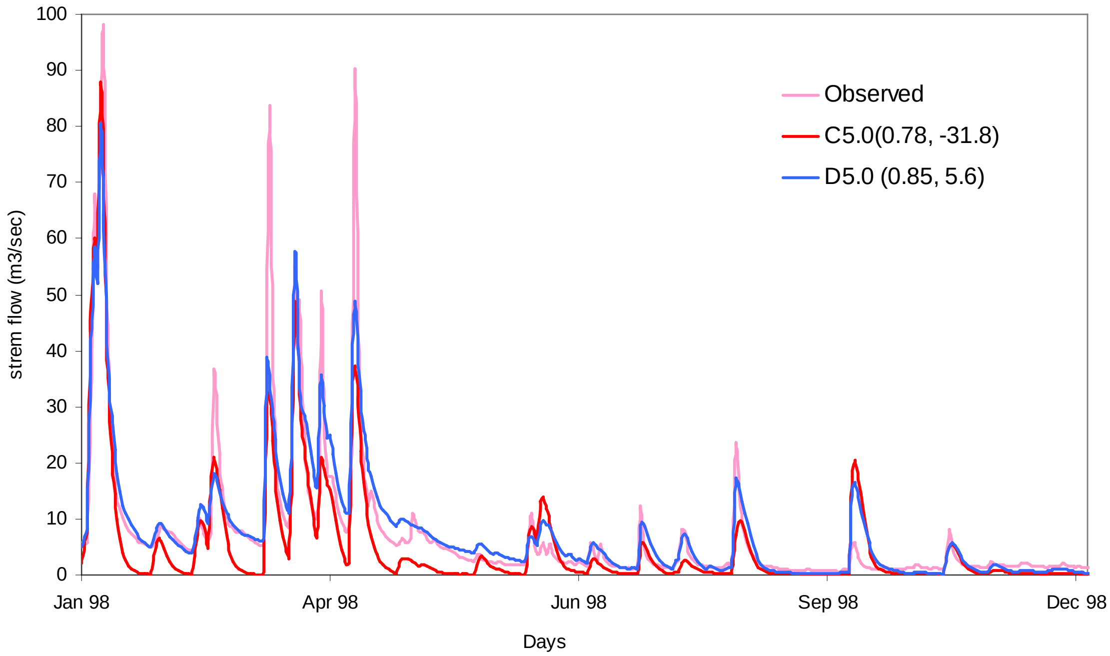


Figure 5.13 Calibrated daily hydrograph in year 1998 for C5.0 and D5.0 configurations (R2NS, Mbias)

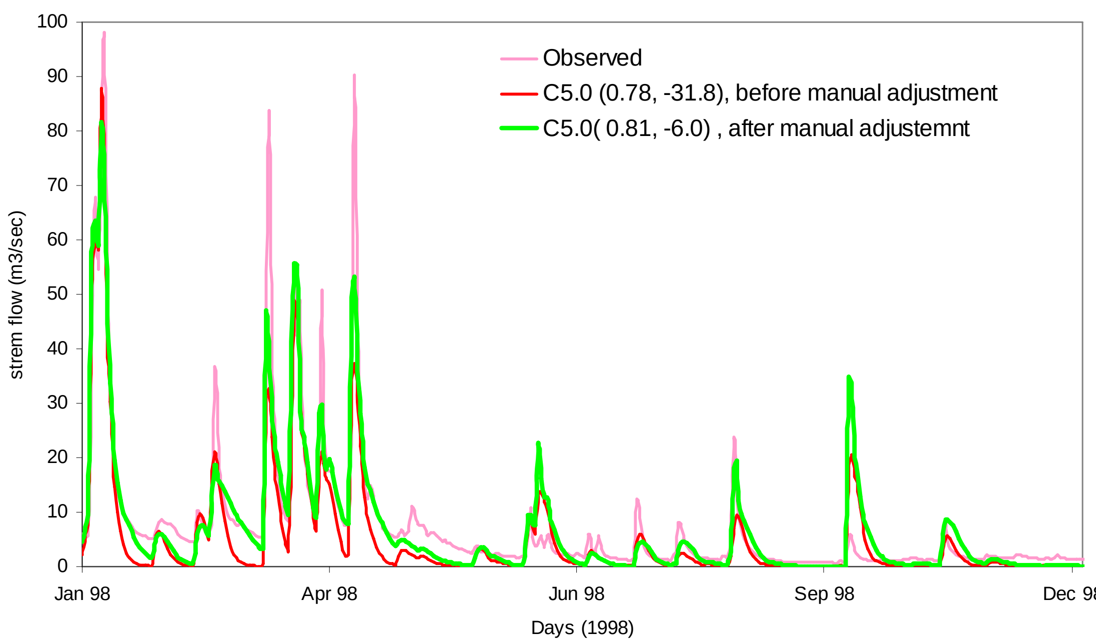


Figure 5.14 Calibrated daily hydrograph in year 1998 for C5.0 configurations before and after manual adjustment (R2NS, Mbias)

Table 5.9 Major water balance components (annual average value, 1993-2003) and model performances before and after manual adjustment for C5.0 model

		Value (mm)	
Sl. No.	Component	Before manual adjustment	After manual adjustment
1	Precipitation	978.0	978.0
2	Snow Fall	113.0	113.1
4	snow melt	105.4	105.4
3	Sublimation	6.5	6.5
4	Surface Runoff	250.0	286.4
5	Lateral Q	7.1	2.2
6	Groundwater Q	0.0	70.4
7	Revap	1.0	0.0
8	Deep Aq Recharge	38.9	12.4
9	Percolation through soil	51.2	82.8
10	WYLD	252.3	353.8
11	Evapotranspiration	671.0	607.8
12	Transmission loss	4.8	5.1
Model performance			
Calibration (1993-19999)	R^2_{NS}	0.71	0.68
	M_{bais}	-26.6%	-0.7%
Validation (2000-2003)	R^2_{NS}	0.55	0.56
	M_{bais}	-33.0%	-0.3%

Final model performances for all configurations are comparable with values reported in literature for daily flow calibration. For example, Wang and Melesse (2006) have reported R_{NS}^2 of 0.51 and 0.31 for calibration and validation period, respectively for Elm River sub-watershed in North Dakota.

Table 5.10 Final model performance after manual adjustment

Model	Calibration period 1993-1999		Validation Period 2000-2003	
	R^2_{NS}	M_{bias}	R^2_{NS}	M_{bias}
A0.5	0.65	-7.8	0.66	6.5
A1.0	0.61	-4.9	0.59	9.8
A2.0	0.66	-11.8	0.67	0.3
A3.0	0.59	-12.2	0.61	1.9
A5.0	0.46	-12.2	0.60	4.2
A7.0	0.60	-6.5	0.61	11.6
B0.5*	0.60	-11.0	0.62	9.8
B1.0	0.66	-9.3	0.66	4.6
B2.0	0.66	-10.7	0.61	1.9
B3.0	0.61	-11.9	0.66	2.1
B5.0	0.43	-10.8	0.50	5.5
B7.0	0.52	-8.3	0.61	9.5
C1.5	0.69	-4.1	0.54	-5.7
C2.0	0.68	-4.4	0.56	-5.3
C2.5	0.67	-2.1	0.58	-2.5
C3.0	0.70	-2.1	0.54	-3.6
C4.0	0.70	-5.3	0.55	-7.3
C5.0	0.68	-0.7	0.56	-0.3
C7.0	0.69	-0.2	0.56	-0.9
C10.0	0.70	-2.1	0.58	-3.7

* No manual adjustment is performed in case of B0.5 model

Vazquez-Amabile et al. (2006) found maximum R^2_{NS} value of 0.65 for calibration period and 0.60 for validation period for SJRW (same watershed as in this research). As explained earlier, R^2_{NS} value alone cannot be used as a sufficient criterion for evaluating model performance because even a high R^2_{NS} value can result into poor model performance in terms of M_{bais}. Therefore, additional indicators such as M_{bais} should be included along with R^2_{NS} while evaluating model results (all referred R^2_{NS} values are taken from Gassman et al. 2007).

Twelve SJRW and sixteen Cedar Creek configurations show different watershed attributes and parameter sets for each configuration, but overall calibration and validation performances in terms of R^2_{NS} and M_{bias} is approximately the same for all configurations. These results are concurrent with the concept of equifinality as suggested by Beven (1993). Parameter uncertainty is explored in more details in Section 5.5.

5.5 Parameter Uncertainty

Parameter uncertainty is evaluated by fixing a threshold value of objective function. If a parameter set gives objective function value below threshold objective function during SCE-UA optimization program, it is characterized as good parameter set. Threshold value has been defined by χ2-statistics corresponding to 97.5 % confidence level. If x^* (x^*_1, x^*_2,…… x^*_p) is the optimum parameter vector corresponding to which SCE-UA algorithms has determined minimum value of objective function (SSE^*) in a particular calibration program, then threshold value for good parameter set (SSE_T) is defined as below:

$$SSE_T = SSE^* \times \left(1 + \frac{\chi^2_{p,0.975}}{n-p}\right) \qquad 5.4$$

where n is number of records used in calibration (n = 2556 for 7 years), and p is number of parameters (19 for SJRW configurations and 14 for Cedar Creek configurations), and

$\chi^2_{p,0.975}$ is χ^2 value corresponding to p degree of freedom and 97.5 % confidence region. For n = 2556 and p = 19, SSE_T = 1.0129 x SSE^*, i.e. SSE_T is 1.29% greater than SSE^*. Please note that SSE^* can be different for each configuration identified by SCE-UA optimization program for each configuration.

5.5.1 SJRW Configurations

A large number of parameter sets are identified as good parameter sets during SCE-UA optimization program. Table 5.11 gives number of good parameter sets for SJRW configurations. However, in case of A1.0, A3.0 and B0.5 configurations number of good parameter sets are very less (< =10), and therefore these configurations are not included in further analysis. Uncertainties in different parameters across different model configurations are shown in Figure 5.14 in the form of modified box plot. Uncertainty ranges for all parameters are normalized from 0 to 100 using the following formula:

$$P_N = \left(\frac{P_G - LB}{UB - LB} \right) \times 100 \qquad 5.5$$

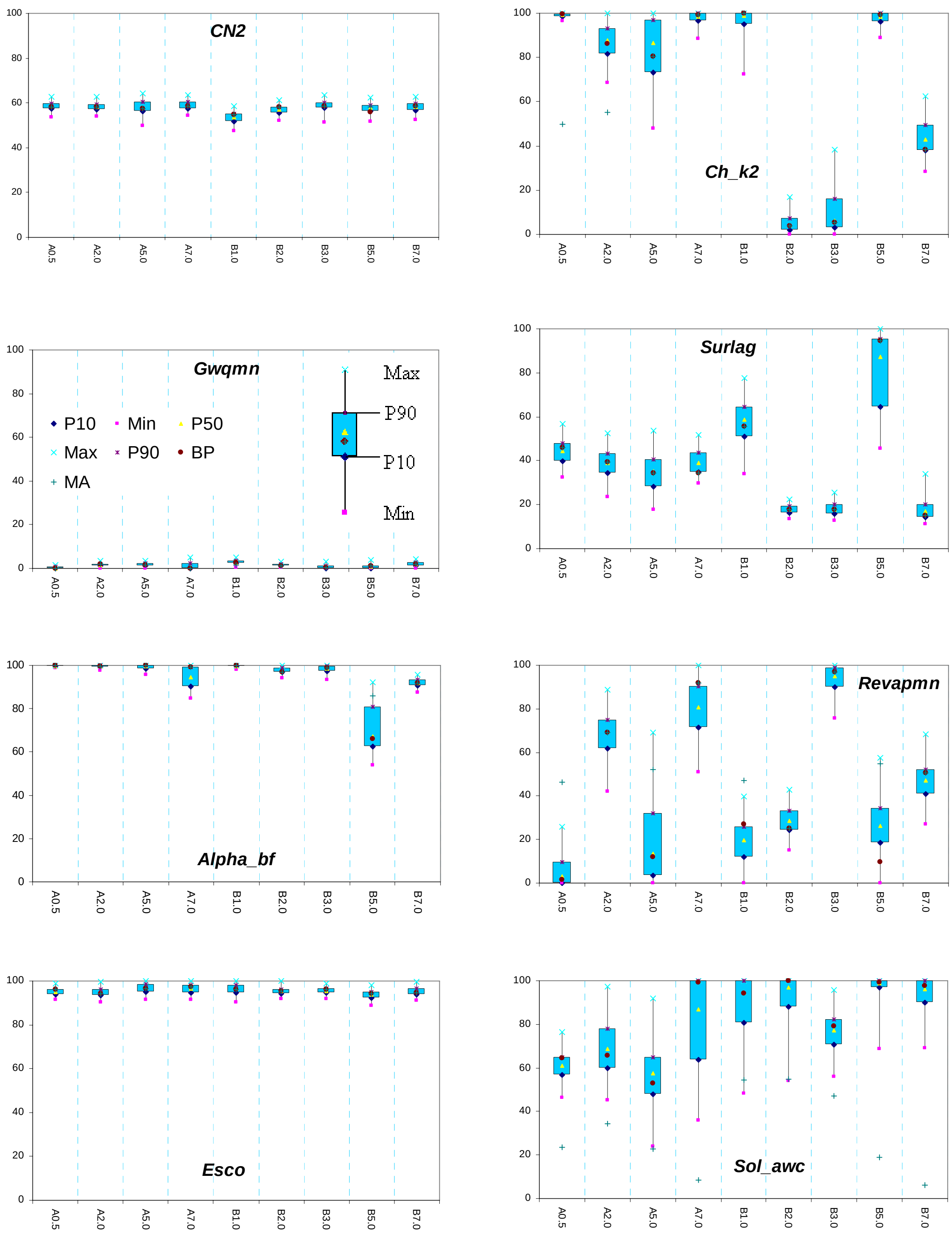
where P_N is normalized relative change (change option (2) and (3)) or value (change option (1)) of a parameter, P_G is the relative change (change option (2) and (3)) or value (change option (1)) of the parameter identified by SCE-UA optimization program, LB and UB are lower and upper bound, respectively. LB, UB, and parameter change option are given in Table 5.2. For example, if SCE-UA identifies 1.5% relative change in $CN2$ after auto calibration then its normalized value with -25% as LB and 25% as UB is $\left[\left(\frac{1.5 - (-25)}{25 - (-25)} \right) \times 100 \right]$ = 53. In the case of change option (2) and (3), no change condition is represented by number 50 on normalized scale, and a number greater than 50 represents positive change, and a number less than 50 represents a negative change. In the case of change option (1), for example, if SCE-UA identifies a value of 200 for $Gwqmn$, then its normalized value with zero as LB and 5000 as UB is represented by $\left[\left(\frac{200 - (0)}{5000 - (0)} \right) \times 100 \right]$ = 4.

Table 5.11 Number of good parameter sets for SJRW models

Model	Total number of runs in SCA-UA optimization program*	Number of good parameter sets	Number of good parameter sets as % of total runs
A0.5	9994	2741	27.43
A1.0	5104	6	0.12
A2.0	9155	2608	28.49
A3.0	4763	10	0.21
A5.0	7905	2911	36.82
A7.0	7811	2248	28.78
B0.5	7150	3	0.04
B1.0	8492	2184	25.72
B2.0	9539	2409	25.25
B3.0	9180	2181	23.76
B5.0	9084	2734	30.10
B7.0	8793	1811	20.60

* Maximum number of allowed runs for each program was 20000, however individual program terminated based on criteria met

It is hypothesized that less uncertain parameter will show less variability across all model runs, and vice versa. It is quite evident from Figure 5.14 that not all parameters are showing equal uncertainty and parameter uncertainty ranges are different for each parameter.



Continued over next page…

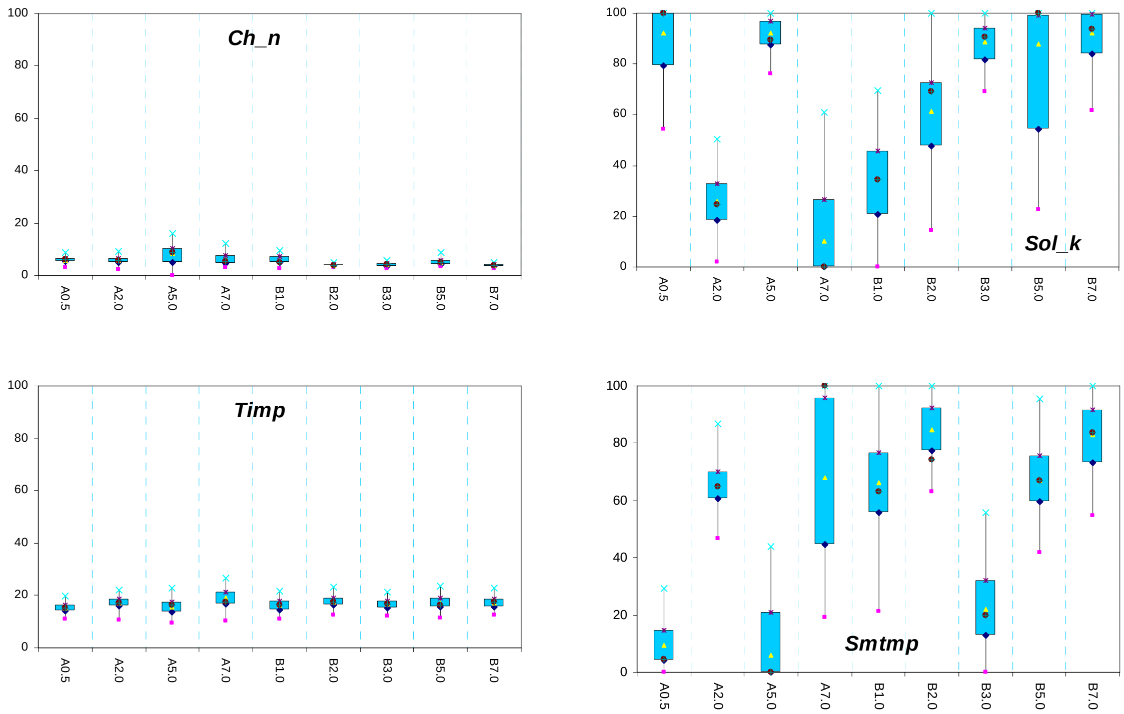


Figure 5.15 Parameter uncertainty range for SJRW configurations

For example, most of *CN2* values (maximum and minimum among all P10 and P90, P10 and P90 represent 10^{th} and 90^{th} percentile, respectively) lie between 52 and 60 (0.5 % and 5.5 % in original scale), *Gwqmn* varies between 0 and 4 (0 and 200 mm in original scale), and *Alpha_bf* varies between 62 and 100 (0.6 to 1.0 in original scale). Similarly *Esco* and *ch_n* also show narrow range of variability; whereas other parameters such as *ch_k2*, *surlag*, *sol_awc, sol_k,* and *Smtmp* show larger range of variability. For example, variability range for *ch_k2, smtmp,* and *sol_awc* are between 2 -100, 0-96, and 48-100, respectively.

Based on average uncertainty score (UC = P90-P10), parameters can be grouped in three classes: Class 1 (UC < 5) contains *Gwqmn, Ch_n, Esco, CN2, timp, Alpha_bf and Canmx,* Class 2 (5 <UC<15) contains *Biomix, Ch_k2, Gw_delay, Surlag*; *Revapmn*, and *sol_awc,* and Class 3 (15<UC<25) contains *Gw_revap, Blai, , Epco, Sol_alb, Smtmp, and Sol_k.* Most of parameters belonging to Class-1 are very sensitive to streamflow output. For example, surface runoff constitutes around 75-80 % of total streamflow which is mostly determined by *CN2* value. Similarly *Gwqmn* determines the fate of baseflow in the model, which is an important part (20-25%) of total streamflow. Parameters showing large variability in Class 2 and 3 are less sensitive to streamflow output.

5.5.2 Cedar Creek Configurations

Table 5.12 shows number of good parameter sets (defined in Section 5.5) for Cedar Creek configurations, while 7 out of 8 watershed configurations with STATSGO data resulted into large number of good parameter sets, only 2 out of 8 watershed configurations with SSURGO data resulted into large number of good parameter sets. Model configurations having number of good parameter sets less than 10 are not included in further analysis. As per average uncertainty score defined in previous section, Class 1 (UC < 5) contains *CN2, Gwqmn, surlag, and Alpha_bf* , Class 2 (5<UC<15) contains *Esco, Ch_n, Sol_awc, Ch_k2, Rchrg_dp, Gw_delay, Revapmn*, and Class 3 (15<UC<25) contains *Gw_revap, epco and canmx.* Similar to SJRW configurations, Class 1 parameters show minimal variability, whereas Class 2 and 3 parameters show higher variability (Figure 5.16). Most parameters included in individual classes are same for both Cedar Creek and SJRW configurations.

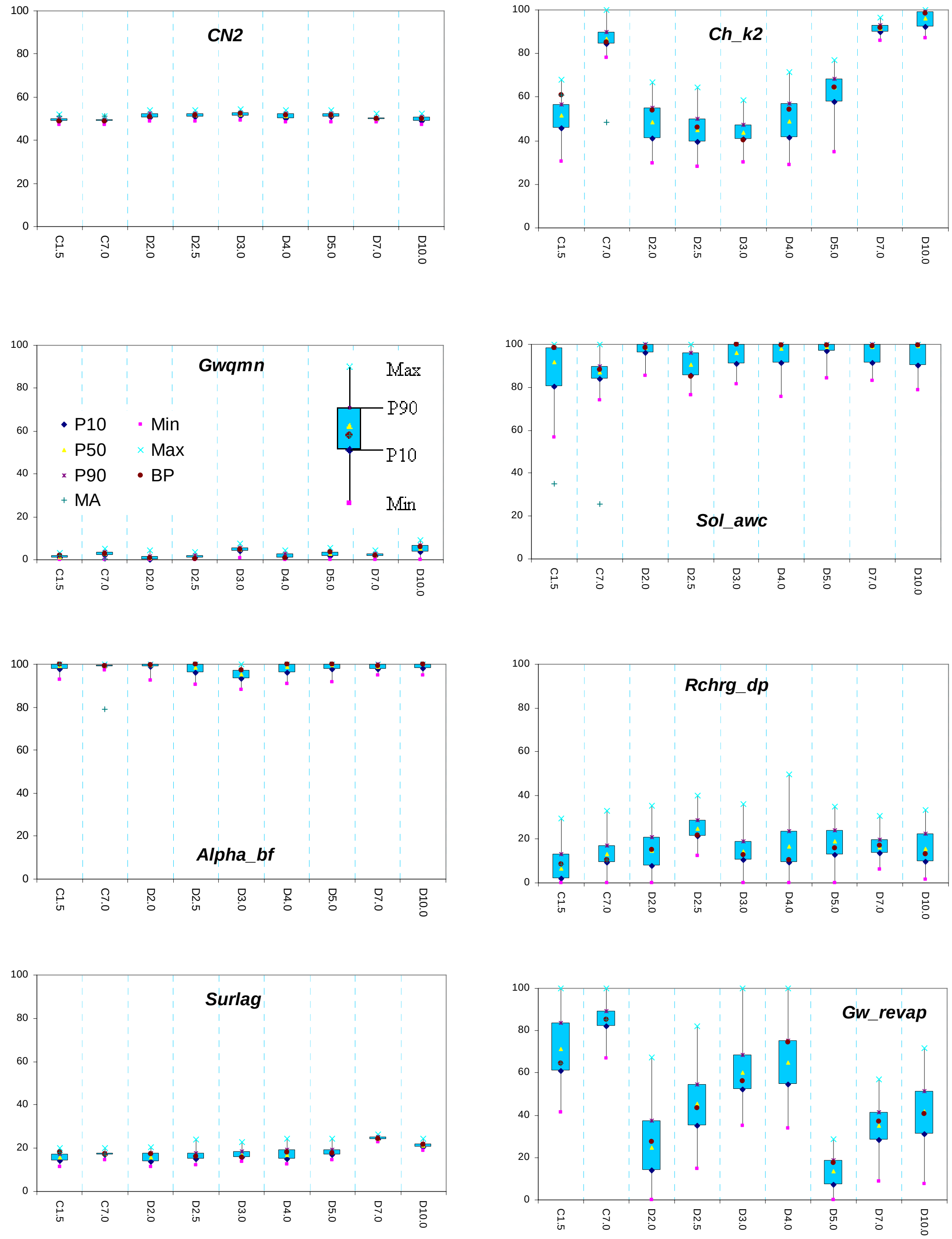
Findings of large number of parameter sets for many configurations follows the *concept of equifinality* (Beven, 1993), but parameter uncertainty range are dependent on individual parameter sensitivity. Not all the parameters are equally uncertain, and more sensitive parameters (Class 1, even a small change in these parameter values can affect model output significantly) show very small range of uncertainty compared to less sensitive parameters (Class 2 and 3, even a larger change in these parameter values do not affect model output significantly). Parameter ranges provided for sensitive parameters appears to be too large, which may cause erroneous result during sensitivity analysis (in LH sampling, during sensitivity analysis provided parameter range is divided into 10 equal intervals with equal probability of every interval).

Table 5.12 Number of good parameter sets for Cedar Creek Models

Model	Total number of runs in SCA-UA optimization program*	Number of good parameter sets	Number of good parameter sets as % of total runs
C1.5	9810	2181	22.23
C2.0	4203	3	0.07
C2.5	3902	1	0.03
C3.0	3601	1	0.03
C4.0	3601	2	0.06
C5.0	4203	2	0.05
C7.0	7552	2107	27.90
C10.0	4805	1	0.02
D1.5	6912	2	0.03
D2.0	6727	1584	23.55
D2.5	6927	1828	26.39
D3.0	7093	1861	26.24
D4.0	5805	1185	20.41
D5.0	6928	1755	25.33
D7.0	7693	1455	18.91
D10.0	6866	1559	22.71

* Maximum number of allowed runs for each program was 20000

Similarly large range of sensitive parameters can affect the computational efficiency during calibration (computational run time). Results from this research suggest re-defining uncertainty range (narrowing down) for sensitive parameters. Results also suggest categorizing of parameters in different groups based on their uncertainty range.



Continued over next page…

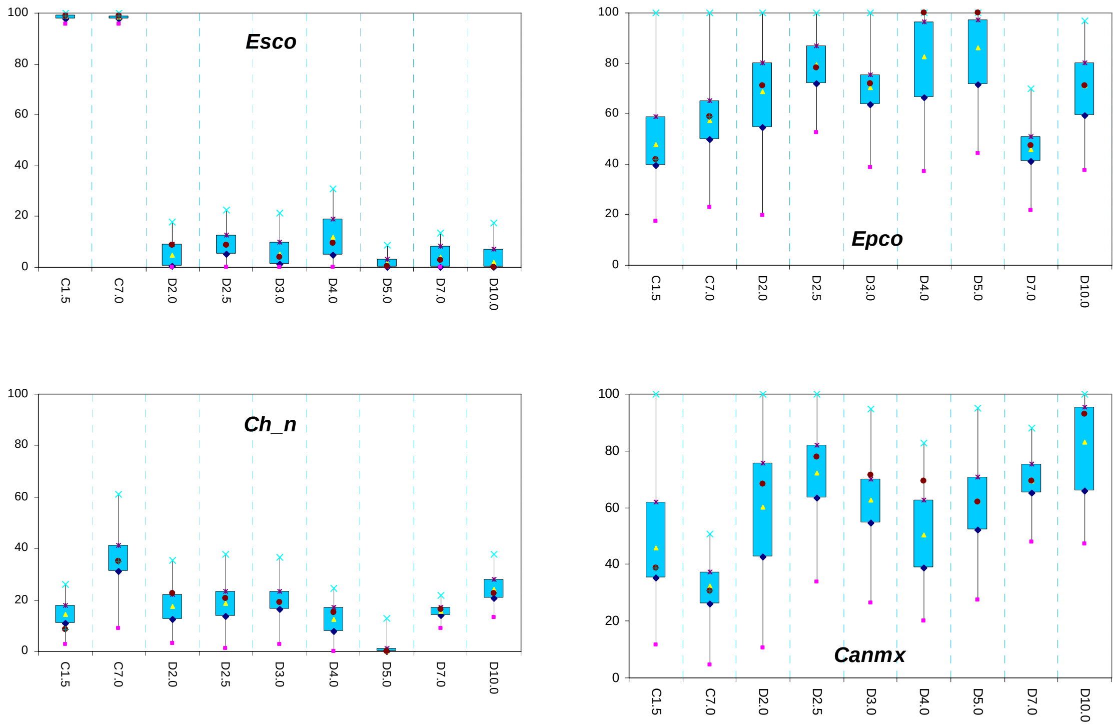


Figure 5.16 Parameter uncertainty range for Cedar Creek configurations

CHAPTER 6 SUMMARY AND CONCLUSIONS

A study on the effects of spatial scale (represented by number of sub watersheds and scale of soil data) on model calibration is presented in this thesis. Different spatial scale watershed configurations are created for St. Joseph River Watershed and Cedar Creek using semi distributed, process-based SWAT model. Many of watershed attributes such as drainage density, channel slope, number of sub watersheds, and number of HRUs differed significantly across different configurations. Watershed attributes such as soil hydrologic group, average *CN2*, and average *sol_awc* are not affected by watershed discretization level (number of sub watersheds) but their values are different for STATSGO and SSURGO soil data.

Twelve SJRW configurations and sixteen Cedar Creek configurations are independently calibrated for large number of parameters (19 for SJRW and 14 for Cedar Creek) using Shuffled Complex Evolution algorithm (SCE-UA) for daily streamflow outputs at respective watershed outlets. Model performance is evaluated in terms of R^2_{NS} and M_{bias}. Average R^2_{NS} for calibration period (1993-1999) and validation period (2000-2003) are 0.56 and 0.66, respectively in case of SJRW configurations. For cedar creek configurations, average R^2_{NS} for calibration period (1993-1999) and validation period (2000-2003) are 0.73 and 0.57, respectively. The following conclusions are drawn from this study:

1. In individual model configuration sets hydrologic response was similar for different levels of watershed discretization. Hence it can be concluded that streamflow calibration is not affected by watershed discretization level. Because SCS Curve Number method is used for surface runoff calculation, and average *CN2* has not

changed significantly across different level of watershed discretization, this can be a reason behind this result.

2. Model configurations with two types of soil data (SSURGO and STATSGO) for SJRW also show similar responses, thus indicating that finer resolution SSURGO soil data did not contribute any new information over coarser resolution STATSGO soil data. Watershed size considered in this study (SJRW) may be too large for finer resolution SSURGO data to have any effect on overall model results.

3. Model performance was found to be sensitive to shift in precipitation trends. For a dry year preceded by a dry year or a wet year preceded by a wet year model performed well. However, for a wet year preceded by dry year or a dry year preceded by wet year, model performance dropped.

4. In terms of $M_{bias,}$ the overall calibration is poor with many of model configurations underestimating the flow in the range of 15 to 20%. Poor performance of M_{bias} is because of bias of sum of square of errors (objective function) towards high flows, and therefore low flow conditions are not calibrated well. To improve model performances with respect to M_{bias}, SWAT parameters were manually adjusted. Poor performances of M_{bias}, are due to less contribution from groundwater to the stream. Hence, SWAT parameters related to groundwater component were adjusted to increase contribution of groundwater to the stream. As a result M_{bias} has improved significantly without any effect on R^2_{NS} (normalized equivalent of *SSE*).

5. The result of different model configurations exhibiting similar responses is in line with concept of equifinality. Parameter uncertainty range for individual model configuration is determined in the form of good parameter sets. All configurations that resulted in large number of good parameters sets (2000-3000) were included in uncertainty analysis. Good parameters across different configurations were compared

in terms of box plot and uncertainty score. Sensitive parameters showed very small range of uncertainty compared to less sensitive parameters.

While the results presented in the thesis can be specific to the watershed considered and model used (SWAT) in this study, it provides a general idea about the spatial scale issue affecting hydrologic modeling in a large basin such as SJRW. Further, parameter uncertainty range seems to be dependent upon sensitivity of individual parameters in a given model structure irrespective of model spatial scale, and this result can be extended to other studies in assigning uncertainty range to individual parameters.

LIST OF REFERENCES

Arabi M., Govindaraju R.S., and Hantush M.M.. 2007 (a). A probabilistic approach for analysis of uncertainty in the evaluation of watershed management practices. Journal of Hydrology. 333: 459-471.

Arabi M., Govindaraju R.S., Engel B. and Hantush M. 2007 (b). Multiobjective sensitivity analysis of sediment and nitrogen process with a watershed model. Water Resources Research. 43, W06409, doi:10.1029/2006WR005463.

Arabi, M., Govindaraju R.S., Hantush M.M., and Engel B. 2006. Role of watershed subdivision on modeling the effectiveness of best management practices with SWAT. Journal of the American Water Resource Association. 42(2): 513-528

Arabi M., 2005. A modeling framework for evaluations of watershed management practices for sediment and nutrient control. Ph.D. Dissertation, Purdue University, West Lafayette, Indiana.

ArcSWAT 1.0.5. Soil and Water Assessment Tool: ArcSWAT. Available at: www.brc.tamus.edu/swat/arcswat.html. Last accessed on 07/15/2007.

Arnold J.G., Srinivasan R., Muttiah R.S., and Williams J.R. 1998. Large area hydrologic modeling and assessment part I: model development. Journal of the American Water Resource Association. 34(1): 73-89.

Bernot M. J., Tank J. L., Royer T. V. and David M. B. (2006). Nutrient uptake in streams draining agricultural catchments of the midwestern United States. Freshwater Biology. 51: 499-509.

Beven K. (2006). A manifesto for the equifinality thesis. Journal of Hydrology. 320: 18-36

Beven K. (1993). Prophecy, reality and uncertainty in distributed hydrological model. Advances in Water Resources, 16: 41-51.

Beven K.J., Binley A.M. (1992). The future of distributed models: model calibration and uncertainty prediction. Hydrologic Processes, 6: 279-298.

Bingner, R.L., Garbrecht J., Arnold J.G., and Srinivasan R. (1997). Effect of watershed subdivision on simulated runoff and fine sediment yield. Transaction of American Society of Agriculture Engineers 40(5): 1329-1335

Black P. E. (1991). Watershed Hydrology. Prentice Hall Advanced Reference Series. Pages 227, 248-251.

Chaplot, V. (2005). Impact of DEM mesh size and soil map scale on SWAT runoff, sediment, and NO3-N loads predictions. Journal of Hydrology. 312: 207-222

Chaplot, V., Saleh A., and Jaynes D.B. (2005). Effect of the accuracy of spatial rainfall information on the modeling of water, sediment, and NO3-N loads at the watershed level. Journal of Hydrology. 312: 223-234

Cotter, A.S., Chaubey I., Costello T.A., Soerens T.S., and Nelson M.A. (2003). Water quality model output uncertainty as affected by spatial resolution of input data. Journal of the American Water Resource Association 39(4): 977-986

Chaubey I., Cotter A.S., Costello T.A., and Soerens T.S. (2005). Effect of data resolution on SWAT output uncertainty. Hydrologic Process. 19: 621-628

Chow V. T. (1959). Open Channel Hydraulics. McGraw-Hill, Inc. Page 120.

Crawford N. H. and Linsley R. K. (1966). Digital simulation in Hydrology: Stanford watershed model IV, Tech. Rep. 39, Dept. of Civil Eng., Stanford University, Stanford, California

Di Luzio, M., Arnold J.G., and Srinivasan R. (2005). Effect of GIS data quality on small watershed streamflow and sediment simulations. Hydrologic Process. 19: 629-650

Di Luzio, M. and Arnold J.G. (2004). Formulation of a hybrid calibration approach for a physically based distributed model with NEXRAD data input. Journal of Hydrology. 298: 136-154

Duan Q., Sorooshian S. and Gupta V. 1992. Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resources Research. 28 (4): 1015-1031

Dunn S. M. (1999). Imposing constrains on parameter values of a conceptual hydrological model using baseflow response. Hydrol. And Earth Sys. Sci. 3: 271-284

Eckhardt K., Fohrer N., and Frede H.-G. 2005. Automatic model calibration. Hydrologic Process. 19: 651-658

Eckhardt, K., Breuer L., and Frede H.-G. 2003. Parameter uncertainty and the significance of simulated land use change effects. Journal of Hydrology. 273: 164-176

Eckhardt, K. and Arnold J.G. 2001. Automatic calibration of a distributed catchment model. Journal of Hydrology. 251: 103-109

FitzHugh, T. W., and Mackay D.S. 2001. Impact of subwatershed partitioning on modeled source- and transport-limited sediment yields in an agricultural nonpoint source model. Journal of soil and water conservation. 56 (2):137-143

FitzHugh, T. W., and Mackay D.S. (2000). Impacts of input parameter spatial aggregation on an agricultural nonpoint source pollution model. Journal of Hydrology. 236: 35-53

Flanagan, D. C., Livingston S. J., Huang C. H., and Warnemuende E. A. (2003). Runoff and pesticide discharge from agricultural watersheds in NE Indiana. ASAE Paper No032006. St. Joseph, Mich.: ASAE.

Gassman P.W., Reyes M. R., Green C.H. and Arnold J.G. 2007. The Soil and Water Assessment Tool: Historical Development, Applications, and Future Research Directions. Transaction of the ASABE 50(4) 1211-1250.

Green W. H, and Ampt G. A. (1911). Studies on soil physics, part I, the flow of air and water through soils. J. Agric. Sci. 4(1) 1:24.

Gupta H. V., Sorooshian S., and Yapo P. O. (1998), Toward improved calibration of hydrologic models: multiple and noncommensurable measures of information, Water. Resources. Research. 34:751-763.

Hargreaves, G. L., Hargreaves G. H., and Riley J. P. 1985. Agricultural benefits for Senegal River Basin. Journal of Irrigation and Drainage Engineering 108(3): 225-230.

Homer C., Dewitz J., Fry J., Coan M., Hossain N., Larson C., Herold N., McKerrow A., VanDriel J. N., and Wickham J. (2007). Photogrammetric Engineering and Remote Sensing. 73 (4): 337-341.

Inamdar S. and Naumov A. (2006). Assessment of sediment yields for a mixed-land use great lakes watershed: lessons form field measurements and modeling. Journal of Great Lakes Research. 32: 471-488

Jha, M., P.W. Gassman, S. Secchi, R. Gu, and J. Arnold. 2004. Effect of watershed subdivision on SWAT flow, sediment, and nutrient predictions. Journal of the American Water Resource Association. 40(3): 811 825

Kalin L. and Hantush M.M. (2006). Hydrologic modeling of an eastern Pennsylvania watershed with NEXRAD and Rain Gauge Data. Journal of Hydrologic Engineering 11(6): 555-569

Kannan N., White S.M., Worrall F., and Whelan M.J. (2007 (a)). Hydrologic modeling of a small catchment using SWAT-2000-Ensuring correct flow partitioning for contaminant modeling. Journal of Hydrology. 334: 64-72

Kannan N., White S.M., Worrall F., and Whelan M.J. (2007 (b)). Sensitivity analysis and identification of the best evapotranspiration and runoff options for hydrological modeling in SWAT-2000. Journal of Hydrology. 332: 456-466.

Lane, L. J., 1982. Distributed Model for Small Semi-Arid WatershedsASCE J. Hydr. Div. 108(HY1O):1114-1131.

Larose, M., Heathman, G.C., Norton, L.D., Engel, B. 2007. Hydrologic and atrazine simulation in the Cedar Creek Watershed using the SWAT model. Journal of Environmental Quality. 36:521-531.

Lin, Z. and Radcliffe D.E. 2006. Automatic calibration and predictive uncertainty analysis of a semidistributed watershed model. Vadose Zone Journal. 5: 248-260

McKay M.D. (1988). Sensitivity and Uncertainty Analysis Using a Staistical Sample of Input Values. Uncertainty Analysis, Y. Ronen, ed. CRC press, Inc. Boca Raton, Florida, 145-186.

McKay M.D., Beckman, R.J. and Conover, W.J., 1979. A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from a Computer Code. Technometrics, 21(2), 239-245.

Mamillapalli, S., 1998. Effect of spatial variability on river basin streamflow modeling. Ph.D. Thesis, Purdue University, West Lafayette.

Melching C. S. and Yoon C. G. 1996. Key sources of uncertainty in QUAL2E model of Passaic River. Journal of Water Resource Planning and Management. 122 (2) 105:113

Monteith J. L. (1965). Climate and the Efficiency of Crop Production in Britain. Phil. Trans. Res. Soc. London Ser. B. 281:277-329.

Morris M.D. (1991). Factorial sampling plans for preliminary computational experiments. Tecnometrics. 33 (2).

Muleta, M.K., Nicklow J.W. and Bekele E.G. (2007). Sensitivity of a distributed watershed simulation model to spatial scale. Journal of Hydrologic Engineering. 12(2): 163-172

Muleta M.K. and Nicklow J.W. (2005). Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. Journal of Hydrology. 306: 127-145

Nash J.E. and Sutcliffe J.V. 1970. River flow forecasting through conceptual models: Part I. A discussion of principles. Journal of Hydrology. 10: 282-290

Nelder J. A., and Mead R.. (1965). A simplex method for function minimization, Comput. J. 7(4), 308-313

Neitsch, S.L., J.G. Arnold, J.R. Kiniry, and J.R. Williams. 2005. Soil and water assessment tool theoretical documentation, version 2005. Temple, Texas: Grassland, Soil and Water Research Laboratory, Agricultural Research Service. Available at: www.brc.tamus.edu/swat/doc.html. Last accessed on 03/18/2008

Priestley C. H. B. and Taylor R. J. (1972). On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. Mon. Weather Rev. 100:81-92.

Peschel J.M., Hann P.K., Lacey R.E. 2003. A SSURGO Pre-Processing Extension for the Arc View Soil and Water Assessment Tool. ASAE Paper No. 032123. St. Joseph. Michigan.

Ponce V. M., and Hawkins R. H. (1996). Runoff curve number: has it reached maturity? Journal of Hydrologic Engineering 1(1): 11-19

Rao A. R. and Han J. 1987. Analysis of objective functions in urban runoff models. Advances in Water Resources, 10: 205-211

Rouhani H., Willems P., Wyseure G., and Feyen J. (2007). Parameter estimation in semi-distributed hydrological catchment modeling using a multi criteria objective function. Hydrologic Process. 21: 2998-3008.

Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Sirinivasan, R., Hauck, L.M., (2001 (a)). Validation of the SWAT model on a large river basin with point and nonpoint sources. Journal of the American Water Resources Association, 37(5): 1169-1188.

Santhi C., Arnold J.G., Williams J.R., Hauck L.M., Dugas W.A., (2001(b)). Application of a watershed model to evaluate management effects on point and nonpoint source pollution. Transactions of ASAE, 44(6): 1559-1570.

Santhi C., Srinivasan R., Arnold J.G., Williams, J.R., (2003). A modeling approach to evaluate the impacts of water quality management plans implemented in the Big Cypress Creek Watershed, Watershed. Second Conference on Watershed Management to Meet Emerging TMDL Environmental Regulations, Albuquerque, NM, pp. 384-394.

Sloan P. G., Morre I. D., Coltharp G. B., and Eigel J. D. (1983).Modeling Surface and Subsurface Stormflow on Steeply-SlopingForested Watersheds. Water Resouces Inst. Report 142, Universityof Kentucky, Lexington, Kentucky.

Sorooshian S., Duan Q. Y., and Gupta V. K. (1993). Calibration of rainfall runoff models- Application of global optimization to the Sacramento Soil-Moisture Accounting Model. Water Resources Research . 29:1185-1194.

Sorooshian S. and Gupta V. K. (1995). Model calibration, in Singh V. P. (Ed.), Computer Models for Watershed Hydrology. Water Resources Publication, Highlands Ranch, CO

St. Joseph River Watershed Initiative (2006). St. Joseph River Watershed Management Plan. Available at: http://www.sjrwi.org/. Last accessed on 03/18/2008

State of the Great Lakes (2007): Highlights. Available at http://www.epa.gov/solec/ last accessed on 03/18/2008.

Tripathi M. P., Raghuwanshi N. S., and Rao G. P. (2006). Effect of watershed sub-division on simulation of water balance components. Hydrologic Process 20. 1137-1156.

USDA NRCS, SSURGO soil data. Available at http://soildatamart.nrcs.usda.gov/ last accessed on 03/18/2008

USGS, NED 1 arc second Digital Elevation model. Available at http://seamless.usgs.gov/ last accessed on 03/18/2008

USGS, NLCD 2001 Land Cover data. Available at http://seamless.usgs.gov/ last accessed on 03/18/2008

van Griensven, A (2005). Sensitivity, auto-calibration, uncertainty and model evaluation in SWAT2005. Draft. Available at http://groups.google.com/group/swatuser/files Last accessed on 03/30/2008

van Griensven, A., and Bauwens W. (2003 (a)). Multiobjective autocalibration for semidistributed water quality models. Water Resources Research. 39(12): 1348, doi:10.1029/2003WR002284

van Griensven, A., and Bauwens W. (2003 (b)). Concepts for river water quality processes for an integrated river basin modeling. Water Science and Technology. 48 (3): 1-8 van Griensven, A., Francos A. and Bauwens W. (2002). Sensitivity analysis and auto-calibration of an integral dynamic model for river water quality. Water Science and Technology. 45 (9): 325-332

Vandenberghe V., van Griensven A., and Bauwens W. (2001). Sensitivity analysis and calibration of the parameters of ESWAT: application to the River Dender. Water Science and Technology. 43 (7) 295:301

Vazquez-Amabile G., Engel B.A., and Flanagan D.C. (2006). Modeling and risk analysis of nonpoint-source pollution caused by atrazine using SWAT. Transaction of the ASABE 49(3): 667-678

Venetis, C. (1969). A study of the recession of unconfined aquifers. Bull. Int. Assoc. Sci. Hydrol. 14(4): 119-125.

Wang, X. and Melesse A.M. (2006). Effects of STATSGO and SSURGO as inputs on SWAT model's snowmelt simulation. Journal of the American Water Resource Association. 42(5): 1217-1236.

Wang, X. and Melesse A. M. (2005). Evaluation of the SWAT model's snowmelt hydrology in a northwestern Minnesota watershed. Transaction of the ASABE 48(4): 1359-1376

White K.L. and Chaubey I. (2005). Sensitivity analysis, calibration, and validations for a multisite and multivariable SWAT model. Journal of the American Water Resource Association. 41(5): 1077-1089

Williams, J.R. (1969). Flood routing with variable travel time or variable storage coefficients. Transaction of ASAE 12(1): 100-103

Yu C., Northcott W. J., and McIsaac. G. F. (2004). Development of an artificial neural network for hydrologic and water quality modeling of agricultural watersheds. Trans. ASAE 47(1):285-290.

Appendix A Pre-Processing of SSURGO Data

SURRGO data for all the 8 counties under SJRW are downloaded from the soil data mart (http://soildatamart.nrcs.usda.gov/). It comes in two parts – spatial and tabular data base. Spatial data (shape files), for all the 8 counties have been merged into a single shape file, rasterized and clipped to the watershed. In the spatial data, different soil series are associated with the unique MUKEY (Map Unit Key) number. Tabular data comes in 61 ASCII text files, but only four of them, map unit, component, horizon and fragments tables are applicable here. In the ASCII format, these files are difficult to handle, hence it is imported to the MS Access SSURGO template (Soildb_IN_2002.mdb). These tables are connected as explained below.

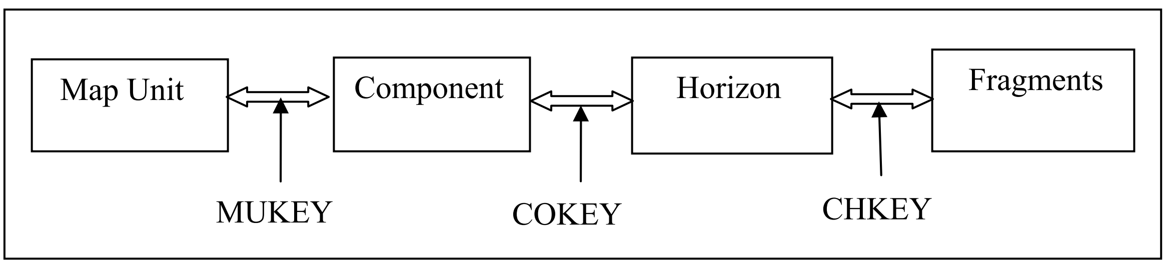


Figure A.1 Tabular data interconnection

While merging map unit, component, horizon and fragments tables, goal is to get soil properties corresponding to each MUKEY. A single map unit can have one or more than one component/s. Layer properties corresponding to a component soil in a map unit are given in the horizon table. Concept of map unit is that it represents an area dominated by one major kind of soils, or more than one kind of soils as per the soil taxonomic classes. Hence a map unit can also have soil classes other than its designated soil class. These included soils are not shown separately because of their too small area to be represented on the map scale. However if properties of these included soil differ significantly form the main soil, they are represented as a separate components in the same map unit area and the area covered by them are given as the percentage of the total map unit area. But this variability within a single map unit cannot be incorporated in the SWAT, because it looks for single data set corresponding to the every map unit (MUKEY). Hence only major or first component (when two components are having equal percentage) has been considered. Properties cannot be made weighted average of the component percentage, because it gives the error when all the components are not having the same number of layers.

For combining component (comp), horizon (chorizon), and fragments (chfrags) tables, SSURGO Extension Tool for AVSWATX (SEA) (Peschel et al., 2003) is used. But before SEA can be used, one field (DESGNVERT) of the chorizon tables is required to be updated, because this field has not been updated in existing SSURGO database for Indiana state (This based on the communication with Mike Wiggintton, Regional SSURGO database manager, NRCS during SWAT user meeting at Purdue University in April-2007). Since present version SEA (SSURGO SWAT 2.0 Extension) program reads the layer number of a soil component from this field, so when either its value is not there or incorrect, SEA program will either give the zero value of the layer properties or it will be incorrect. Field DESGNVERT can be updated with respect to values in the HZDEPT_R field, which gives the depth top of the each layer from the top soil surface. So for the first layer of each component it will have zero value and will keep increasing till the last layer in that component is reached. When it again encounters first layer of the next component its value will be reset to zero. So, the layer number (1, 2, 3…) corresponding to a soil component can be entered in the DESGNVERT field. This updating has been done in the MS Access with the help of specially written function. Once this is done, SEA can generate SSURGO database table (ssurgo.dbf) corresponding to each county.

One more step is required, before this table can be appended to usersoil database. SEA generates SSUGRO table along with all the components in a map unit, it is represented as different sequence in the same map unit. But as explained above, SWAT can take only one component corresponding to every map unit. So the minor components are to be removed. This has been done with the help of macro written by Dr. Venkatesh Merwade in the Arc Map. Then this dataset can be appended to usersoil database of SWAT2005.mdb for each of the counties. There is still some map units (2 % of total map units in the case of SJRW SSURGO data) for which there no tabular data is there i.e. soil properties are not defined. "These areas essentially have no soil and support little or no vegetation" (Soil Survey Manual – Part 3). Two major areas included in this category are urban land (covered by streets, parking lots, roads, building etc) and water (streams, lakes, ponds and estuaries). For these map units soil properties form the adjacent area can be assigned (Wang and Melesse, 2006), but there is no specific guideline on attribute values for these soil types. Once properties corresponding to each map units have been entered in user soil database, it is ready for use in the SWAT program. Figure A.2 gives the flow chart for pre-processing of SSURGO data base.

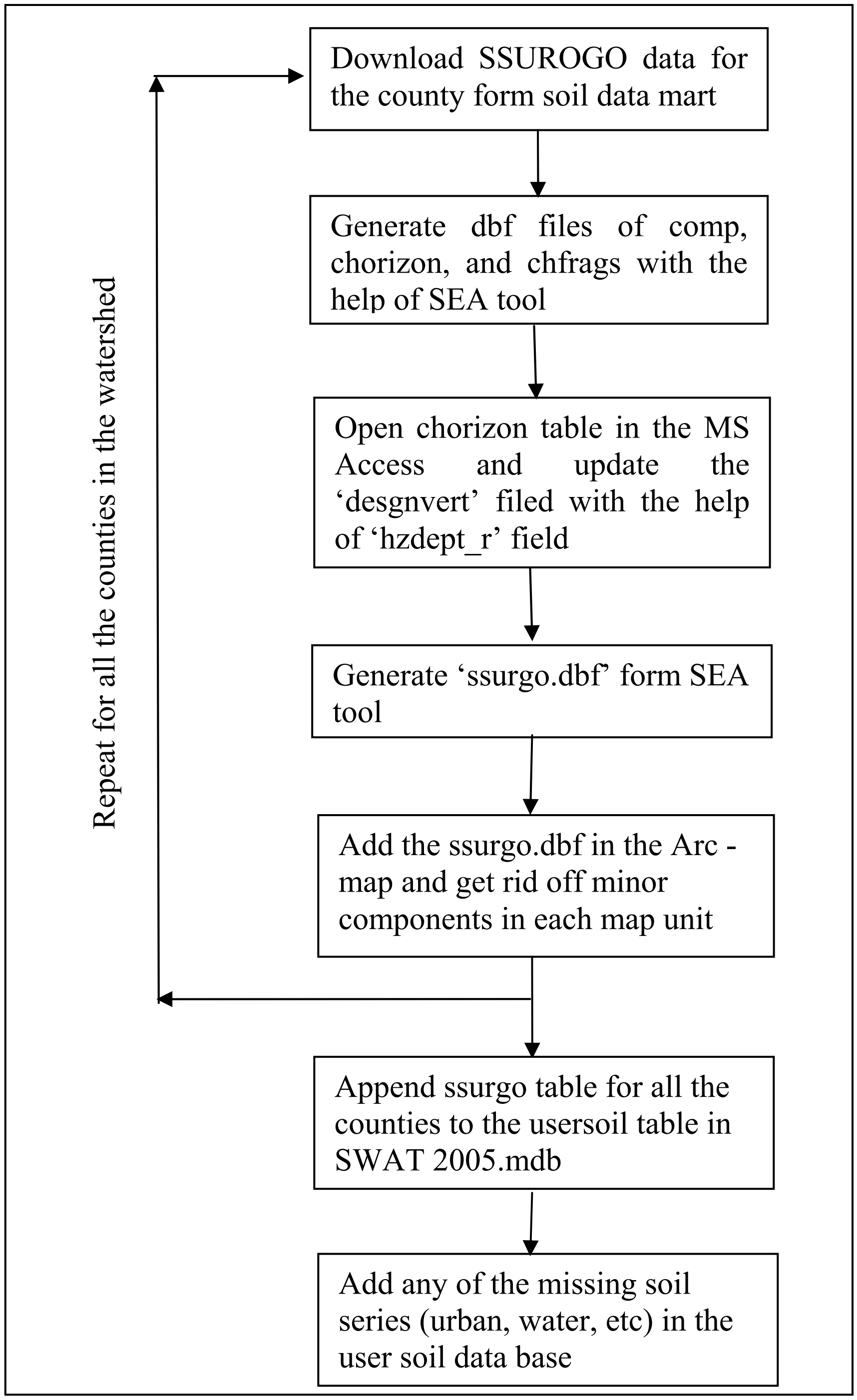


Figure A.2 Flow chart for preprocessing of SSURGO data

Appendix B Swat Hydrologic Parameters

B.1 SCS Curve Number (*CN2*)

SCS Curve Number method calculates surface run-off using following equations:

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \qquad \text{B.1}$$

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \qquad \text{B.2}$$

where Q_{surf} is rainfall excess (mm) or accumulated surface runoff in a day having rainfall R_{day} and R_{day} is > $0.2S$ (initial abstraction). CN is the Curve number for the day and S is the retention parameter defined in Equation B.2. CN value is a function of land use, its treatment or practice, soil hydrologic group and antecedent moisture condition for the day. Q_{surf} increases in a non linear fashion with increase in CN value. Figure B.1 shows a typical graph for effect of percentage change in the *CN2* value on surface runoff generation for a given rainfall event. Percentage increase in Q_{surf} is higher as compared to the percentage increase in *CN2* value. Also, lower *CN2* values (70, 80) show higher sensitivity compared to the higher *CN2* value (90). One evident message form this graph is that one should not change *CN2* values in a step of 10 % or so, it will have profound impact on surface runoff and there by infiltration and initial abstraction also.

Area average *CN2* value for the watershed has not changed significantly (1-2 % increase) for different sub-watersheds division level. Any higher percentage change in the

CN2 value (more than 2%) for independently calibrated models will mask effect sub-watershed division level on runoff calculation.

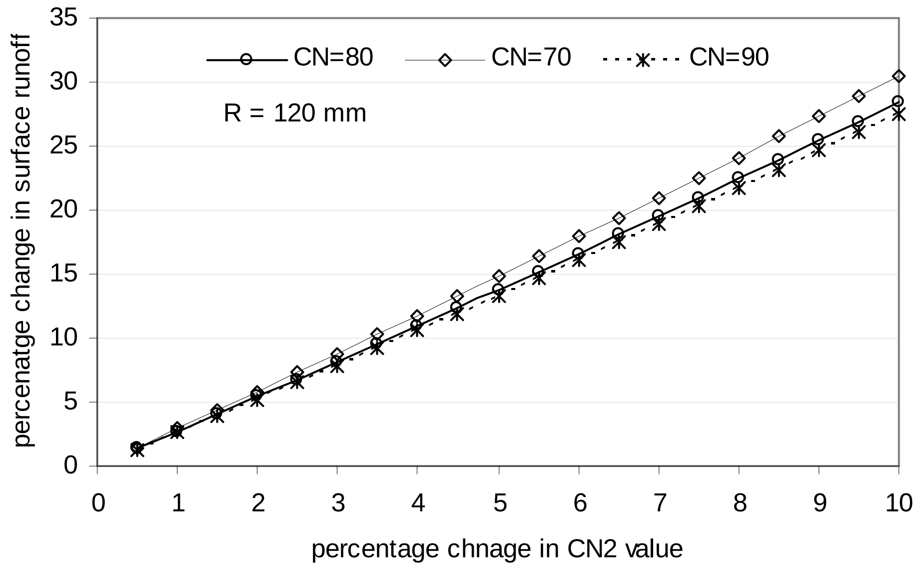


Figure B.1: Effect of change in CN2 value on surface runoff

B.2 Baseflow recession constant (*Alpha_Bf*)

Baseflow recession constant determines how fast baseflow contribution to the streamflow declines after the recharge has ceases. When shallow aquifer receives no recharge, SWAT uses following equation to determine base flow contribution to the stream:

$$Q_{gw} = Q_{gw,0} . \exp(-\alpha_{gw} .t) \qquad \text{B.3}$$

Where Q_{gw} (mm water) is the groundwater flow into the main channel at any time t (day), $Q_{gw,0}$ (mm water) groundwater flow into the main channel at beginning of the recession ($t = 0$), α_{gw} is baseflow recession constant, and t (days) is the time lapsed since the beginning of the recession. α_{gw} value ranges between 0 to 1. Its higher values (~1) signifies rapid decline in the baseflow following cessation of recharge in the aquifer and also indicates high drainage and little storage capacity of the shallow aquifer. This parameter can be seen more as shape parameter (affecting shape of hydrograph) than parameter like *CN2* which affects volume/magnitude of hydrograph.

B.3 Surface runoff lag (*surlag*)

Time of concentration (t_{conc}) increases sub-basin size increases for higher CSA. When time of concentration becomes greater than 1 day, only a portion of the surface runoff generated in single day is able to reach main stream and remaining portion is stored in the sub-basin to be released in next day. SWAT uses following formula to calculate surface runoff reaching to the stream in a given day.

$$Q_{surf} = (Q'_{surf} + Q_{stor,i-1}).\left(1 - \exp\left[\frac{-surlag}{t_{conc}}\right]\right) \qquad \text{B.4}$$

Where Q_{surf} (mm water) is the amount of surface runoff discharged to the main channel on a given day, Q'_{surf} (mm water) is the amount of surface runoff generated in the sub-basin on the given day, $Q_{stor,i-1}$ (mm water) is the surface runoff stored or lagged from the previous day, *surlag* is runoff lag coefficient, and t_{conc} (hrs) is time of concentration for the sub-basin.

To maintain the same Q_{surf} reaching to the stream *surlag* should increase with increase in sub-watershed size, whereas for a given time of concentration higher value of the surface lag will make higher portion of the surface runoff reaching to the stream i.e. hydrograph will show the accentuated peak, and vice versa. This can again be termed as shape parameter for the same reason as explained above.

B.4 Soil evaporation compensation factor (*Esco*)

When evaporation demand from soil layer exists[2], SWAT divides it to each layer in the soil profile using following formulae:

$$E_{soil,ly} = E_{soil,zl} - E_{soil,zu} \cdot esco \qquad \text{B.5}$$

[2] Evapotraspiration (E_o) demand first met by canopy water, then remaining demand (E_o') is met by plant transpiration and sublimation/soil evaporation. If evaporative demand form sublimation (in case of snow cover on the soil) is not sufficient then evaporative demand from soil layer exist.

$$E_{soil,Z} = E_s^{"} \frac{z}{z + \exp(2.374 - 0.00713 \cdot z)} \qquad \text{B.6}$$

Where $E_{soil,ly}$ (mm water) is evaporative demand for the layer *ly*, $E_{soil,zl}$ (mm water) is evaporative demand at lower boundary and $E_{soil,zu}$ (mm water) is evaporative demand at upper boundary, $E_{soil,z}$ (mm water) is the evaporative demand at depth *z*, E_s*"* (mm water) is the maximum soil water evaporation on a given day and *esco* is soil evaporation compensation factor.

In above formula upper layer contributes heavily to evaporative demand (top 10 mm contributes to 50 % of the maximum evaporative demand). If any layer of soil does not have sufficient water available to meet its evaporative demand, then left over demand is not met by another layer and consequently evaporation met from soil layer is less. User can distribute demand more evenly to lower layer by adjusting *Esco* value. In the typical example shown in Figure B.2, evaporative demand (200 mm in this case) from soil layer between 10 and 15 mm (shown by value at 15 mm) is only 22 mm for esco = 1, where as it increases to 52 mm for esco = 0.7. Die off behavior shown in the graph (Figure B.2) is due to the fact that once demand is met, there is no further demand from the layer below that. So if user has prior knowledge of that top soil layer may not have sufficient water for evaporation (for example sandy soil layer), he/she can accordingly adjust *esco* to be this demand by lower soil layer.

B.5 Soil Available Water capacity (*Sol_Awc*)

Soil available water capacity is the difference between water content at the field capacity and the water content at wilting point. Although their values are given in the soil data base as layer properties for each soil type, still this is a calibration parameter; because, SWAT calculates filed capacity of the soil layer based on the available water capacity of the layer and water is allowed to percolate only when water content in that soil layer exceeds its field capacity. SWAT first calculates wilting point water content for the layer and adds it to available water capacity of the layer to get field capacity water content of the soil layer as per following formulae:

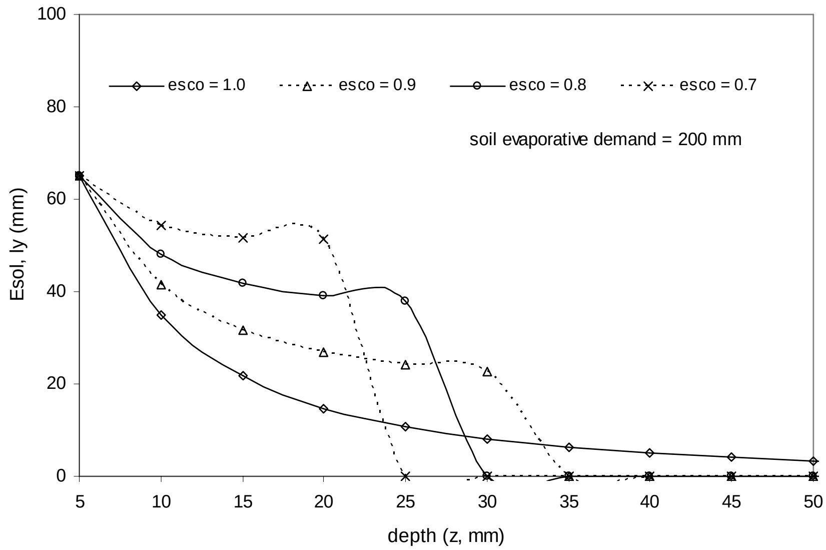


Figure B.2 Effect of *Esco* on evaporation demand form different soil layers

$$WP_{ly} = 0.40 \cdot \frac{m_c \cdot \rho_b}{100} \qquad \text{B.7}$$

$$FC_{ly} = WP_{ly} + Awc_{ly} \qquad \text{B.8}$$

Where WP_{ly} is the water content at wilting point, m_c percent clay content of the layer, ρ_b is the bulk density for the soil layer (mg m^{-3}), FC_{ly} is the water content at field capacity and Awc_{ly} is the available water capacity of the soil layer.

Higher values of Awc_{ly} will lead to higher FC_{ly}, i.e. less water is allowed to percolate to next layer and finally to shallow aquifer, hence less groundwater recharge to the stream and more water is available for evapotranspiration. If model is predicting very high evaporation and less groundwater recharge than the expected, reducing *Sol_Awc* can help in reducing evaporation and increasing groundwater percolation to aquifers.

B.6 Saturated hydraulic conductivity (*Sol_k*)

Saturated hydraulic conductivity determines travel time of percolation in each soil layer. Travel time for percolation in a soil layer is calculated using following formula.

$$TT_{perc} = \frac{SAT_{ly} - FC_{ly}}{K_{sat}} \qquad \text{B.9}$$

Where TT_{perc} is the travel time for percolation (hrs), SAT_{ly} (mm water) is the amount water content in the soil layer when completely saturated, FC_{ly} (mm water) is the water content of the soil layer at field capacity, and K_{sat} (mm/hr) is the saturated hydraulic conductivity for the layer. Higher values of K_{sat} make more water to percolate to the next layer by decreasing the travel time in the soil layer.

B7.0 Groundwater delay (*Gw_delay*)

Water leaving the lowest layer in the soil profile does not enter shallow aquifer on the same day it leaves soil profile. Water movement in the vadose zone has been modeled using equation proposed by Venetis (1969) as given below:

$$w_{rchrg,i} = (1 - \exp(-1/\delta_{gw})) \cdot w_{seep} + \exp(-1/\delta_{gw}).w_{rchrge,i-1} \qquad \text{B.10}$$

Where $w_{rchrg,i}$ (mm water) is amount of recharge entering aquifer on day *i*, δ_w (days) is the delay time or drainage time in overlaying geologic formation, w_{seep} (mm water) is total amount of water exiting the bottom of soil profile on day *i*, and $w_{rchrg,i-1}$ (mm water) is amount of recharge entering the aquifer on day *i-1*. Higher value of *GW_delay* (δ_w) will make less water to reach shallow aquifer on day *i*.

B.8 Deep Aquifer Percolation coefficient (*Rchrg_dp*)

Total water entering shallow aquifer (w_{rchrg}) is portioned into two parts, one goes into deep aquifer and other remains in shallow aquifer. *Rchrg_dp* determines fraction of total daily recharge (w_{rchrg}) will go into deep aquifer. Amount of water entering into deep aquifer is given by following formula:

$$w_{deep} = (Rchrg\_dp) * w_{rchrg} \qquad \text{B.11}$$

Where w_{deep} is the amount of water moving into deep aquifer on day *i* (mm water), *Rchrg_dp* is aquifer percolation coefficient, and w_{rchrg} is total recharge occurring to both aquifers on day *i*. Water entered into deep aquifer become water lost for the system, it drains outside the watershed in the model. Hence higher value of *Rchrg_dp* will make high water loss from the system. Therefore, *Rchrg_dp* value should be accordingly adjusted to keep sufficient water in the system.

B.9 Revap Coefficient (*Gw_revap*) and Revap threshold (*Revapmn*)

SWAT allows water to move from the shallow aquifer to overlaying unsaturated zone if the overlying layer becomes dry to meet the evapotranspiration demand. This process is termed as 'Revap'. Water can revaporate from shallow aquifer if the aquifer has more water than the threshold value required (*Revapmn*). Maximum amount of the water that can be removed form the aquifer is determined by the revap coefficient as given in the following formula.

$$W_{revap,mx} = \beta_{rev} \cdot E_o \qquad \text{B.12}$$

Where $W_{revap,mx}$ is the maximum amount of water that can move into the soil zone in response to water deficiency (mm water), β_{rev} is the *revap* coefficient, and E_o is the potential evapotranspiration for the day.

B.10 Threshold water level in shallow aquifer for baseflow (*Gwqmn*)

This is the minimum water required to be present in the shallow aquifer for groundwater to go into the stream. *Gwqmn* value needs to be adjusted to correct baseflow part of the hydrograph, however its uncertainty range in the model is quite high form 0 to 5000 mm. A high value of *Gwqmn* may not allow any water present in shallow aquifer to become part of streamflow and stream will become dry during no surface flow conditions.

B.11 Manning's "n" for main channel (*Ch_n2*)

Surface flow generated during precipitation events and baseflow contributed by shallow aquifer is routed through network of streams/channels in the model, SWAT uses manning's equation for uniform flow to calculate flow rate and velocity in a reach segment as given below:

$$q_{ch} = \frac{A_{ch} \cdot R_{ch}^{2/3} \cdot slp_{ch}^{1/2}}{n} \qquad \text{B.13}$$

$$v_{ch} = \frac{R_{ch}^{2/3} \cdot slp_{ch}^{2/3}}{n} \qquad \text{B.14}$$

Where q_{ch} (m^3/s) is rate of flow in the channel, A_{ch} (m^2) is cross section area of the channel, R_{ch} (m) wetted perimeter of the channel and slp_{ch} (m/m) is channel slope, n is Manning's "n" for the channel (roughness coefficient) and v_c is the flow velocity (m/s). For each time step (daily basis) A_{ch} is calculated as function of volume of available water to be routed in the channel as given below:

$$A_{ch} = \frac{V_{ch}}{1000 \cdot L_{ch}} \qquad \text{B.15}$$

Where A_{ch} (m^2) is cross section area of the channel, V_{ch} is volume of water stored in the channel (m^3), and L_{ch} (km) is the channel length. Once A_{ch} is known, water depth is the channel can be determined from user provided channel bed width and SWAT assumed trapezoidal channel cross section with side slope of 1:2, hence wetted perimeter $R_{ch.}$

For natural stream with few trees, stone or brush *Manning's "n"* value varies from 0.025 to 0.065. In Chow's book (1959) its value for the "natural stream with some what irregular side slope, fairly even, clean and regular bottom; in light gray silty clay to light tan silt loam, very little variation in cross section" is given as 0.035.

B.12 Effective hydraulic conductivity for the main channel (*Ch_K2*)

When channel receives no groundwater contribution during that period it may loose water to the aquifer. Transmission loss from the main channel is calculated using following equation.

$$t_{loss} = K_{ch} \cdot TT \cdot R_{ch} \cdot L_{ch} \qquad \text{B.16}$$

Where t_{loss} (m^3 water) is channel transmission loss, k_{ch} (mm/hr) is effective hydraulic conductivity of the channel alluvium, TT (hr) is flow travel time, R_{ch} (m) is the wetted perimeter of the channel and L_{ch} (km) is the channel length. Depending upon the channel bed material its hydraulic conductivity value ranges from > 127 mm/hr (very clean gravel and large sand) to 0.025-2.5 mm/hr (consolidated bed material: high silt-clay content). For perennial streams, which receive continuous groundwater contribution, effective conductivity value will be zero. This parameter is of particular importance for loosing streams due to significant impact of spatial scale on channel length.

B.13 Maximum potential leaf area index (*Blai*)

Leaf area index is ratio of green leaf area to the land area for the given crop type, its value changes during the growing season of the crop and calculated as the fraction of the maximum leaf area index of the crop type (given in the SWAT database). It affects initial abstraction and evapotranspiration in HRUs. In SCS curve number method canopy interception is included in the initial abstraction term along with surface storage; hence this parameter may not be very important for surface runoff calculation using the SCS curve number method.

B.14 Maximum canopy storage (*Canmx*)

This is the maximum amount of water that can be intercepted by the plant canopy when it is fully developed. In SCS curve number method canopy interception is included in initial abstraction. Similar to *Blai, Canmx* is also not an important parameter while using the SCS curve number method for surface runoff calculation.

B.15 Plant uptake compensation factor (*Epco*)

Since root density is highest near the soil surface and decreases with depth, water uptake by the plant roots from the upper layer is much greater than in lower layers and so is the potential uptake from different layers in the soil profile. In SWAT 50% of the total water uptake occurs in the upper 6% of the root zone. But if upper layer of the soil profile does not contain enough water to meet the potential water uptake demand, SWAT allows deficient water demand to be compensated by the lower layers. Following equation is used to adjust the potential water uptake form the lower layers.

$$W'_{up,ly} = W_{up,ly} + W_{demand} \cdot Epco \qquad \text{B.17}$$

Where $W'_{up\ ly}$ is the adjusted potential water uptake form layer *ly* (mm water), $W_{up,ly}$ is the potential uptake for the layer *ly* (mm water), W_{demand} is the water uptake demand not met overlaying soil layers. *Epco* value varies from 0 to 1, as *Epco* value approaches 1.0, model allows more water uptake demand to be met by lower layers in the soil.

B.16 Biological mixing efficiency (*Biomix*)

This is the efficiency of redistribution of the soil constituent in the soil caused by biota (e.g. earthworms) activity. Biological mixing efficiency increases as the tillage practice shifts form conventional tillage to conservative tillage and to no-till practice. Its default value is 0.20.

B.17 Snow fall threshold temperature (*Sftmp*)

This threshold temperature determines whether precipitation is snow fall or rain fall. If daily mean temperature is less that *sftmp* then precipitation is considered as snow fall and vice versa.

B.18 Snow pack temperature lag factor (*Timp*)

When snow on the ground persists for a long time, it is called snow pack. Snow pack temperature lag factor determines influence of the previous day snow pack temperature on the current day snow pack temperature. *Timp* value varies between zero and one. When its value approaches to 1, current day air temperature has increasingly greater influence on the snow pack temperature, whereas if its value approaches to zero, previous day snow pack temperature has greater influence on the current day snow pack temperature. Snow pack temperature for present day is given by the following formula:

$$T_{snow(d_n)} = T_{snow(d_n-1)} \cdot (1 - Timp) + \overline{T}_{av} \cdot Timp \qquad \text{B.18}$$

Where $T_{snow(d_n)}$ (degree C) is the snow pack temperature on a given day, $T_{snow(d_n-1)}$ (degree C) is the snow pack temperature on the previous day, and $\overline{T}_{av}$ (degree C) is the mean air temperature on the given day.

B.19 Snow melt base temperature (*Smtmp*)

This is base temperature above which snow melt occurs. Snow melt is calculated using following formula:

$$SNO_{mlt} = b_{mlt} \cdot sno_{\mathrm{cov}} \cdot \left[\frac{T_{snow} + T_{mx}}{2} - Smtmp\right] \qquad \text{B.19}$$

Where SNO_{mlt} is the amount of snow melt on a given day (mm water), b_{mlt} is melt factor for the day (mm water/day- degree C), sno_{cov} is the fraction of HRU covered by the snow, T_{snow} is the snow pack temperature on a given day (degree C), and T_{mx} is the maximum air temperature on a given day. For SJRW this parameter is calibrated, for Cedar creek it has taken as constant 0.56 degree C.

B.20 Snow melt factor on June 21 (*Smfmx*) and on December 21(*Smfmn*)

Seasonal variation in the melt factor is incorporated using different values of melt factor on June 1 (maximum) and December 21 (minimum) as per following equation:

$$b_{mlt} = \frac{(b_{mlt6} + b_{mlt12})}{2} + \frac{(b_{mlt6} - b_{mlt12})}{2} \cdot \sin\left(\frac{2\pi}{365} \cdot (d_n - 81)\right) \qquad \text{B.20}$$

Where b_{mlt} is the melt factor for the day (mm water/day – degree C), b_{mlt6} is the melt factor for June 21 (*Smfmx*), b_{mlt12} is the melt factor for December 21 (*Smfmn*) and d_n is the day number of the year.

Appendix C Auto Calibration Control Parameters

C.1 parasolin.dat

Maximum number of trials allowed before optimization is terminated:	20000
Maximum number of shuffling loops in which the criterion value:	5
Percentage by which the criterion value must change:	0.01
Number of complexes in the initial population:	10
Initial random seed:	1645
Number of points in each complex:	5
Number of points in a sub-complex:	8
Number of evolution steps allowed for each complex before complex shuffling:	5
Istat	1
Iprob, when iprob=1 90% probability ; iprob=2 95% probability; iprob=3 97.5% probability	3
Number of objective functions to be included in global optimization criterion (0=all objective functions)	0
Interval in hypercube	10

C.2 objmet.dat

1 1 1 1 1.000

C.3 responsmet.dat

1 1 1 1 0.000

C.4 chnagepar.dat

Corresponding to SJRW and Cedar Creek are given in Table 5.2 and 5.3

Note: Details regarding these input files can be found in SWAT documentation "Sensitivity, auto calibration, uncertainty and model evaluation in SWAT 2005".