MODELING TOOLS FOR ECOHYDROLOGICAL CHARACTERIZATION

by

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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Biological & Agricultural Engineering
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Abstract

Ecohydrology, a sub-discipline of hydrology, deals with the ecological impacts of and interactions with the hydrological cycle. Changes in hydrology of the Great Plains rivers, and their impacts on water quality, water resources, aquatic ecosystems, and fish species distributions have been documented. The major goal of this study was to develop and test methods to analyze watershed-level ecohydrological characteristics. The specific objectives were (a) to detect past temporal trends and spatial variability in hydrologic indices, (b) to evaluate the presence and/or extent of spatial and temporal relationships between climatic and ecohydrological variables and riverine historical data on fauna species density and distribution, and (c) to assess model calibration strategies for accurate ecohydrological indicator simulation.

The Kansa River Basin (KRB), which has substantial land use, soil and climate variability, as well as variation in anthropogenic drivers (dams, diversions, reservoirs, etc.), was the focus of this study. Thirty eight hydrological indicators were generated using the indicators of hydrologic alterations software for 34 stations in the KRB using 50-year streamflow records and trend analysis using Mann-Kendall, Seasonal Kendall, and Sen's slope estimator tests. Across the KRB a decreasing trend was evident for annual mean runoff, summer and autumn mean runoff, 30-day, 90-day minimum flows, and 1-day, 3-day, 7-day, 30-day and 90-day maximum flows. Most of the significant negative trends were observed in the High Plains ecoregion. Two hydrologic indicators, high-flow pulse count and mean summer streamflow, were significantly different in streams that lost two indicator fish species, indicating that changes in streamflow have altered the fish habitat of this region.

The Soil and Water Assessment Tool (SWAT) biophysical model calibrated using a multi-objective framework (multi-site, multivariable and multi-criteria) was able to simulate most of the ecohydrological indicators at different hydrological conditions and scales. The SWAT model provided robust performance in simulating high-flow-rate ecohydrologic indicators. However ecohydrologic indicators performance was highly dependent on the level of calibration and parameterization. The effect of calibration and parameterization on ecohydrologic indicators performance varied between watersheds and among subwatersheds.

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Abstract

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Dedication

I would like to dedicate this Doctoral dissertation to my father, Dr. Nagamuthu Sinnathamby who never gave up on me.

Abbreviations and Symbols

Ab	Above
ALFA_BF	Baseflow recession constant (days)
ARS	Agricultural Research Service (USDA)
C	Creek
CDL	Crop Data Layer
Cfs	Cubic feet per second
Cms	Cubic meter per second
CANMX	Maximum canopy storage
CN	Curve Number
CN2	Curve Number for antecedent moisture condition 2
CNCOEF	CN Coefficient
CORN	Corn
CT	Center of timing
DEM	Digital Elevation Model
EPA	Environmental Protection Agency
EPCO	Plant uptake compensation factor
ESCO	Soil evaporation compensation coefficient (SWAT)
ESRI	Environmental Systems Research Institute
GHCN	Global Historical Climatology Network
GIS	Geographical Information System
GRSG	Grain Sorghum
Gw_Revap	Groundwater revap coefficient
GWQMIN	Depth of water in shallow aquifer require for return flow (mm)
HAF	Hydrologic Alteration Factor
HUC	Hydrological Unit Code
HRU	Hydrological Response Unit
ICN	Daily curve number calculation method
IHA	Indicators of Hydrologic Alteration
KRB	Kansas River Basin
KARS	Kansas Applied Remote Sensing
KS	Kansas State

K-S	Kolmogorov-Smirnov
LAI	Leaf Area Index
PET	Potential evapotranspiration
PHUs	Potential Heat Units
NASS	National Agricultural Statistics Service
NCDC	National Climatic Data Center
NE	Nebraska State
NEXRAD	Next Generation Weather Radar
NSIP	National Streamflow Information Program
NLCD	National Land Cover Dataset
NR	Near
NRCS	Natural Resources Conservation Service (USDA)
NSE	Nash-Sutcliffe Efficiency
PBIAS	Percent bias (%)
QA/QC	Quality assurance and quality control
R in USGS streams	River
R	Pearson Correlation Coefficient
R^2	Coefficient of determination
RSR	Ratio of the root mean square error to the standard deviation
SF	South Fork
SOYB	Soybean
SSURGO	Soil Survey Geographic Database
ST	State
STATSGO	State Geographic Database
SURLAG	Surface runoff lag coefficient
SWAT	Soil and Water Assessment Tool (river basin model)
U.S.	United States
USDA	United States Department of Agriculture
USGS	United States Geological Survey
WRI	Water Resource Indicator
WWHT	Winter Wheat

Chapter 1 - Introduction

1.1 General Background

The term ecohydrology indicates study of the natural system at the interface between ecological (i.e., the science on interactions among organisms and their environment) and hydrological (i.e., the science concerned with processes of the hydrological cycle, and their spatial and temporal distributions) sciences. The term was popularized in the early 1990s and quickly adopted by fields of study ranging from plant physiology to engineering. It can be defined as the integration of large-scale, long-term hydrologic process with the dynamics of ecosystems (Zalewski et al., 1997; Zalewski, 2002, 2010; Kundzewicz, 2002). Ecological processes are shaped by hydrology and, vice versa, ecologic communities and interactions shape hydrological processes (Zalewski, 2000). Therefore, understanding ecohydrology, the hydrology/biota interactions, enhances the overall integrity of aquatic ecosystems in the face of natural and anthropogenic drivers, and provides a systemic framework for sustainable usage and restoration of ecosystem properties.

The relationship among climate, stream flow, and riverine flora and fauna is an important aspect of ecohydrological study (Bradford et al., 2003). Ecological characterization at watershed scale improves scientific understanding of hydrologic and ecosystem process and their biota interactions. River ecosystems have a hierarchical structure and natural boundaries, and have both natural drivers (watershed and channel hydrology, geomorphology, etc.) as well as anthropogenic drivers (dams, diversions, reservoirs, etc.). Therefore, the river basin represents a suitable scale for ecohydrological studies and modeling.

Changes in the Great Plains rivers and streams, and consequently their impact on water quality, water resources, aquatic ecosystems, and fish species distributions, have been documented by many studies (Angelo, 1994; Sophocleous, 1998, 2002; Dodds et al., 2004, Gido et al., 2010). Dodds et al. (2004) referred to Great Plains streams as highly endangered, and recommend them as a model system for studying ecological disturbances. Hydrology is the most fundamental of the physical templates of all streams, and flooding and drying are prominent characteristics of Great Plains streams. Hydrology controls the aquatic ecosystem function through influenced organisms. Great Plains streams support many unique and sometime endangered biota and play a vital role in ecosystem services. Changes in the streams have the potential to alter stream communities. Watershed-level ecohydrological characteristics studies are helpful for the understanding of potential future changes hydrological regime and associated ecological impacts.

1.2 Ecohydrological Modeling

Ecohydrological modeling has been gained impetus and importance in recent decades. Physically based (sometimes also called process-based) continuous dynamic models include mathematical representation of physical, biological, geochemical, and hydrological processes, and combine physical, conceptual, and semi-empirical elements, which together are referred to as an ecohydrological model (Krysanova et al., 1998, 2014). Ecohydrological models contain a hydrological module, as master element, and vegetation and biogeochemical cycles as sub-models. These three components usually couple to include all important interactions and feedbacks between the processes. With climate variables being the external drivers, these models are designed to adequately represent natural processes at the watershed scale.

The Soil and Water Assessment Tool (SWAT) is a physically based, watershed scale, continuous simulation model developed by the USDA Agricultural Research Service (ARS) (Arnold et al., 1998; Neitsch et al., 2004, 2005) and extensively used throughout the world (Gassman et al., 2007; Douglas-Mankin et al., 2010; Tuppad et al., 2011; Arnold et al., 2012). SWAT spatially disaggregates the study area through delineating watersheds into subbasins and hydrological response units (HRUs). Studies have demonstrated that SWAT provides reasonable simulation of crop growth, soil water, surface water, and groundwater movement as well as sediment and nutrient transport for both large and small watershed scales (Luo et al., 2008).

SWAT is a process-based conceptual model that also includes empirical components. It focuses on a water balance with two phases, a land phase of the hydrologic cycles that controls water balance for each subbasin, and a routing phase of hydrologic cycle that connects the channel network of the watershed to the outlet. The model is built around the following basic expression of the water balance:

$$SW(t) = SW(t-\Delta t) + Rday(t) - Qsurf(t) - Ea(t) - wseep(t) - Qgw(t) \quad (1)$$

where SW(t) is the soil water content on day t (mm), SW(t–Δt) is the soil water content on day t–Δt (mm), Rday is the amount of precipitation (mm), Qsurf is the surface runoff (mm), Ea is the evapotranspiration (mm), wseep is the amount of water entering the vadose zone from the soil profile (mm), and Qgw is the return flow (mm). Climate variables function as an input parameter during water balance calculations.

A majority of SWAT applications use SCS curve number (CN) method (USDA-SCS, 1972) to simulated runoff volume from each HRU. The CN determines the amount of direct runoff for a given 24-hour rainfall event, with the retained amount typically infiltrating into the unsaturated zone. The SWAT model estimates sediment loads as a function of landscape and channel erosion or deposition. Potential evapotranspiration can be estimated in SWAT using three methods: Penman-Monteith (Monteith, 1965; Allen et al., 1986), Priestley-Taylor (Priestley-Taylor, 1972), and Hargreaves (Hargreaves et al., 1975). The actual soil water evaporation is estimated by using exponential functions of soil depth and water content. Plant transpiration is simulated as a linear function of potential evapotranspiration and leaf area index.

Plant growth in SWAT is simulated using a simplified version of the generic crop growth model from EPIC (Williams et al., 1984; Williams and Singh, 1995), as described in Neitsch et al. (2005). Total plant biomass is incremented daily based on an atmospheric-CO_2-dependent radiation use efficiency applied to intercepted photosynthetically active radiation. This potential biomass accumulation is attenuated by the maximum among several possible limiting plant stresses (water, temperature, N, or P) (Luo et al., 2008). Leaf area index (LAI), green leaf area per unit land area, is also incremented daily on the basis of accumulated potential heat units (PHUs), and is also attenuated by a plant-stress factor. LAI increases until a crop-specific maximum LAI is achieved, then remains constant until onset of senescence, after which it declines linearly to zero at harvest. Similarly, canopy height increases until a crop-specific maximum is reached, and it remains at this height through the remainder of the growing season. Root biomass is incremented daily as a fraction of total plant biomass ranging from 0.4 at emergence to 0.2 at maturity according to accumulated PHUs. Root depth for annual crops is incremented daily according to accumulated PHUs until maximum root depth for that crop is achieved. Harvested crop yield is simulated as a fraction, defined by a harvest index, of either total or above-ground biomass, according to whether harvest removes grain only or additionally removes plant biomass.

1.3 Hydrological Indicators

The concept of “natural flow regime” proposed by Poff et al. (1997) explains the strong linkage between the flow regime and aquatic ecosystem structure, function, and diversity. It also defined five major streamflow characteristics that are related to aquatic habitat: seasonal pattern of flows (high flows [> 75th percentile] may influence productivity and diversity of an ecosystem), timing of extreme flows (spawning cues of fish and compatibility with life cycles of organisms), frequency and duration of floods and droughts (duration of stressful condition), seasonal and annual flow variability (may benefit native species), and rate of change of flow (influences species persistence and coexistence). Assessing these streamflow characteristics is important to understand natural and altered flow regimes on riverine biota.

Hydrological indices characterize a particular region in terms of ecologically relevant flow variability explains overall regional and global hydrologic regime variability, and identify human perturbation-sensitive flow characteristics (Olden and Poff, 2003). Some of these indicators (e.g., center of timing) also have been used to detect physical habitat alteration (Richter et al., 1996).

With the increasing utility of hydrologic indices in riverine research, Olden and Poff (2003) provided a comprehensive review of 171 currently available hydrologic indices. Their results show that indicators of hydrologic alteration (IHA) adequately represent all 171 hydrologic indices and captures the majority of the information provided by them.

1.4 Rationale

Lotic (flowing-water) ecosystems respond to natural and anthropogenic stresses in the river system. These stresses can causes changes in structure and function of the ecosystem. River hydrology and its spatial and temporal variations control habitat conditions within riverine system and play a major role in structuring the biotic diversity of the lotic ecosystem. Changes in streamflow regime may alter or modify habitat attributes and impair native ecosystem. Detection and quantification of past trends, changes, and variability of flow regime by assessing hydrologic indices is helpful for understanding potential future changes hydrological regime and associated ecological impacts.

Numerous documents show rivers in the Kansas River Basin have had dramatic flow changes over the past several decades (Perry, 2002, 2004; Aguilar, 2009). However the prevalence and severity of streamflow alteration and its potential ecological consequences have not been quantified.

1.5 Study Goals and Objectives

The overall goal of this research was to improve the development and analysis of watershed-level ecohydrological characteristics. This research had three components, which are organized in separate chapters in this dissertation. The goals and objectives of each chapter are described below.

Chapter 2 quantifies the fundamental ecohydrological elements of Kansas River Basin (KRB). The goal was to assess observed variability, trends, and relationships between and among various climatic, ecohydrological, and biotic variables at watershed scale. The specific objectives were to:

1) Quantify temporal and spatial trends in climatic and ecohydrological variables (water resource indicators [WRIs] and Indicators of Hydrologic Alteration [IHAs]) using long term climate and non-impounded watershed streamflow data in the KRB;
2) Determine the presence and/or degree of spatial and temporal relationships between climatic variables, ecohydrological indicators, and ecoregions of the KRB; and
3) Evaluate the presence and/or extent of spatial and temporal relationships between climatic and ecohydrological variables and riverine historical data on flora and fauna species density and distribution.

Chapter 3 developed and demonstrated a multi-objective framework for calibration and validation of the Soil and Water Assessment Tool (SWAT) watershed model to enhance simulation of ecohydrological indicators. The goal of this study was to compare and evaluate the effect of single and multi-objective calibration protocols on the simulation of ecohydrological indicators. The specific objectives were to:

1) Develop a biophysical model of current conditions using a distributed parameter watershed model (SWAT) for two different watersheds with different hydrologic conditions and scales within the KRB;
2) Assess multiple parameterization, calibration and validation strategies that highlight the model performances at different spatial scales, which are essential for accurate ecohydrological indicator simulation; and

3) Demonstrate and quantify the benefits of multi-objective calibration protocol for modeling ecohydrological indicators.

Chapter 4 evaluated SWAT as a tool to simulate ecohydrologically relevant indicators. The goal of this study was to provide insights on the suitability of SWAT to function as an ecohydrological model. The specific objectives were to:

1) Assess the applicability of SWAT model for simulating WRIs and IHAs at watershed level; and
2) Evaluate calibration uncertainty in simulating magnitude and timing of flow at subwatershed and watershed scale.

Overall, this dissertation will provide future modelers with a framework for simulating ecohydrological indicators using a commonly applied watershed model. This study will use SWAT as the watershed model, but a similar approach could be adapted to other hydrological models. Specific guidance will be given about a process to calibrate SWAT (or watershed-level models in general), and the impact of each step of the calibration process on ecohydrological simulation quantified and assessed. The synoptic trend analysis of climatic and hydrologic parameters in the study area (KRB) will provide a foundational summary of the ecohydrological conditions in this basin and will be used to help interpret ecohydrological analyses of individual watersheds within the basin in later chapters. Throughout the discussions, applications (for example using published fish distribution data in Kansas) and potential applications of these ecohydrologic analyses will be explored. The dissertation also will provide useful tool to predict future changes in flows, identify related impact on fauna distribution and responses to individual mitigation scenarios.

The overall goal of this dissertation is to advance the science of watershed hydrologic models to the broader application of ecohydrological indicator simulation. To this task, existing tools are applied, methods of their application enhanced, and coupling of the tools explored to provide a greater complexity and resolution of ecohydrological information using a platform with global acceptance and applicability.

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Chapter 2 - Quantifying fundamental ecohydrological elements of Kansas River Basin (KRB)

Abstract

Characterizing climatological and hydrological conditions of a watershed and their changes over time can foster an understanding of the streamflow variability and resultant changes in ecological processes of streams. The objective of this study was to assess if trends in climatic and ecohydrologic conditions were interrelated, more consistent within ecoregions than between ecoregions, or correlated to observed changes in aquatic species presence and distribution.

Mann Kendall's tau, Seasonal Kendall tau and Sen's slope were used to identify trends of water resource indicators (WRIs) and Indicators of Hydrologic Alteration (IHAs) at 34 stream gaging stations during a 50-year period (1962-2012) in the Kansas River Basin. The daily discharge data (cfs) were converted to runoff (mm day^{-1}) to standardize the effects of drainage area on streamflow generation and used for analysis in this study.

The majority of the stations show decreasing trend in annual flow per unit area with both Mann Kendall and Seasonal Kendall tests. Maximum statistically significant decreasing trend (7.65 mm per 50 years) was observed in the High Plains ecoregion. The overall observed decreasing annual average runoff was consistent with decreasing rainfall patterns and increasing annual average temperature, but the correlation between runoff and precipitation or temperature was not significant. Other factors, such as groundwater depletion, terracing (particularly in western Kansas) and changes in land use and farming practices (such as contour farming, crop rotation, pasture improvement, and conservation reserve program) also may have been related to the decreasing annual trends in runoff. A majority of High Plains ecoregion streamflow gaging stations also showed decreasing trends in all four seasons, whereas gaging stations in the other three ecoregions, Central Great Plains, Western Corn Belt, and Flint Hills, showed increasing trends during winter and spring and decreasing trends in summer and autumn. Streamflow stations in the High Plains ecoregion also demonstrated decreasing trends in 1-day to 90-day maximum and minimum flow per unit area and increasing trends in number of zero-flow days and baseflow index of mean 7-day-minimum flows. The majority of streamflow stations in the Central Great Plains ecoregion demonstrated statistically significant increasing trends in

minimum flows and number of zero-flow days and positive trends in baseflow index. The positive trend in baseflow index may have resulted from the contribution of return flow from the irrigation in this region. All stations, except one in the Central Great Plains ecoregion, showed negative trends for all maximum runoff indicators. Most stations showed decreasing trends in numbers of low pulses and high pulses, and high-pulse duration. However, most stations showed increasing trends in low-pulse duration. A greater occurrence of negative trends in rise rate and positive trends in fall rate demonstrated a greater threat of drought than flooding in these ecoregions. Significant trends observed in the number of flow reversals over the study period show higher variability in Central Great Plains, Flint Hills, and Western Corn Belt ecoregions. The results of this study also show that the majority of stations (79%) exhibited decreasing trends in center of timing of annual runoff. The smaller magnitudes of trend slope (± 4 days per 50 years) show that there has been no apparent shift in the hydrologic regime. The decreasing trends observed in a majority of the stations for annual, summer, and autumn flows may exhibit a shift in habitat availability or suitability for aquatic, riparian community and wild animals.

Two species (Plains minnow [*Hybognathus placitus*] and Common shiner [*Luxilus cornutus*]) were not present ($p = 0.05$) during the sampling period (2000-2012) in streams with greater decreasing trends of mean summer daily flows, high pulse flow (> 75^{th} percentile) count, and median duration of high pulse flows. These results demonstrate the importance of changes in these ecohydrological indices on distributions of these faunal species and suggests factors that could be targeted in restoration activities. However, the effect may differ based on ecoregion, climate, and individual species requirements. Decreasing trends in all minimum and maximum flows may exhibit an additional habitat threat, especially in the High Plains ecoregion. In addition, increasing trends of fall rate and decreasing trends in high and low pulse numbers show higher drought potential and increasingly unsuitable conditions for spawning, migration and survival for aquatic organisms in this region.

2.1 Introduction

Climate change and human activities cause major impacts on hydrological processes (Schulze, 2000), including alterations to magnitudes and spatio-temporal patterns of temperature, precipitation, and evapotranspiration. These alterations directly impact regional hydrological cycles. The impact of climate change on hydrology have been reported by many researchers

(Gleick and Chalecki, 1999; Groisman et al., 2001, Hodgkins et al., 2003, Hodgkins et al., 2005; Novotny and Stefan, 2007). Besides climate change, human induced land-use change also affects the hydrological regime and temporal and spatial variations (Poff et al., 2006). Temporal and spatial variation in hydrological regimes reported across North America indicates the impact of climate and landscape on streamflow generation (Poff, 2002; Bower et al., 2004). Brunsell et al. (2010) reported significant warming, with the largest trends of 0.04 °C $year^{-1}$ in summer and fall, and altered precipitation, with a slight increase in winter and decrease in summer and fall, for the 21^{st} century in Kansas. These reported results were obtained from decadally averaged monthly outputs of 21 A1B scenario global climate models under the Special Report on Emissions Scenarios used in the Intergovernmental Panel on Climate Change (IPCC) Assessment Report 4. These changes are expected to have profound implications for hydrological regimes of the Kansas River Basin (KRB), potentially making KRB extremely vulnerable to drought (Brunsell et al., 2010). With the anticipated response of vegetation to the dominant climate forcing in the region (Lin and Brunsell, 2013), an additional hydrological shift through land cover change also can be expected.

The natural flow paradigm developed by Poff et al. (1997) explains the strong linkage between the flow regime and aquatic ecosystem structure, function, and diversity. Alteration in natural flow regime, especially extreme conditions, has an important influence on aquatic organisms (Jowett and Duncan, 1990). In addition, the temporal patterns of streamflow – including timing, frequency, and duration of extreme events, both flood and drought; daily, seasonal and annual variability; and rates of change – are critical to ecological function (Richter et al., 1996; Poff et al., 1997). Identifying hydrological indices and their changes over historical periods can foster an understanding of the streamflow variability that is believed to be important to ecological processes in streams.

Water resource indicators (WRIs), such as monthly, seasonal, and annual flows and center of timing of annual flows, have been used on many studies of the hydrological impacts of climate change (Dibike and Coulibaly, 2005; Merritt et al., 2006; Toth et al., 2006; Shrestha et al., 2013). In addition, the Indicators of Hydrologic Alteration (IHAs) (Richter et al., 1996; The Nature Conservancy, 2009), an expanded version of the WRIs, are considered to reflect the most influential hydrological factors to be considered in ecological studies (Risbey and Entekhabi, 1996; Poff et al., 1997; The Nature Conservancy, 2009). These indicators provide detailed representations of the hydrologic regime and characterize intra-annual variability in water conditions. Richter et al. (1996) identified these indicators as biologically relevant and described them as useful hydrological variables in limnology due to their great hydrological relevance. Some of these indicators (e.g., center of timing) also have been used to detect physical habitat alteration (Richter et al., 1996).

The IHAs include five ecologically significant groups with 33 annual hydrological variables (Table 2.1). These five groups indicate the magnitude of monthly water conditions, magnitude and duration of annual extreme water conditions, timing of annual extreme water conditions, frequency and duration of high and low pulses, and the rate and frequency of water condition changes (The Nature Conservancy, 2009). The magnitude of water conditions defines the availability or suitability of habitat. The timing and frequency of occurrence of specific water conditions can be related to the life-cycle requirements (e.g., spawning), degree of stress, or mortality associated with extreme water conditions. The duration and the rate of change of daily flow can be used to determine the severity of specific water conditions, such as drought and floods. A list of IHAs and WRIs used in this study and their brief ecological significance is given in Table 2.1.

Description of past trends, changes, and variability of IHA and WRI parameters of historical streamflow is helpful for understanding the potential future changes to hydrological regime and associated ecological impacts. This information can be used in evaluation and regulation of water supplies, recreation, aquatic-life habitat, and pollution control (Perry et al., 2002) and is important for managing agricultural, ecological and other socio-economic sectors in the region.

Table 2.1 **Indicators of hydrologic alterations (IHAs) and water resources indicators (WRIs) evaluated in this study (after Richter et al. (1996) and Shrestha et al. (2013)).**

Hydrologic Indicators	Examples of Hydrologic Influence	Examples of Ecological Influence
Water Resource Indicators		
Annual volume Center of timing of annual flow (day of occurrence of 50% annual flow) Seasonal flows (6 parameters)	Annual water balance, magnitude and timing of seasonal conditions	Availability and suitability of habitat for aquatic and terrestrial organisms
Indicators of Hydrologic Alterations (IHAs)		
Group 1 (Parameters 1-12):		
Magnitude of monthly water conditions (mean value for each month)	Magnitude of monthly water availability	Suitable habitat availability; influence on secondary variables (e.g., water temperature, oxygen, soil moisture)
Group 2 (Parameters 13-24):		
Magnitude and duration of annual extreme water conditions: Annual mean 1-day, 3-day, 7-day, 30-day, 90-day minimum and maximum (m^3s^{-1}) Number of zero-flow days Baseflow index: 7-day-minimum flow mean (for WY)	Magnitude of annual flood and drought conditions	Duration of stressful conditions (high and low flows)
Group 3 (Parameters 25-26):		
Timing of annual extreme water conditions (day of each annual 1-day minimum and maximum)	Timing of annual flood and drought conditions	Spawning cues for fish; compatibility with life cycles of organisms
Group 4 (Parameters 27-30):		
Frequency and duration of high and low pulses Number of low (annual median –25th percentile) and high (annual median +25th percentile) pulses in a year, median duration of low and high pulses within each year (days)	Frequency and duration of high and low-flow conditions	Availability of floodplain habitat; influences channel morphology (e.g., bed load transport)
Group 5 (Parameters 31-33):		
Rise/fall rate (median of all positive/negative changes in flow between consecutive days), number of reversals	Rate and frequency of hydrograph changes	Drought (falling levels), flooding (rising levels) or desiccation stress for low mobility organisms

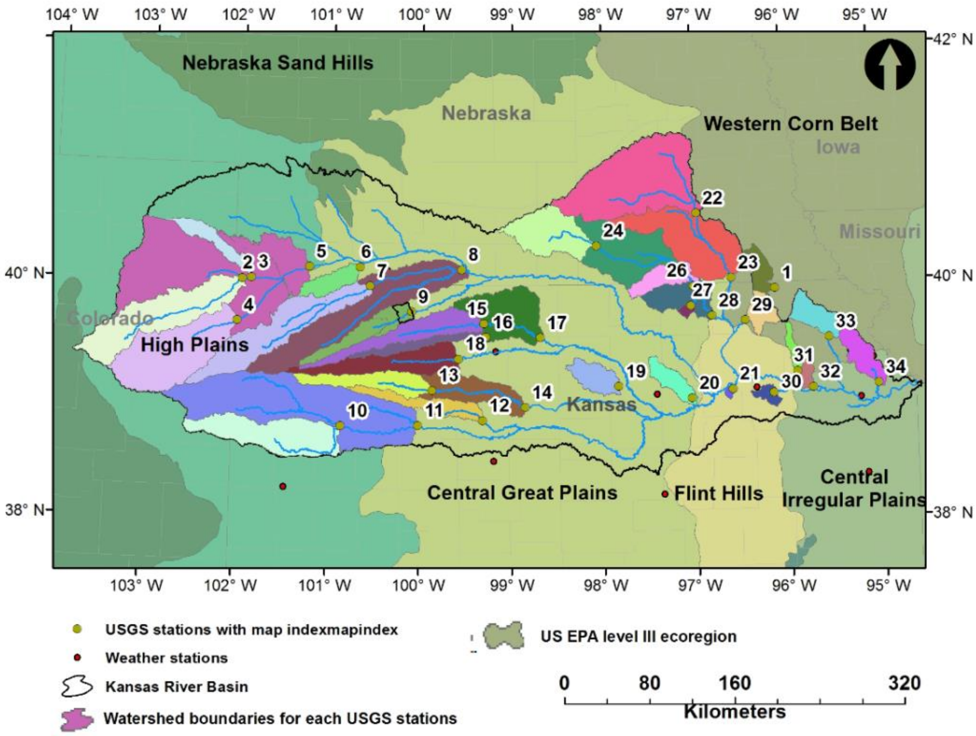
The objectives of this study were to quantify temporal and spatial trends in climatic and ecohydrological variables (water resource indicators [WRIs] and Indicators of Hydrologic Alteration [IHAs]) using long term climate and non-impounded watershed streamflow data in the KRB; determine the presence and/or degree of spatial and temporal relationships between climatic variables, ecohydrological indicators, and ecoregions of the KRB; and evaluate the presence and/or extent of spatial and temporal relationships between climatic and ecohydrological variables and riverine historical data on faunal species density and distribution. The hypotheses of this study are that surface water and aquatic habitat suitability has altered historically within the KRB, and temporal variation of hydrological indicator trends exhibits an ecoregional structure.

2.2 Methodology

2.2.1 Study area

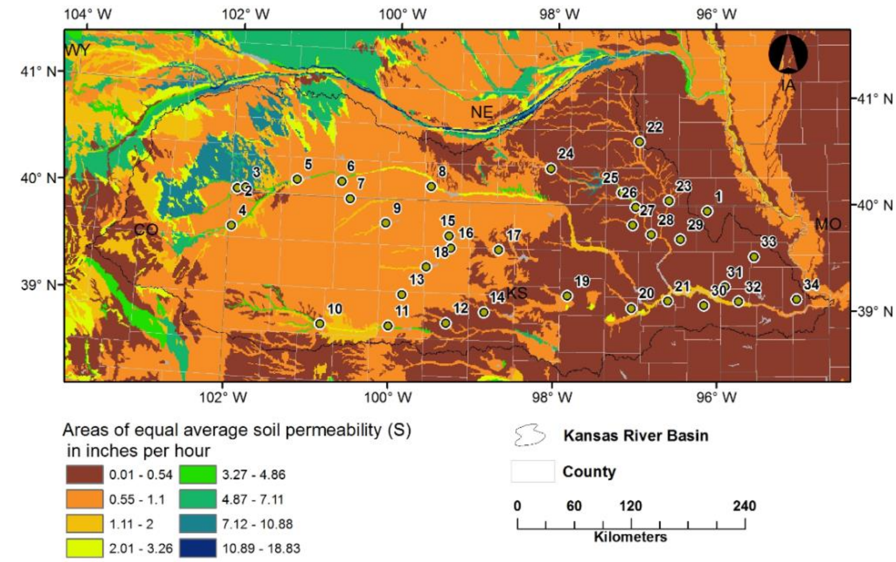
The Kansas River Basin (KRB) is located within the northern portion of Kansas, as well as parts of southern Nebraska and eastern Colorado (Figure 2.1). The Kansas River is vitally important to the social, economic, and ecological character of these regions. It is formed by the union of the Republican River and the Smoky Hill River, and its outflow forms a confluence with the Missouri River. The KRB covers an area of 155,000 km^2 (60,000 mi^2) and includes some of the largest tracts of native prairie left in the United States. It spans six U.S. Environmental Protection Agency (EPA) level-3 eco-regions: High Plains, Central Great Plains, Flint Hills, Western Corn Belt Plains, Central Irregular Plains, and Nebraska Sand Hills (Figure 2.1). The Central Plains ecoregion was recognized as one of the largest agricultural producing areas in the U.S., where food production has significant implications to the global economy and food security (Easterling et al., 1993). All these current conditions make the KRB an important region for agriculture and conservation.

Figure 2.1 Location of Kansas River Basin (KRB), USGS stream gages (green filled circles), watershed boundaries for each stream gaging station and weather station (red dots) used in this study, and EPA level III eco-regions within study area. Map index numbers are defined in Table 2.2.



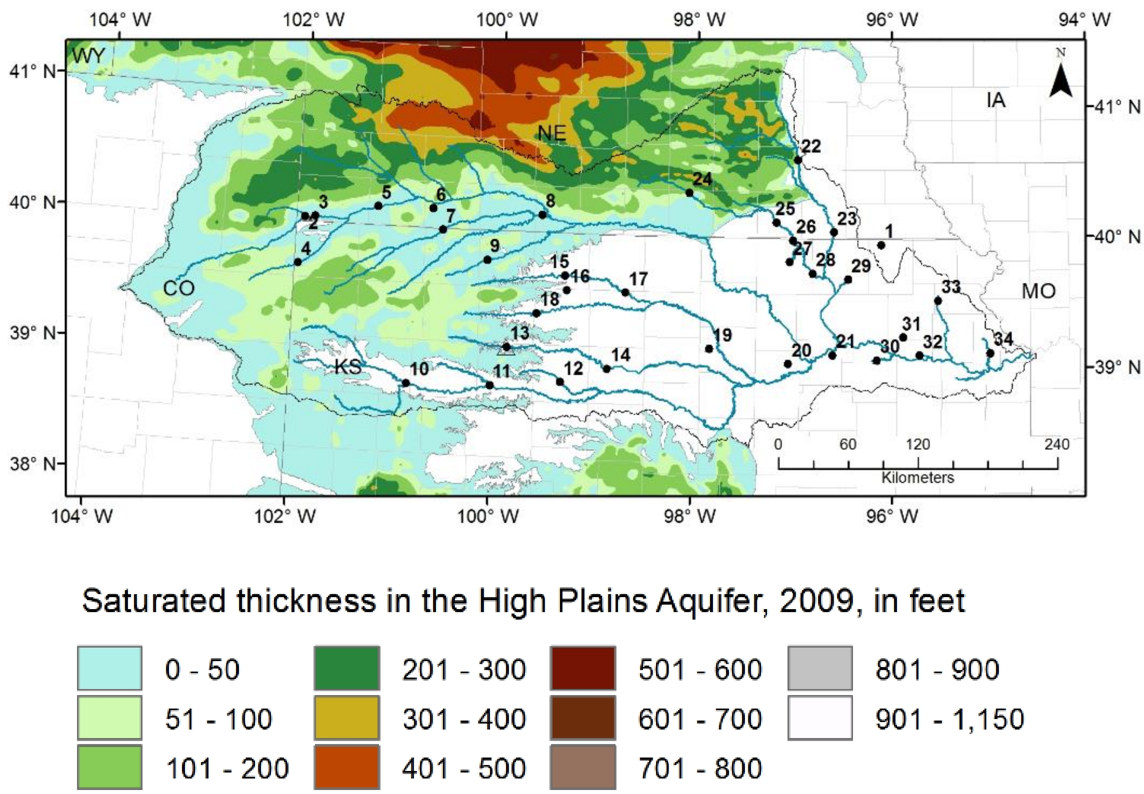
The KRB has a prevailing east-to-west precipitation gradient and spatial variability in biophysical factors (e.g., soil quality, water availability, land use), which provides a range of conditions for hydroecological study. Agriculture and prairie are dominant land covers of the KRB. Croplands are distributed primarily in the central to west, grasslands are located in the east, and woodland or forest found as riparian vegetation in the east. Prairie ranges from short-grass in the west to tall-grass in the east. Future shifts in land cover are expected with increasing biofuel demands in the Midwest Corn Belt region. KRB has an average rainfall about 1000 mm year^{-1} in the east and 400 mm year^{-1} in the west (Lin and Brunsell, 2013). Also KRB shows a wide gradient of soil permeability (Figure 2.2), with lowest levels in the eastern one-third and moderate to high levels in the western two-thirds. The highest permeability is observed in northwestern KRB. The flood potential in areas with low soil permeability area is higher than in areas with higher soil permeability. The higher soil permeability areas tend to allow more infiltration and lower runoff (Rasmussen and Perry, 2001; Perry et al., 2002). This may allow greater baseflow contribution to the stream (Perry et al., 2002).

Figure 2.2 Areas of equal average soil permeability in Kansas River Basin (after Rasmussen and Perry, 2001; Perry et al., 2002). Map index numbers are defined in Table 2.2.



The High Plains Aquifer, one of the largest aquifers in the U.S., is beneath nearly half of KRB (Figure 2.3). The groundwater condition in High Plains Aquifer is generally defined as unconfined. Its saturated thickness ranges from 15.2 m (50 ft) to about 350.5 m (1,150 ft) (McGuire et al., 2012). The High Plains Aquifer underlays the nation’s primary agriculture regions. In parts of Texas, Oklahoma and southwestern Kansas, the High Plains Aquifer has had more than 30.5 m (100 ft) decline in water level due to pumpage of groundwater for irrigation (Luckey et al., 1981; McGuire, 2001).

Figure 2.3 Saturated thickness in the High Plains Aquifer in 2009 (after McGuire et al., 2012). Map index numbers are defined in Table 2.2.



2.2.2 Dataset and site selection

A set of 34 gauging stations from U.S. Geological Survey (USGS) (Figure 2.1; Table 2.2) located across the Kansas River Basin were used in this study. These stations were selected based on Brimley et al. (1999) and Harvey et al. (1999) station selection criteria: (i) sites with natural flow condition, (ii) absence of diversions and dams or other significant regulations, (iii) minimum 20 years of data, (iv) expected longevity of the station in the future, and (v) accurate data.

Table 2.2 USGS stations and descriptions along with map index numbers assigned for this study.

Map index	USGS Station Code	Station name	Drainage area (km^2)	Period of record used in this study (yrs)	Ecoregions	Drainage area within selected ecoregion (% of total)
1	06814000	Turkey C NR Seneca, KS	713.83	50	Western Corn	100%

					Belt	
2	06821500	Arikaree River at Haigler, NE	5622.58	50	High Plains	100%
3	06823500	Buffalo Creek near Haigler, NE	488.21	50	High Plains	100%
4	06827000	SF Republican R NR CO-KS ST Line, KS	5313.84	50	High Plains	100%
5	06828500	Republican River AT Stratton, NE	21006.47	50	High Plains	99%
6	06836500	Driftwood Creek Near MC cook, NE	935.01	50	Central Great Plains	83%
7	06846500	Beaver C at Cedar Bluffs, KS	4357.76	50	High Plains	67%
8	06847500	Sappa Creek Near Stamford, NE	9855.95	50	Central Great Plains	52%
9	06847900	Prairie Dog C Ab Keith Sebelius Lake, KS	1536.19	50	Central Great Plains	62%
10	06860000	Smoky Hill R At Elkader, KS	9033.35	50	High Plains	90%
11	06861000	Smoky Hill R Nr Arnold, KS	12897.80	50	High Plains	76%
12	06863500	Big C Nr Hays, KS	1417.27	50	Central Great Plains	85%
13	06866900	Saline R Nr Wakeeney, KS	1801.59	50	Central Great Plains	52%
14	06867000	Saline R Nr Russell, KS	3856.96	50	Central Great Plains	78%
15	06871000	Nf Solomon R At Glade, KS	2424.41	50	Central Great Plains	82%
16	06871500	Bow C Nr Stockton, KS	903.71	50	Central Great Plains	70%
17	06872500	Nf Solomon R At Portis, KS	6217.07	50	Central Great Plains	92%
18	06873000	Sf Solomon R Ab Webster Re, KS	2698.83	50	Central Great Plains	71%
19	06876700	Salt C Nr Ada, KS	1056.44	50	Central Great Plains	100%
20	06878000	Chapman C Nr Chapman, KS	776.42	50	Central Great Plains	100%
21	06879650	Kings C Nr Manhattan, KS	11.51	32	Flint Hills	100%
22	06881000	Big Blue River Near Crete, NE	7024.25	50	Central Great Plains	95%
23	06882000	Big Blue R At Barneston, NE	11512.53	50	Central Great Plains	86%
24	06883000	Little Blue River Near Deweese, NE	2573.64	50	Central Great Plains	100%
25	06884000	Little Blue River Near Fairbury, NE	6133.18	50	Central Great Plains	100%
26	06884025	Little Blue R At Hollenberg, KS	7171.95	32	Central Great Plains	100%
27	06884200	Mill C At Washington, KS	908.41	50	Central Great Plains	100%
28	06884400	L Blue R Nr Barnes, KS	8655.96	50	Central Great Plains	100%
29	06885500	Black Vermillion R Nr Frankfort, KS	1062.87	50	Western Corn Belt	100%
30	06888500	Mill C Nr Paxico, KS	842.35	50	Flint Hills	100%
31	06889200	Soldier C Nr Delia, KS	385.66	50	Flint Hills	65%

32	06889500	Soldier C Nr Topeka, KS	748.58	50	Western Corn Belt	52%
33	06890100	Delaware R Nr Muscotah, KS	1131.97	32	Western Corn Belt	100%
34	06892000	Stranger C Nr Tonganoxie, KS	1092.72	50	Western Corn Belt	56%

Daily mean discharge data for water years (WYs) 1962-2012 (where WY extends for 12 months ending on September 30 of the stated year) were extracted from the USGS National Streamflow Information Program (NSIP) website. All stations have a minimum of 30 years of data with catchment size from 11.5 to 21,006.5 km^2 with a median catchment size of 2113 km^2. A large majority of sites (82%) had more than 50 years of data over the study period. Three stations (06879650, 06884025, and 06890100; map index numbers 21, 26, and 33) have data only for WYs 1980-2012. In this study a minimum 30-year period is assumed to be long enough to ensure validity of the trend results (Kite, 1991; Kahya and Kalayci, 2004). To ensure a high level of accuracy, the quality of the data for each station was further assessed, and only the "approved for publication data" (USGS, 2014) were used in this study. Only active hydrometric stations were used for the analysis. Quality assurance and quality control (QA/QC) procedures for measuring USGS stream stage, and measuring stream discharge can be found in Sauer and Turnipseed (2010) and Turnipseed and Sauer (2010).

The watershed draining to each USGS streamflow station was assumed to represent conditions of the predominate ecoregion within the watershed boundaries. In all cases, the predominant ecoregion represented at least 50% of the watershed area (Figure 2.1). Table 2.2 presents the USGS stations used in this study, drainage area and the approximate percentage area under selected ecoregion. The map index given for each stream is used in the maps and tables presented in this study.

2.2.3 Calculation of ecologically relevant hydrological variables

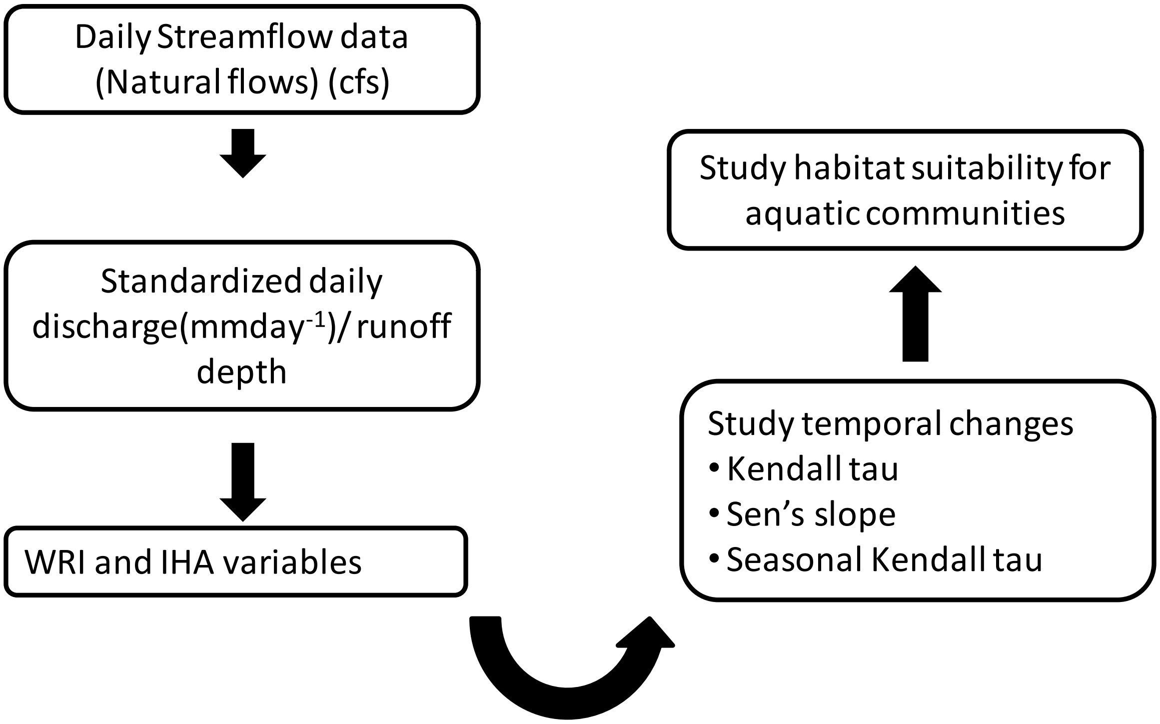
For the calculation of ecologically relevant hydrological variables, daily average discharge data (cfs) obtained from the USGS NSIP website database were converted to daily average runoff depth (mm day^{-1}) to standardize the effects of drainage area on streamflow generation (Monk et al., 2011), and all remaining analyses were undertaken using runoff depth data. First, six WRIs were calculated for the analysis. The seasonal mean values were calculated as the average flow per unit area from March through May for spring, June through August for summer, September through November for autumn, and December through February for winter. The center of timing (CT) of annual flow (day of occurrence of 50% annual flow from October 1 through September 30) was calculated from

$$CT = \sum(t_i q_i) / \sum q_i, \quad (2.1)$$

where t_i is time (days) from October 1 (beginning of WY) and q_i is the corresponding flow per unit area (mm day^{-1}) for day i.

In addition, a set of 33 IHA (Table 2.1) variables were calculated using Nature Conservancy's IHA software for WYs (October 1 through September 30). The initial 50 WYs of data (1962-2012) were used in calculation, which was more than the 35 years of data recommended (The Nature Conservancy, 2009). Because of the skewed nature of hydrological datasets, non-parametric statistics were used. This results in presentation of median values for all IHA parameters, except 1-day to 90-day minimums and maximums. The 1-day to 90-day minimums and maximums were calculated from moving averages of every possible period. If multiple periods have the same value, the earliest period will be reported. The 25^{th} and 75^{th} percentile flows were used as the thresholds for low and high pulse calculations. The flow reversals were calculated by dividing the hydrological record into 'rising' and 'falling' periods, which corresponded to periods in which daily changes in flows were either positive (rising) or negative (falling). IHAs characterize statistical magnitude and timing of events (e.g., annual maximum/ minimum 3-, 7-, 30-, and 90-day mean flows), intra-annual and inter-annual variability in flow conditions (e.g., rise/fall rate and number of reversals in the hydrograph). Detailed descriptions of the IHAs and their ecological significance can be found in the foundational IHA articles (Richter et al., 1996; Poff et al., 1997; The Nature Conservancy, 2009) and subsequent user studies (Monk et al., 2011). The overall approach used in this study is presented in Figure 2.4

Figure 2.4 Overall approach used in this study



2.2.4 Trend analysis Techniques

In order to increase confidence in the existence of trend in streamflow time series, the weekly average streamflow per unit area from each site was evaluated for trends using two trend tests: Mann-Kendall (Mann, 1945; Kendall, 1975; Kendall and Gibbons, 1990), and the Seasonal Kendall (Hirsch et al., 1982; Yu et al., 1993). Both tests are non-parametric correlation statistical tests and generally considered as appropriate tools in detecting linear trends of hydrological time series data. Moreover, Sen's estimator of slope (Sen, 1968) was included in the analysis to estimate the true slope (change per unit time). Brief descriptions of these methods are given below.

Mann-Kendall test: The Mann-Kendall test, using the Kendall's tau statistic, is widely used to assess the significance of trends in hydro-meteorological time series. The nonparametric trend test was first proposed by Mann (1945) and further studied by Kendall (1975). The Mann-Kendall test computes a monotonic trend in a time series based on the Kendall rank correlation and does not depend on the magnitudes of the data values. As the Mann-Kendall test is not affected either by extreme values or skewness in the data, it is considered as an effective method to measure the trends in the streamflow (Rasmussen and Perry, 2001). The null hypothesis of this test states that there is no trend in the series. Mann-Kendall's tau measures the correlation between two series and ranges between -1 and 1. In this study, significance was tested at p values of 0.05 and 0.10 (where p is the probability that a true null hypothesis of no trend is erroneously rejected). The MATLAB code written by Burkey (2006) was used to calculate Mann-Kendall tau and Sens's slope.

Sen's estimator of slope: The Sen's slope estimates the true slope (absolute change over time) when there is a linear trend. Sen's slope estimator has been widely used in hydro-meteorological time series.

Seasonal Kendall test: The Mann-Kendall test was revised by Hirsch et al. (1982) to include seasonality in the test. The Seasonal Kendall test is a generalized form of the Mann-Kendall test and widely used for monthly water quality time series analysis. The Seasonal Kendall computes Kendall tau separately for each month and analyzes the results separately for each month over the period of record. This test was applied to identify significant trends in monthly flows per unit area, mean precipitation and mean average temperature. The Seasonal Kendall test was performed using MATLAB codes written by Burkey (2008).

2.2.5 Precipitation and Temperature Trend analysis

The Mann-Kendall and Seasonal Kendall tests were applied to 16 precipitation stations and 17 temperature stations. The data were gathered from Kansas State University weather data library (http://www.ksre.ksu.edu/wdl/, accessed on 5/22/2014), which includes data from the National Climatic Data Center's database. All the stations, except Beatrice temperature station, had 50 years of data (1962-2012 water years). Beatrice had 48 years of data (1962-2011 water years). In addition Pearson correlation coefficient (R) was used to analyze the trends between flow and weather data.

2.2.6 Ecological Influences

Five ecohydrological indicators: mean spring daily discharge, mean summer daily discharge, zero-flow days, high-flow (> 75th percentile) pulse count, and median duration of high-flow pulses, are considered to have high ecological influence (Mims and Olden, 2012; Gido et al., 2013), and were selected to simplify analysis and eliminate redundancy with other ecohydrologic indicators. Fish occurrence data (presence/absence) for the sites throughout Kansas were gathered from Kansas Aquatic Gap Database, which includes collections from the

Kansas Department of Wildlife, Parks and Tourism, museum records, university research collections and various other sources. The database includes more than 7000 sites (collected between 1860 and 2009) represented by 133 fish species. The fish presence/absence data are recommended to examine long-term functional responses of fish assemblages to hydrology rather than abundance (Mims and Olden, 2012; Gido, 2014, personal communication). For the analysis, the fish-gage pairs were identified in close geographic proximity by intersecting survey sites and gage watersheds using ArcGIS. While selecting fish-gage pairs, the survey sites were selected within 20 river kilometers and checked to ensure that they were not separated by an impoundment (Mims and Olden, 2012).

Most reservoirs of KRB were constructed and irrigation agriculture was initiated at low level during 1947 to 1962. Prior to 1947, streams were presumed to be natural and unimpounded. Rapid impoundment development and increase in irrigated land acreage (primarily in western Kansas) occurred during 1963 to 1977 time period (Cross and Moss, 1987; Eberle, 2007). To analyze the relationship between ecohydrological variables and riverine fish species, the data were divided into two time periods: historic time period (1860-1950) and present time period (2000-2012). Historic period was selected similar to Kansas Fishes Committee (2014) and present period was selected because the selected time period has comprehensive survey of many streams in the State and also allows sufficient time for time lag effects of reservoir construction and groundwater pumping to occur (Gido et al., 2010). Thereafter, if specific fish species were present for > 3 years during historic period, their presence was calculated for the present period for each selected gage along with their ecohydrological indicator trends. Two-sample t-test (assuming unequal variance) was used to test if species responses to ecohydrological trends among two categorized by presence or absence from the two time-period groups: Historic/Present + Current/Present and Historic/Present + Current/Absent. For this analysis, fish species native to Kansas that are also identified as threatened or need conservation were selected. A brief description of the fish species used in this study is given below. Detailed information can be found in Kansas Fishes Committee (2014).

Plains minnow *(Hybognathus placitus):* The Plains minnow occurs in shallow perennial streams. An adult Plains minnow is about 13 cm (5 in.) in length. The Plains minnow was abundant and widely distributed throughout the KRB and started to decline since 1970 (Taylor and Eberle, 2014). Changes in the streamflow volume, pattern and the fragmentation by dams were identified as major sources of decline (Perkin and Gido, 2011). The Plains minnow has been listed as a threatened species in Kansas.

Common shiner (*Luxilus cornutus*): Common shiner occupies streams with coarse substrates. Adults are commonly 8-13 cm (3-5 in.) length, and total length can range up to 18 cm (7 in.). The Common shiner was extirpated from the northwestern streams due to turbidity and dewatering and has been listed as a species in need of conservation in Cathcart (2014).

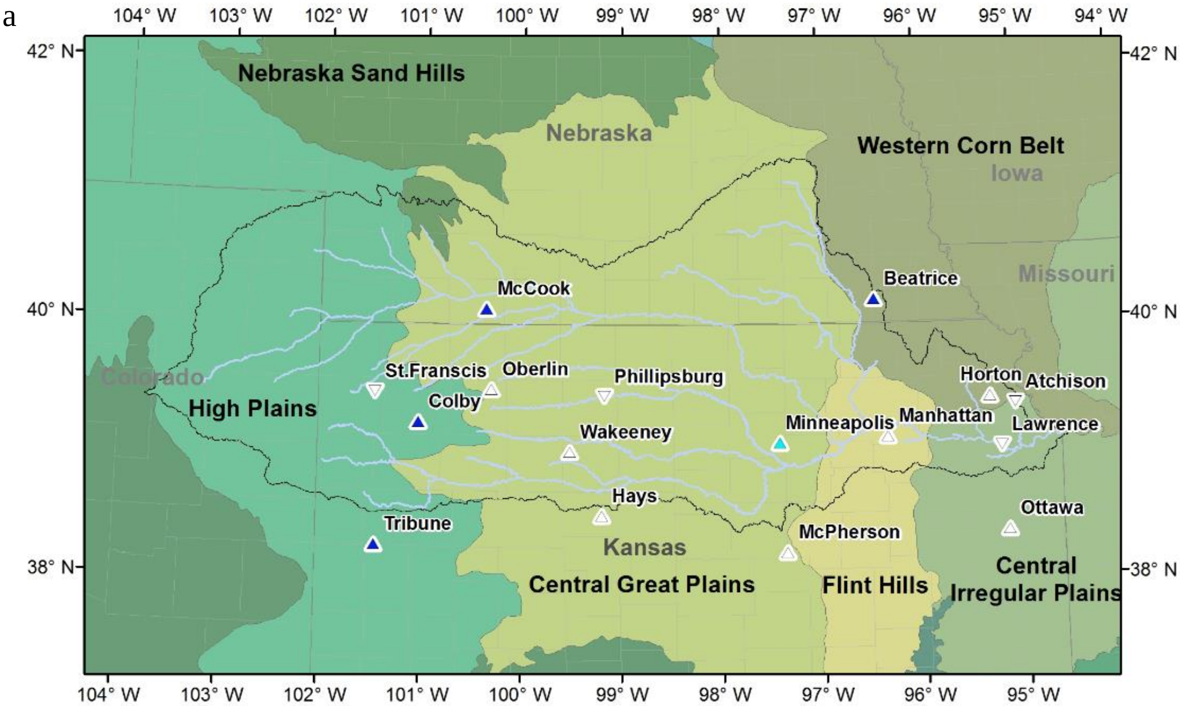
2.3 Results and Discussion

2.3.1 Climate trend analysis

The Kendall and Seasonal Kendall analysis of precipitation and temperature are presented in Figure 2.5. Both tests yielded similar trends but varied by magnitude and significance (Table 2.3 and 2.4). Both tests showed an overall increasing trend in precipitation and temperature. Similar increasing trends in precipitation have been observed in other studies (Hu et al., 1998; Garbrecht et al., 2004; Rahmani et al., 2014) throughout the State of Kansas. Many ecoregions included stations with both increasing and decreasing temperature and precipitation trends (Figures 2.6 and 2.7). The highest increase in precipitation trend was observed in Beatrice station located in the Western Corn Belt ecoregion. The highest increasing and decreasing trends in temperature were observed in Wakeeney and Beatrice, respectively.

Figure 2.5 Trends of average annual precipitation based on a) Mann-Kendall and b) Seasonal Kendall, and temperature based on c) Mann-Kendall and d) Seasonal Kendall at selected NCDC stations of Kansas River Basin for water years 1962-2012.

a



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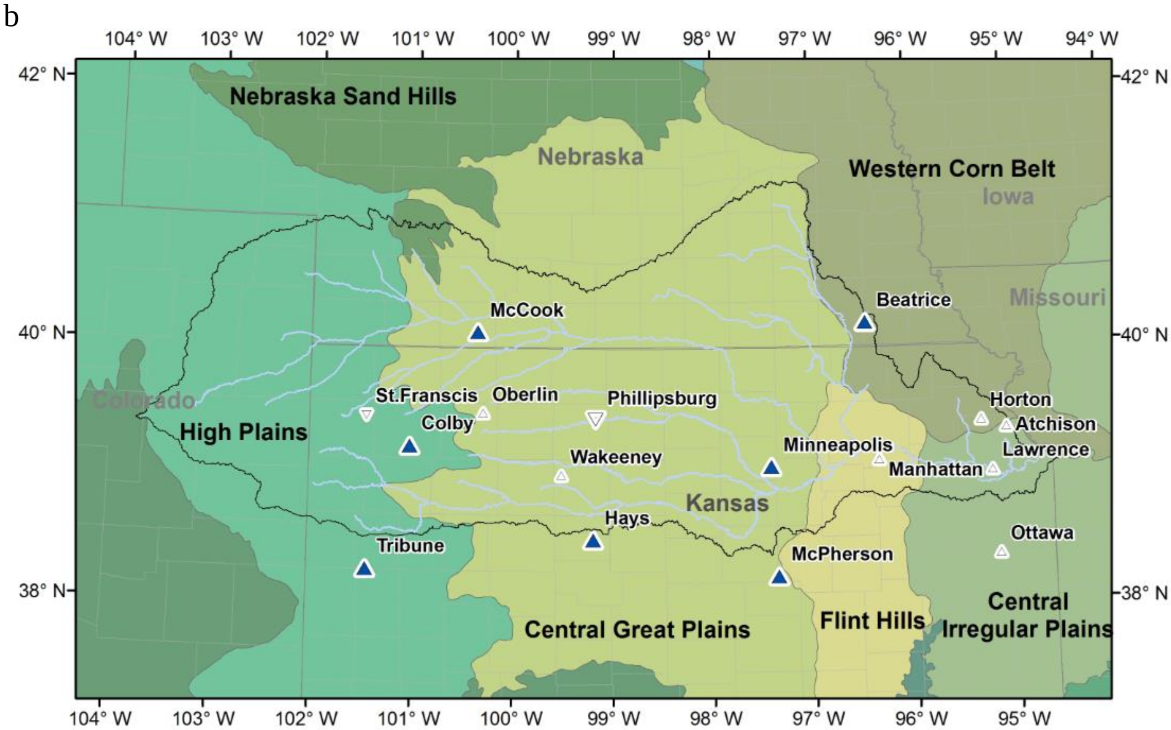

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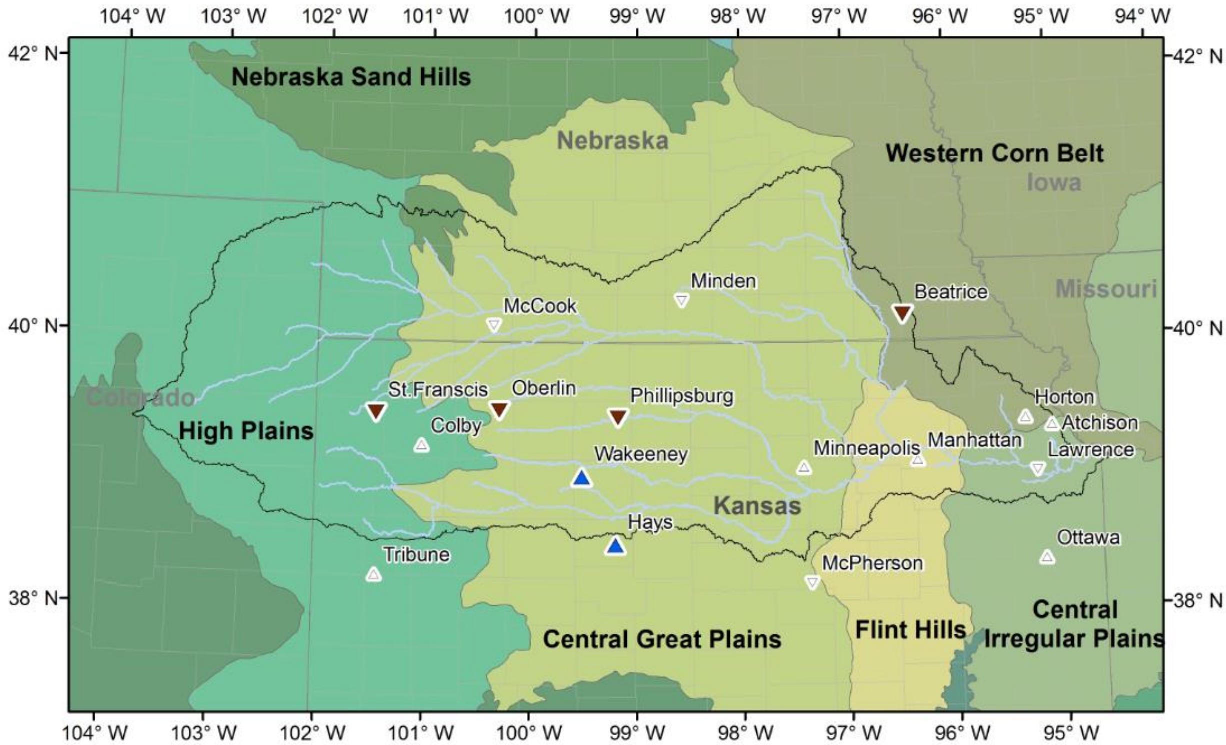
Nebraska Sand Hills
Nebraska
Western Corn Belt
Iowa
Missouri
Colorado
High Plains
Kansas
Central Great Plains
Flint Hills
Central
Irregular Plains
Minden
McCook
Beatrice
St.Franscis
Oberlin
Phillipsburg
Colby
Wakeeney
Hays
Tribune
Minneapolis
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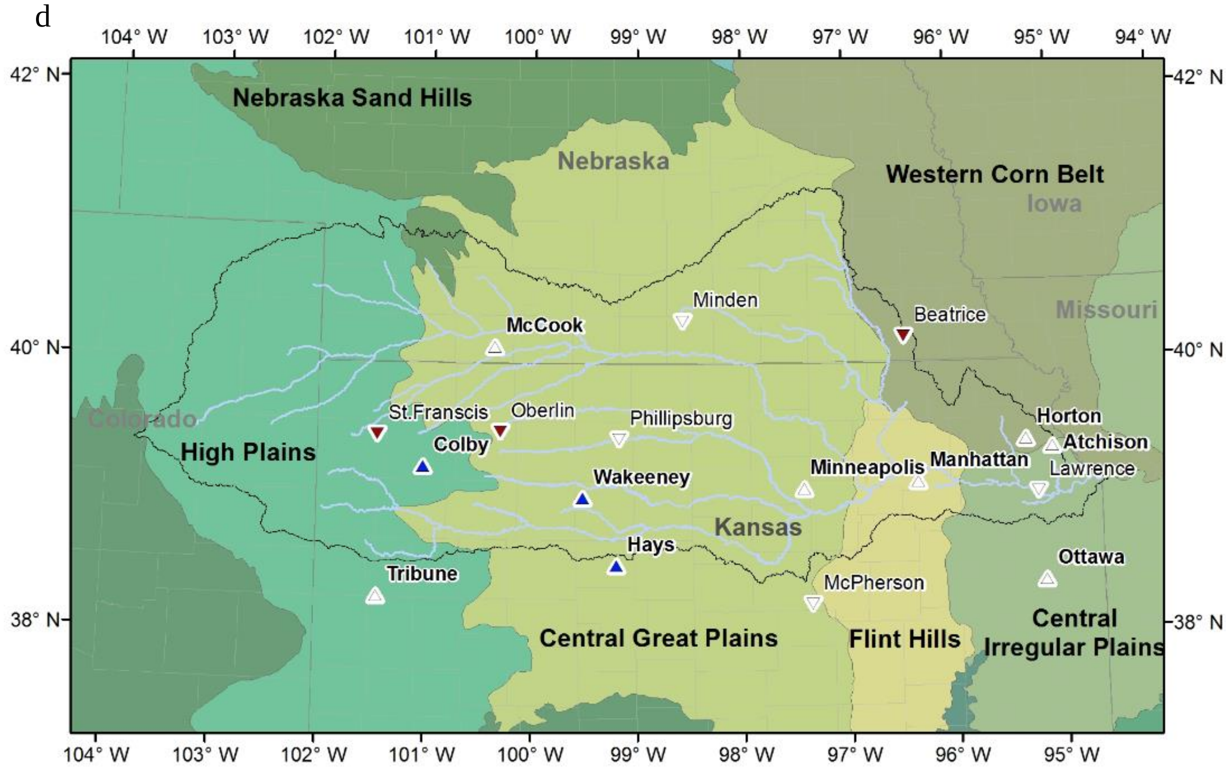
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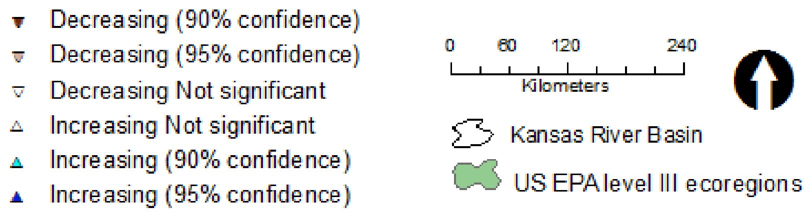


Table 2.3 Kendall tau and Sen's slope for trends in precipitation and temperature. Bold numbers show statistically significant trends at 95% confidence.

		Precipitation		Temperature	
Station Name	COOPID	Kendall tau	Sen's slope (in. per 50year)	Kendall tau	Sen's slope (^{o}F per 50year)
Horton	143810	0.05	0.49	0.01	0.11
Atchison	140405	-0.03	-0.31	0.08	0.81
Manhattan	144972	0.05	0.55	0.04	0.36
Beatrice	250622	**0.26**	**2.70**	**-0.34**	**-3.40**
Minneapolis	145363	0.17	1.75	0.06	0.58
Minden				-0.04	-0.44
Phillipsburg	146378	-0.01	-0.11	-0.15	-1.56
Wakeeney	148495	0.04	0.37	**0.32**	**3.33**
Oberlin	145906	0.04	0.41	**-0.26**	**-2.70**
McCook	255310	**0.24**	**2.44**	0.01	0.15
St. Francis	147093	-0.01	-0.15	**-0.21**	**-2.13**
Hays	143527	0.09	0.96	**0.28**	**2.92**
Tribune	148235	**0.19**	**1.97**	0.07	0.70
Ottawa	146128	0.06	0.57	0.05	0.47
McPherson	145152	0.14	1.43	-0.10	-1.04
Lawrence	3997	-0.06	-0.60	-0.06	-0.65
Colby	141699	**0.21**	**2.18**	**0.19**	**2.00**

Table 2.4 Seasonal Kendall tau and Sen's slope for trends in precipitation and temperature. Bold numbers show statistically significant trends at 95% confidence. The Seasonal Kendall computes Kendall tau separately for each month and analyzes the results separately for each month over the period of record and report combined/ overall values for a year.

		Precipitation		Temperature	
Station Name	COOPID	Seasonal Kendall tau	Sen's slope (in. per 50year)	Seasonal Kendall tau	Sen's slope (^{o}F per 50year)
Horton	143810	0.03	0.00	0.00	0.00
Atchison	140405	0.01	0.00	0.04	0.01

Manhattan	144972	0.03	0.00	0.01	0.00
Beatrice	250622	**0.20**	0.00	**-0.20**	-0.08
Minneapolis	145363	**0.09**	0.00	0.02	0.01
Minden				-0.03	-0.01
Phillipsburg	146378	-0.01	0.00	-0.05	-0.02
Wakeeney	148495	**0.02**	0.00	**0.14**	0.05
Oberlin	145906	0.01	0.00	**-0.12**	-0.04
McCook	255310	0.18	0.00	0.00	0.00
St.Franscis	147093	-0.02	0.00	**-0.07**	-0.02
Hays	143527	**0.06**	0.00	**0.11**	0.04
Tribune	148235	**0.08**	0.00	0.02	0.01
Ottawa	146128	0.03	0.00	0.01	0.00
McPherson	145152	**0.06**	0.00	-0.05	-0.02
Lawrence	3997	0.02	0.00	-0.02	-0.01
Colby	141699	**0.10**	0.00	0.04	0.02

Figure 2.6 Sen's slope magnitude and significance for trends in precipitation across the ecoregions: High Plains, Central Great Plains, Flint Hills (FH), Western Corn Belt (WCB) and Central Irregular Plains (CIP). Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends were not significant at p=0.10.

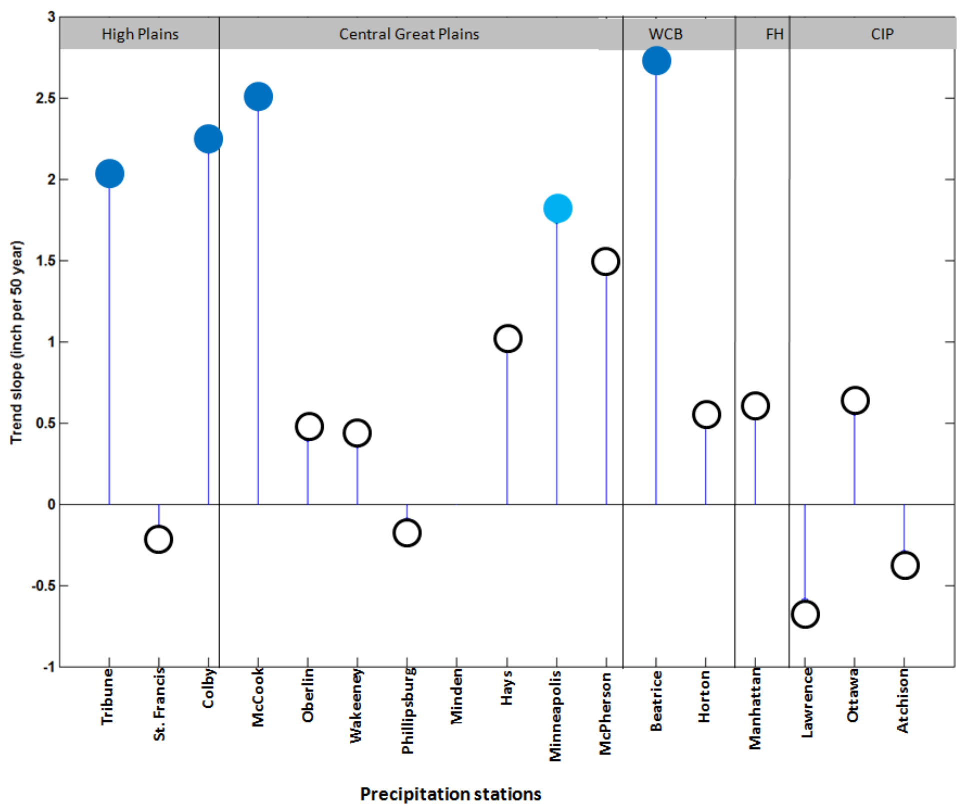
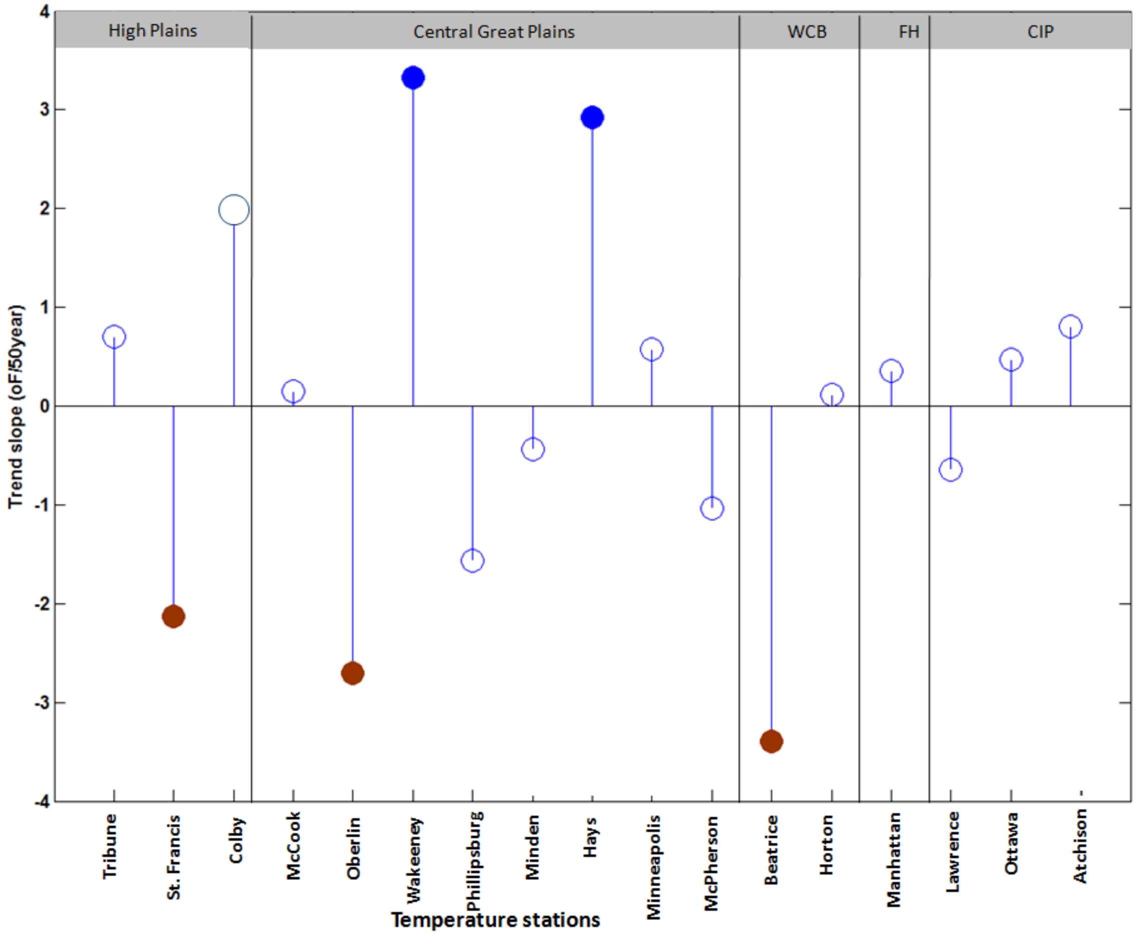


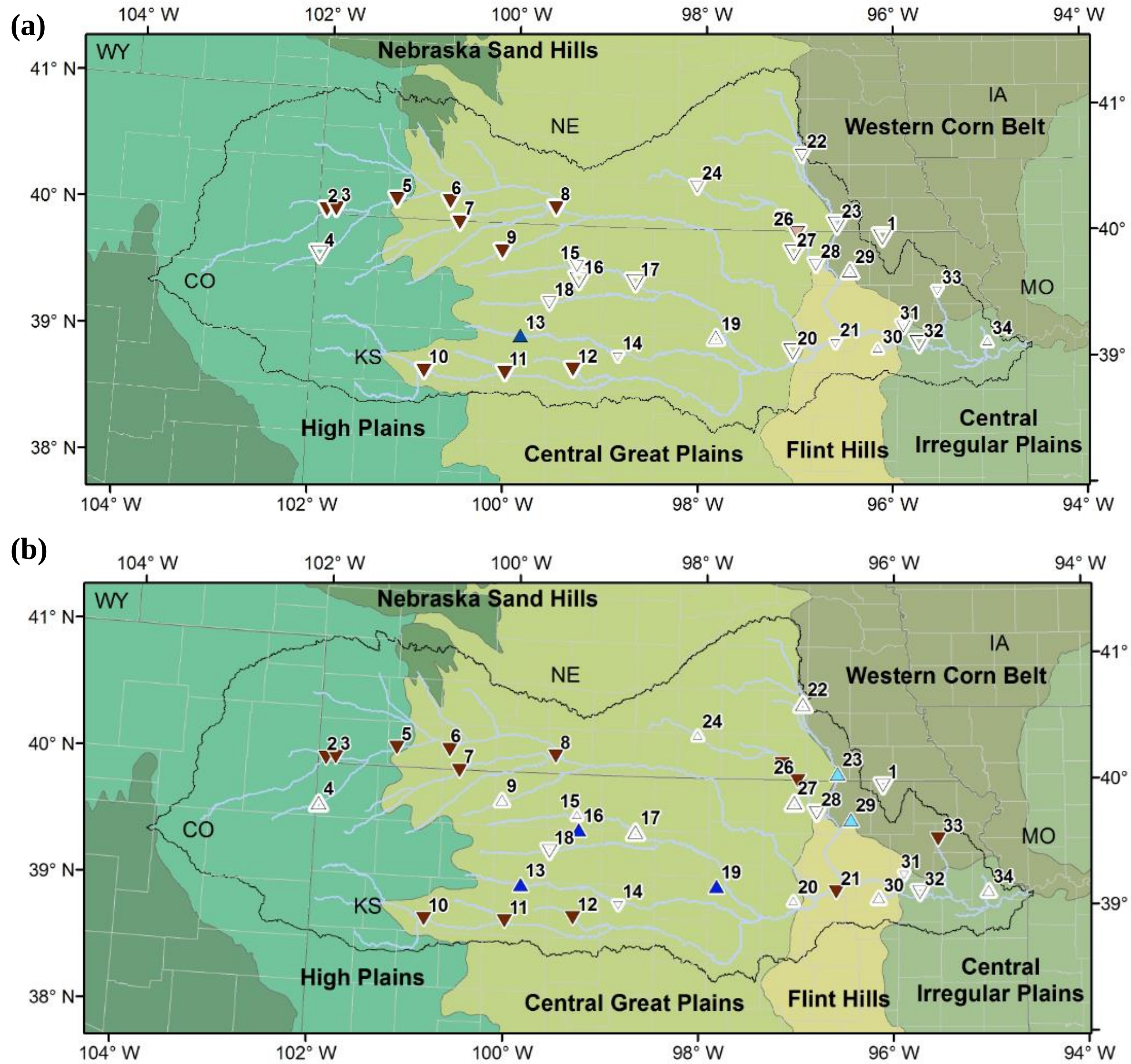
Figure 2.7 Sen's slope magnitude and significance for trends in temperature across the ecoregions: High Plains, Central Great Plains, Flint Hills (FH), Western Corn Belt (WCB) and Central Irregular Plains (CIP). Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends was not significant at p=0.10.



2.3.2 Annual mean flow per unit area

The spatial distribution of trends in annual mean flow per unit area for the 50-year study period are presented in Figure 2.8. The trends were calculated with both Mann-Kendall and Seasonal Kendall tests. The majority of the stations show similar trends for both tests. More stations show negative trends (map indices 1-12, 14-18, 20-28, 31-34) than positive trends (map indices 13, 19, 29, 30) within the entire KRB. The Seasonal Kendall tests showed fewer stations with negative trends (Table 2.5). Also Seasonal Kendall produced lesser magnitude of slope for all condition (Table 2.6). However with Seasonal Kendall, the significance of the test increased in both conditions. These results indicate that there is seasonality in runoff at most stations. Higher seasonal variation was observed in Central Great Plains ecoregion.

Figure 2.8 Results of (a) Mann-Kendall tau and (b) Seasonal Kendall tau for trends in average annual runoff at selected stream-gaging stations of Kansas River Basin for water years 1962-2012. Upward and downward pointing triangles represent increasing (blue) and decreasing (red) trends, respectively. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) colors. Open triangles indicate that trend was not significant at p=0.10.



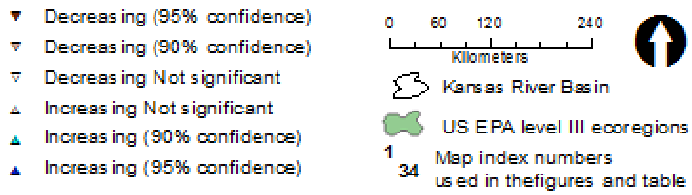


Table 2.5 The number of streamflow gaging stations (n = 34) with significant increasing or decreasing trends in mean annual streamflow per unit area (runoff depth) at p = 0.10 (or p = 0.05 in parentheses).

	Ecoregion				Overall
	High Plains	Central Great Plains	Flint Hills	Western Corn Belt	
Based on Mann-Kendall					
Increasing Trend	0 (0)	2 (1)	1 (0)	2 (0)	5 (1)
Decreasing Trend	7 (6)	17 (4)	2 (0)	3 (0)	29 (10)
Based on Seasonal Kendall					
Increasing Trend	1 (0)	11 (2)	1 (0)	2 (0)	15 (2)
Decreasing Trend	6 (6)	8 (5)	2 (1)	3 (1)	19 (13)

Table 2.6 Mann-Kendall and Seasonal Kendall tau and Sen's slope for trends in annual flow. Bold numbers show statistically significant trend at 95% confidence.

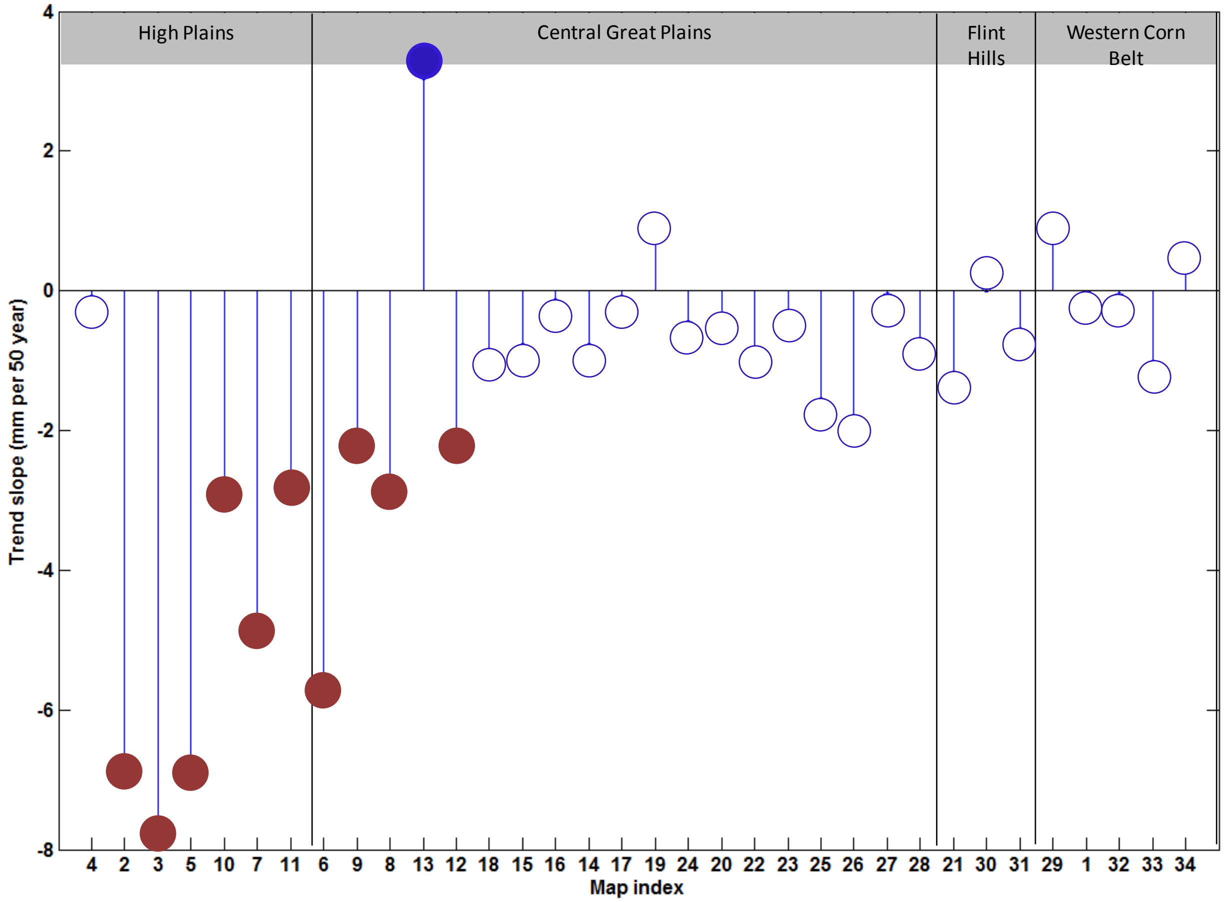
	Mann-Kendall		Seasonal Kendall	
Map index	tau	Sen's slope mm/50yrs	tau	Sen's slope mm/50yrs
1	-0.01	-0.07	0.00	0.00
2	**-0.65**	**-6.71**	**-0.48**	**0.00**
3	**-0.74**	**-7.65**	**-0.48**	**0.00**
4	-0.01	-0.13	0.03	0.00
5	**-0.65**	**-6.74**	**-0.43**	**0.00**
6	**-0.54**	**-5.56**	**-0.34**	**0.00**
7	**-0.46**	**-4.71**	**-0.21**	**0.00**
8	**-0.26**	**-2.71**	**-0.12**	**0.00**
9	**-0.20**	**-2.05**	0.02	0.00
10	**-0.27**	**-2.76**	**-0.23**	**0.00**
11	**-0.26**	**-2.66**	**-0.09**	**0.00**
12	**-0.20**	**-2.05**	**-0.08**	**0.00**
13	**0.29**	**3.09**	**0.31**	**0.00**
14	-0.12	-1.27	-0.04	0.00

15	-0.08	-0.83	0.00	0.00
16	-0.02	-0.18	**0.09**	**0.00**
17	-0.01	-0.13	0.03	0.00
18	-0.09	-0.89	-0.02	0.00
19	0.07	0.75	**0.10**	**0.00**
20	-0.04	-0.37	0.00	0.00
21	-0.15	-1.22	-0.15	0.00
22	-0.08	-0.86	0.04	0.00
23	-0.03	-0.34	0.05	0.00
24	-0.05	-0.50	0.01	0.00
25	-0.16	-1.61	**-0.09**	**0.00**
26	-0.23	-1.84	**-0.14**	**0.00**
27	-0.01	-0.10	0.04	0.00
28	-0.07	-0.73	-0.02	0.00
29	0.07	0.75	0.05	0.00
30	0.01	0.05	0.01	0.00
31	-0.06	-0.60	-0.03	0.00
32	-0.01	-0.10	0.00	0.00
33	-0.13	-1.07	-0.08	0.00
34	0.03	0.31	0.01	0.00

Stream gauges located in High Plains and Flint Hills ecoregions generally showed decreasing trends based on Kendall test, indicating a reduction in mean streamflow (Figure 2.8, Figure 2.9 and Table 2.6). In the High Plains ecoregion, 6 out of 7 stations (86%) showed significant decreasing trends at the 95% confidence level. The majority of the stations in other two ecoregions, Central Great Plains and Western Corn Belt, showed decreasing trends. Decreasing streamflow volume in western Kansas has been supported by previous trend studies in this study area (Jordan, 1982; Angelo, 1994; Rasmussen and Perry, 2001; Perry et al., 2002; Perry et al., 2004). Two stations showed increasing trends in Central Great Plains ecoregion, and one was significant at 95% confidence level. For the entire KRB, records from 29 of the 34 stations (85%) showed decreasing trends, with 34% of them significant at 95% confidence.

When seasonality was considered (using the Seasonal Kendall test) 44% of stations of KRB showed an increasing trend in annual flow (Table 2.6) and 38% of the streams showed a significant negative trend. The High Plains ecoregion had the highest percentage of negative trends followed by Central Great Plains.

Figure 2.9 Sen's slope magnitudes and significance of trends in annual streamflow. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends was not significant at p=0.10.



Irrigated agriculture is considered to be a primary factor in the change of perennial streams into intermittent stream in the KRB, especially western Kansas (Perry, 2004; Aguilar, 2009). The streams considered as perennial streams in 1960s were reported as intermittent streams in 1990 (Perry, 2004). Western KRB has lower flow streams compared to eastern KRB because of the regional gradient in precipitation and soil characteristics. The western two-thirds of the KRB typically has moderate to high permeability soils (Figure 2.2) and the eastern one-third has lower permeability soils. The KRB has an east-west precipitation gradient with less north-south variation. These differences lead to lower discharge streams in the western region and higher discharge streams in the eastern region. With the variation in discharge, irrigation pumping, agricultural management practices and soil and water conservation structures probably have had a higher impact on High Plains streams compared to other ecoregions. This may explain why High Plains streams had greater decreasing trends in annual flow per unit area compared to others (Figures 2.8 and 2.9; Tables 2.5 and 2.6).

2.3.3 Seasonal mean flow per unit area

Seasonal streamflow across the ecoregions demonstrated both increasing and decreasing trends (Figure 2.10, Table 2.7). In the High Plains ecoregion the seasonal streamflows per unit area for most stations decreased for all seasons over the study period, which is consistent with the observed decreasing annual trends (Figure 2.9). In the Central Great Plains, Flint Hills and Western Corn Belt ecoregions, the overall annual trends were decreasing (Figure 2.9), but these trends varied seasonally. A slight majority of stations showed seasonal trends during winter (increasing) and summer and autumn (decreasing) (Figure 2.10). A majority of the stations in the Central Great Plains, Flint Hills and Western Corn Belt ecoregions showed slight increasing trends for spring months (March to May), but only one station was significant at 95% confidence level. In autumn (September to November), a majority of stations in these three ecoregions showed slight decreasing trends, but only four stations were significant at 90% confidence level or better. These overall trends, positive in the spring and negative in the autumn (Table 2.7), indicate a shift in timing of the annual cycle of the hydrologic regime (Zhang et al., 2001).

The KRB receives nearly 70% of annual precipitation during April to September (Sophocleous, 1998). The magnitude of annual precipitation increases from west to east and therefore the streams. The seasonal streamflow trends where smaller in the Central Great Plains, Flint Hills and Western Corn Belt streams than in High Plains streams (Figures 2.6 and 2.10) where the magnitude of annual precipitation is higher (Aguilar, 2009). In the High Plains, for seasons in which the magnitude of annual precipitation is low due to less precipitation and a moisture deficit (more potential evapotranspiration than precipitation) (Sophocleous, 1998; Aguilar, 2009), the decreasing trends are more prominent.

Figure 2.10 Sen's slope magnitudes and significance of trends in seasonal streamflows per unit area. Filled circles show statistically significant trend at 95% confidence. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) colors. Open circles indicate that trends was not significant at p=0.10.

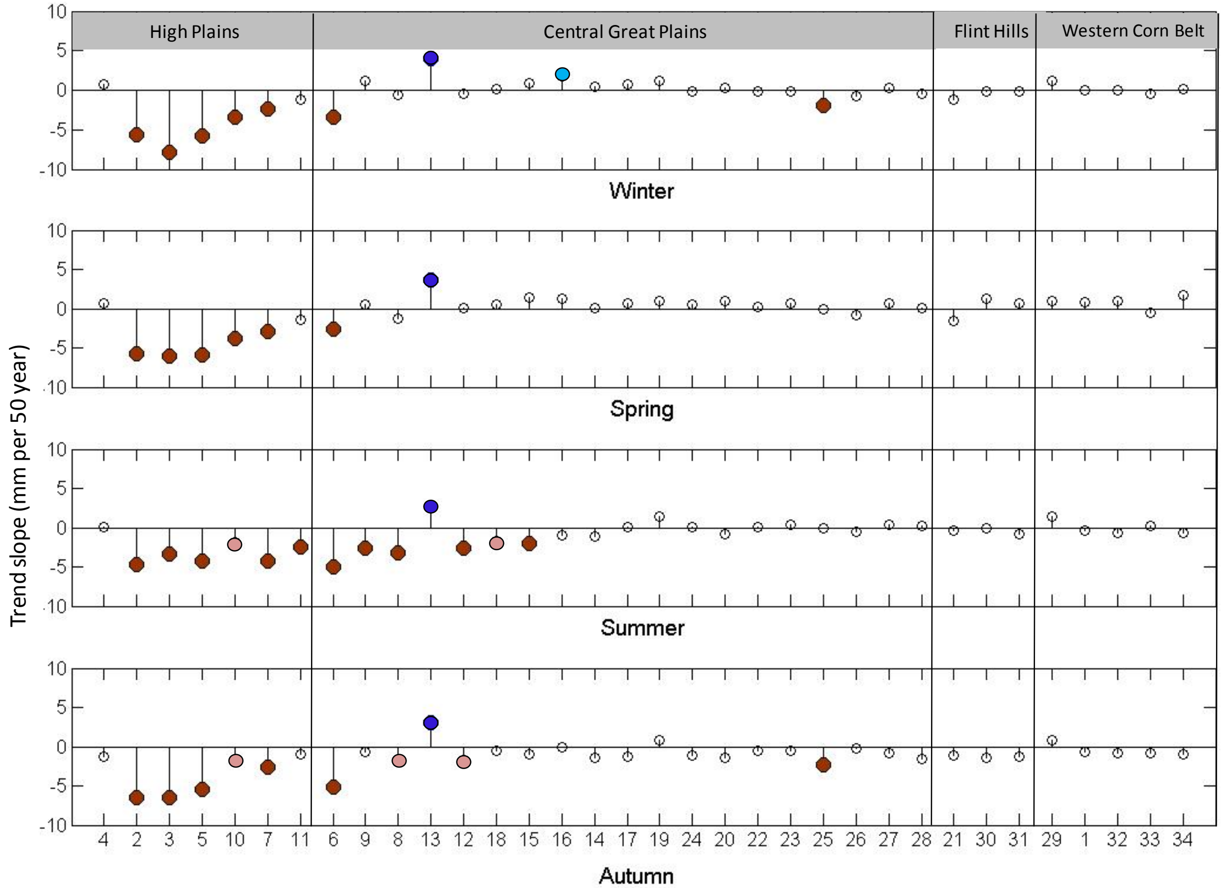


Table 2.7 Number of stations showing increasing and decreasing trends in seasonal streamflow across the ecoregions. Numbers within parenthesis show statistically significant trend at 95% confidence.

	High Plains	Central Great Plains	Flint Hills	Western Corn Belt	Overall
Winter					
Increasing Trend	1	10(1)	0	4	15(1)
Decreasing Trend	6(5)	9(2)	3	1	19(7)
Spring					
Increasing Trend	1	15(1)	2	4	22(1)
Decreasing Trend	6(5)	4(1)	1	1	12(6)
Summer					

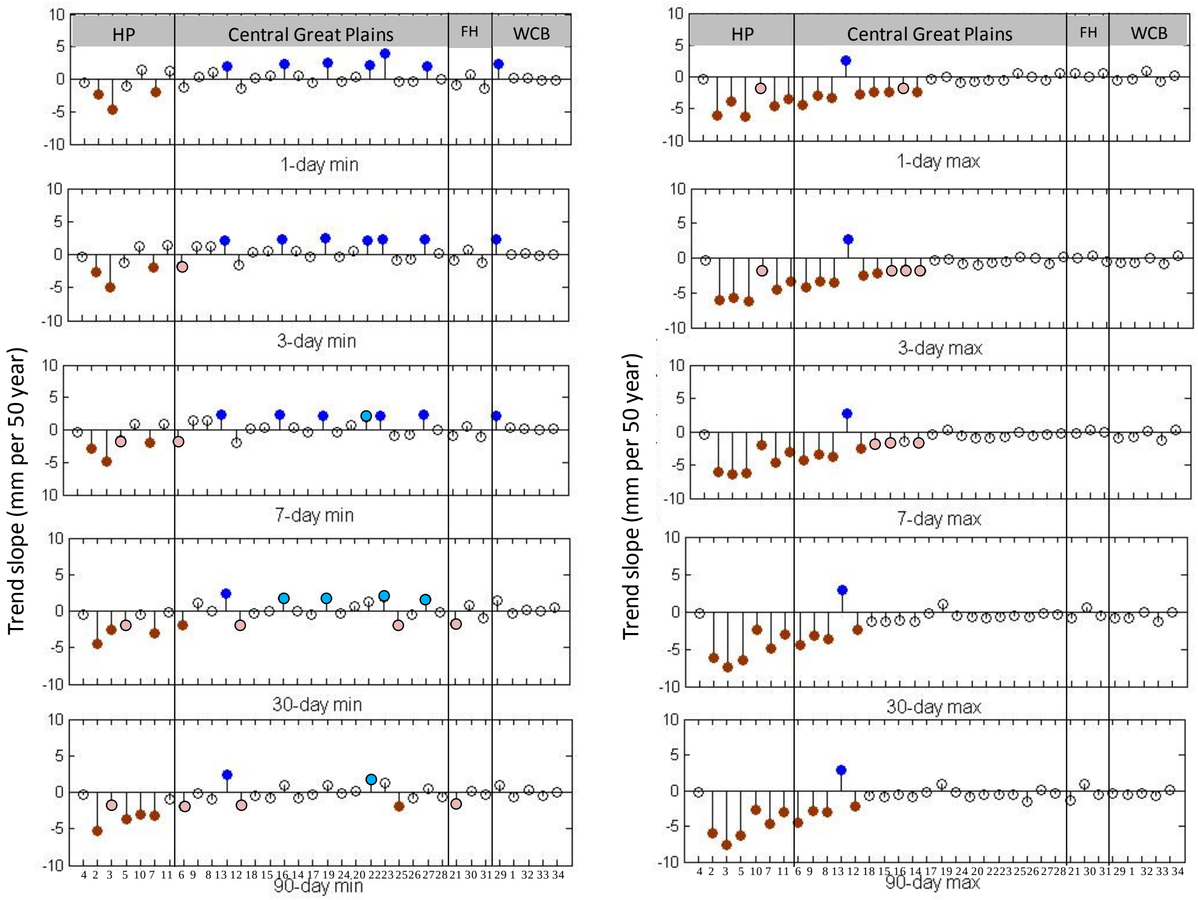
Increasing Trend	1	8(1)	0	2	11(1)
Decreasing Trend	6(5)	11(5)	3	3	23(10)
Autumn					
Increasing Trend	0	2(1)	0	1	3(1)
Decreasing Trend	7(4)	17(2)	3	4	31(6)

Trends in annual mean runoff can be the result of many factors. Increase in the frequency, intensity, or amount of rainfall and increase in temperature are the most direct potential causes. Increased rainfall frequencies and intensities can yield greater average streamflows. Also as temperature increases, more evaporation and reduced streamflow result.

2.3.4 Extreme water conditions

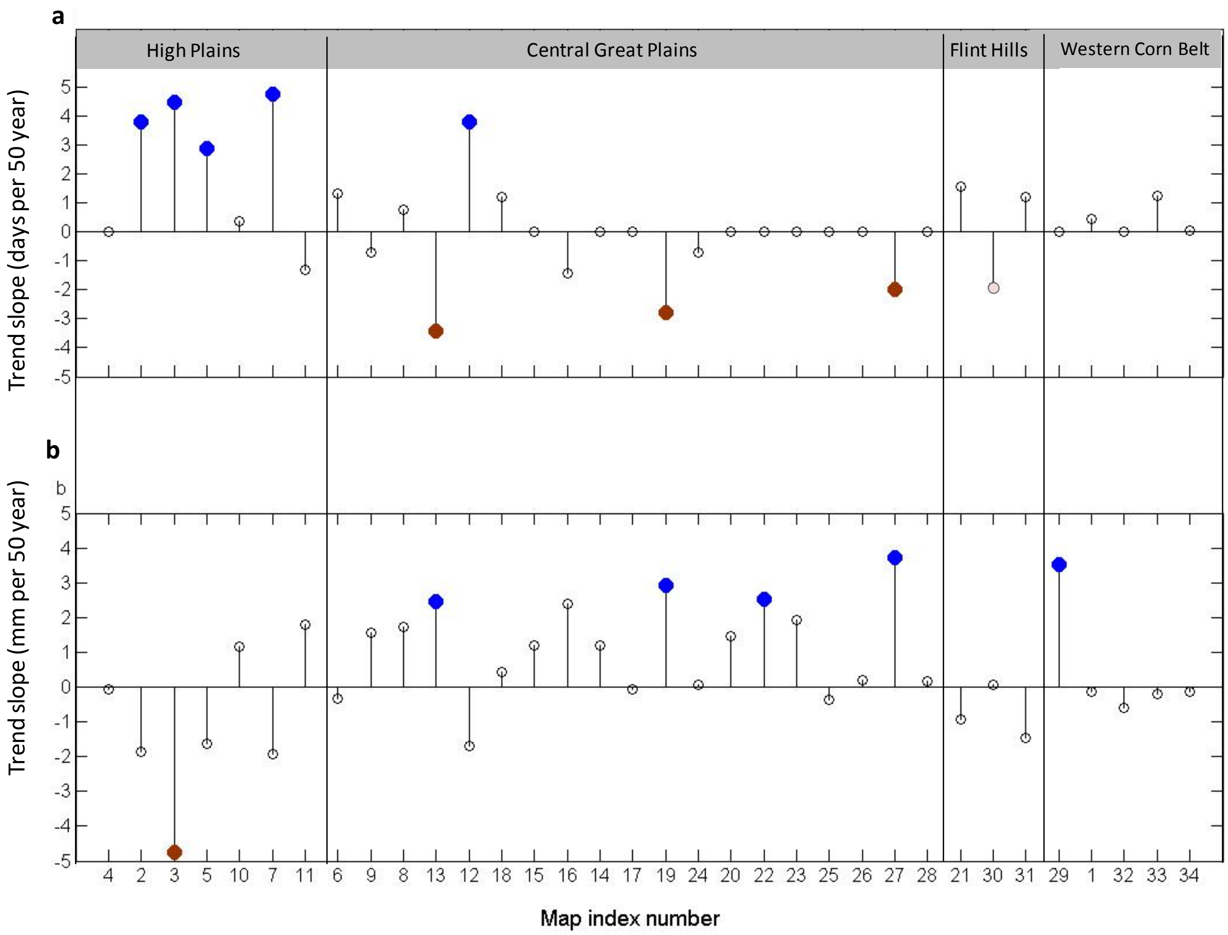
Trends for each station were fairly consistent across all levels of flow minimums or maximums, but trends varied across stations and ecoregions. Most of the 34 stations (76%) showed negative trends for all duration levels of maximum flows (Figure 2.11). Most stations in the High Plains showed significant (p=0.05 or 0.10) decreasing trends for all levels of flow minimums and maximums, except station 4 (decreasing, but not significant) and stations 10 and 11 (decreasing for 30- and 90-day minimum flows and increasing for 1-, 3- and 7-day minimum flows, but generally not significant). Most stations in the western Central Great Plains also showed significant decreasing trends for flow maximums at all duration levels west of station 18 (except station 13) and at lower duration levels (less than 7-day) west of station 14. Trends were near zero (not significant) for most stations in the eastern Central Great Plains, Flint Hills, and Western Corn Belt ecoregions.

Figure 2.11 Sen's slope magnitude and significance of trends in 1- to 90-day minimum flows (left) and 1- to 90-day maximum flows (right) across the ecoregions: High Plains (HP), Central Great Plains, Flint Hills (FH), and Western Corn Belt (WCB). The X-axis of graphs denotes map index in similar order like other graphs. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends was not significant at p=0.10.



Increasing trends in number of zero-flow days and baseflow index (7-day-minimum baseflow mean) also were seen for the High Plains ecoregion (Figure 2.12). The stations located in the western half of the Central Great Plains ecoregion, expect station 13, showed statistically significant decreasing trends for all duration levels of maximum flows. Decreasing trends in maximum flows were associated with decreasing trends in annual flows at those stations (Figure 2.8). A majority of Central Great Plains ecoregion stations showed increasing trends (6 stations were statistically significant) for all duration levels of minimum flows (Figure 2.11) and baseflow index (with 5 of the stations being statistically significant) (Figure 2.12). The positive trend in baseflow index and may reflect the contribution of return flow from the irrigation in this region. The stations located in Flint Hills and Western Corn Belt ecoregions did not show significant trends.

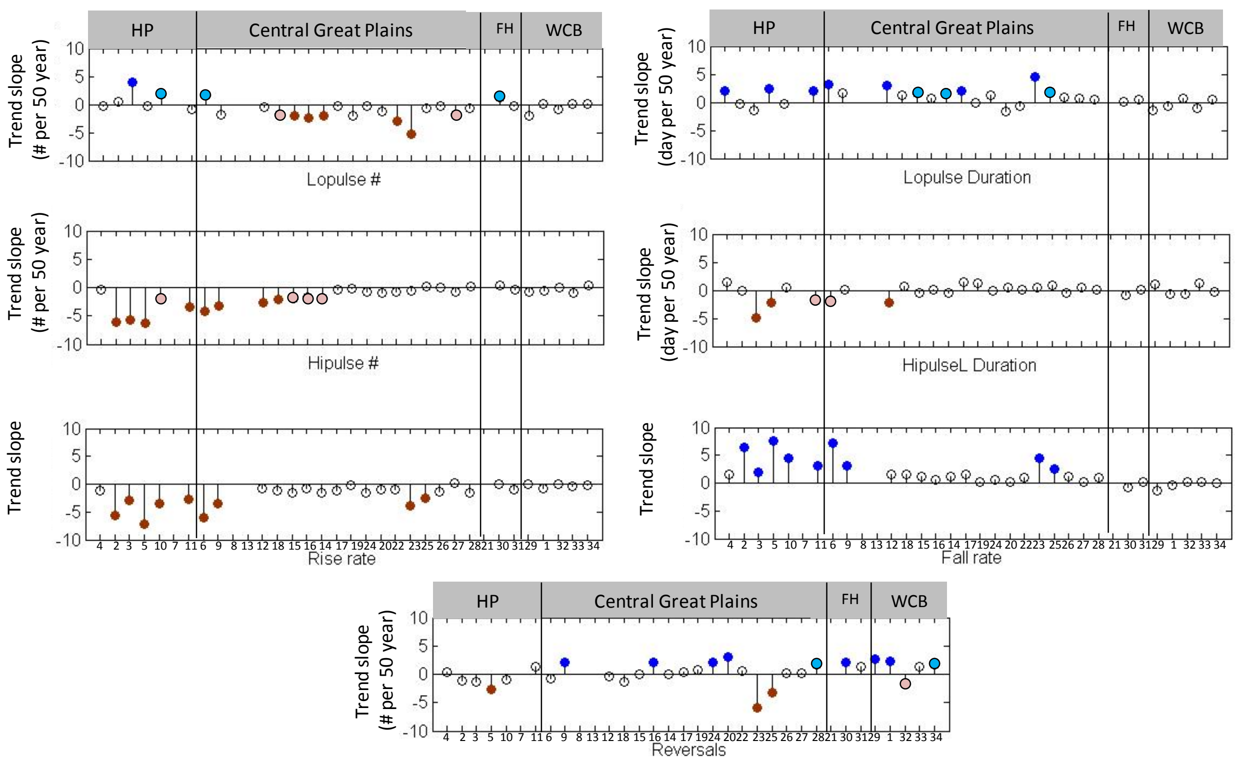
Figure 2.12 Sen's slope magnitude and significance of trends in a) zero flow days and b) baseflow index (7-day-minimum baseflow mean). Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends was not significant at p=0.10.



Low-flow pulse (< 25th percentile of daily flows) and high-flow pulse (> 75th percentile of daily flows) events were analyzed and displayed (Figure 2.13) by frequency (counts per year) and median duration (days) of high and low pulse events (Group 4; Table 2.1) and rate and frequency of water condition changes (Group 5; Table 2.1). Some stations (7, 9 13 and 21) were removed from these analyses because they had missing values and to avoid truncated pulses (The

Nature Conservancy, 2009). Most stations in the High Plains and western Central Great Plains showed significant decreasing trends in the number and duration of high-flow pulses and significant increasing trends in duration of low-flow pulses, but results for number of low-flow pulses were mixed for stations across ecoregions (Figure 2.13). A majority of stations showed negative trends in rise rates and positive trends in fall rates (Figure 2.11), both of which indicate an increasing threat of drought incidence. Significant trends observed in the number of flow reversals over the study period showed higher variability in Central Great Plains, Flint Hills and Western Corn Belt ecoregions (Figure 2.13).

Figure 2.13 Sen's slope magnitude and significance of trends in low- and high-flow pulse frequency and duration, rise and fall rates, and reversals. The X-axis of graphs denotes map index in similar order like other graphs. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends was not significant at p=0.10.



2.3.5 Trends in Timing of Streamflow

2.3.5.1 Center of timing

A decreasing trend in the center of timing of annual streamflow indicates a shift in annual streamflow towards an earlier day. In this study, the majority of stations (79%) exhibited decreasing trend in center of timing (Figure 2.14; Table 2.8). The only significant trends were negative trends (p=0.10) found at 8 (out of 19) stations in the western Central Great Plains ecoregion, with 9 of the remaining 11 stations having nonsignificant decreasing trends. Five (out of 7) High Plains stations, 1 (out of 3) Flint Hills stations, and 4 (out of 5) Western Corn Belt stations also showed negative (nonsignificant) trends. The magnitudes of trend slope are within ± 4 days per 50 years (Figure 2.14), which shows that there has been little to no substantial shift in the hydrologic regime.

Figure 2.14 Sen's slope magnitudes and significance of trends in the center of timing annual streamflow. Solid circles show statistically significant trend at 95% confidence. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) circle colors. Open circles indicate that trends was not significant at p=0.10.

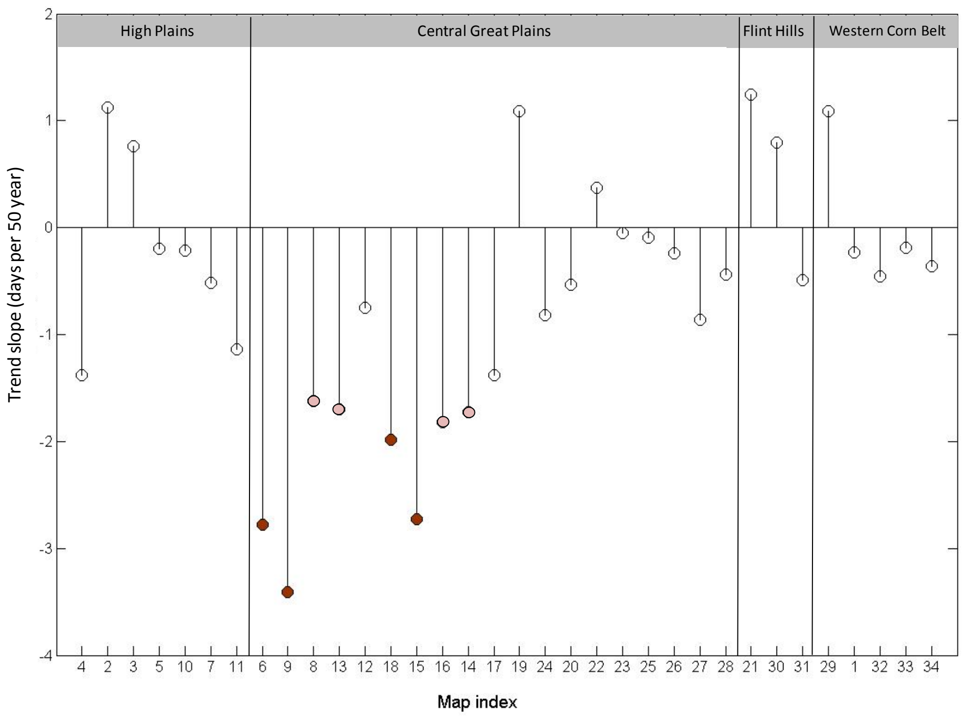


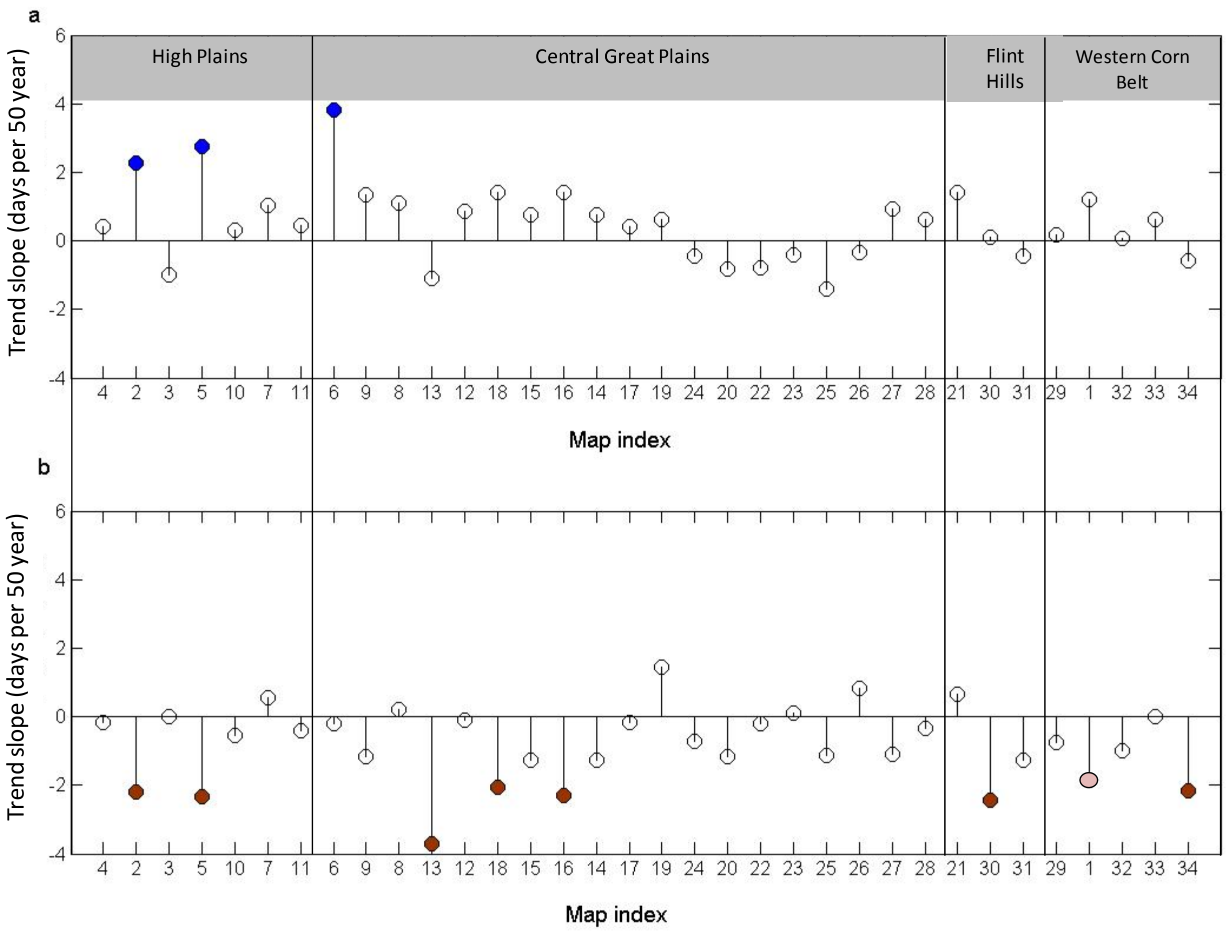
Table 2.8 Number of stations showing increasing and decreasing trends across ecoregions for centroid of annual flow per unit area. Numbers within parenthesis show statistically significant trend at 95% confidence

	Ecoregion				
	High Plains	Central Great Plains	Flint Hills	Western Corn Belt	Overall
Increasing Trend	2	2	2	1	7
Decreasing Trend	5	17(4)	1	4	27(4)

2.3.5.2 Date of annual maximum and minimum flows

Figure 2.15 shows the date of annual minimum runoff tends to be occurring later and the date of annual maximum runoff tends to be occurring earlier for a majority of the stations tested. However, only three stations in the High Plains and western Central Great Plains ecoregions had significant (p=0.05) increasing trends, and one to three stations in each of the four ecoregions showed significant (p=0.05 or 0.10) decreasing trends.

Figure 2.15 Sen's slope magnitudes and significance in trends in the date of a) annual minimum and b) annual maximum flows. Solid circles show statistically significant trend at 95% confidence. Trend significance is indicated by darker (p=0.05 or 95% confidence) and lighter (p=0.10 or 90% confidence) colors. Open circles indicate that trends was not significant at p=0.10.



2.3.6 The influence of climatic variables on annual average runoff

The overall observed decreasing trend in annual average runoff can be caused by changes in rainfall patterns and increasing annual average temperature. The Pearson correlation coefficient (R) results show 0.63 correlation between annual average flow trends and annual average precipitation trends and 0.41 correlation between annual average flow trends and annual average temperature trends. However, neither of these is significant at the 90% confidence level (Table 2.9). This may be because of the smaller sample size (7) of this analysis (Table 2.9).

Other than precipitation and temperature, groundwater depletion, terracing (particularly in western Kansas), and changes in land use and farming practices (such as contour farming, crop rotation, pasture improvement, and conservation reserve program) also can be related to the decreasing annual trend (Rasmussen and Perry, 2001).

Table 2.9 Pearson correlation coefficient (R) between observed flow and weather trends

Map index	USGS Station Code	Observed Flow Trend mm/ 50 year	Weather station	Observed Annual Average Precipitation Trend	Observed Annual Average Temperature Trend
7	6846500	**-4.71**	St. Francis	-0.15	**-2.13**
13	6866900	**3.09**	Colby	**2.18**	**2**
14	6867000	-1.27	Wakeeney	0.37	**3.33**
15	6871000	-0.83	Oberlin	0.41	**-2.7**
23	6882000	-0.34	Beatrice	**2.7**	**-3.4**
30	6888500	0.05	Manhattan	0.55	0.36
34	6892000	0.31	Horton	0.49	0.11
			Atchison	-0.31	0.81
Pearson correlation coefficient (R)				0.63	0.41

2.3.7 Ecological Influences

Streamflow is the major variable controlling the river's physical, biological and chemical process and determines ecological integrity of the system (Poff et al., 1997). The t-test results between flow trends and distribution of fish species (Plains minnow [*Hybognathus placitus*] and Common shiner [*Luxilus cornutus*]) showed the detrimental effect of flow-regime change on native fish species of Kansas (Table 2.10). Mean summer daily discharge and high-flow pulse count have significant effects on both Plains minnow and Common shiner distribution (Figures 2.16 and 2.17). Both species were not found in the streams with greater decreasing trends of mean summer daily flows during the sampling period (2000-2012). However they were present during the historical period. Decreasing summer flows trend and species disappearance can be related to unsuccessful spawning events. Plains minnow spawns during summer period (Distler et al., 2014). Since Plains minnow eggs are buoyant in nature, there should be sufficient flow to maintain the buoyancy of the eggs. Where there is insufficient water the eggs could be damaged and killed or dried due to extreme temperature (Taylor and Eberle, 2014). Similarly, the Common shiner spawns normally from late April to early July with peaks in mid-May (Cathcart, 2014). They use already-built nests by other species or the male shiner excavates pits in shallow riffle. If there is not sufficient water to form riffles, the spawning events of Common shiner will not be successful.

Table 2.10 Mean trends (Kendall tau) in ecohydrological indicators for 16 streamflow stations in the Kansas River Basin over the study period (1962 to 2012) in which indicator species went from being present historically (1860-1950) to being either absent or present currently (2000-2012).

	Plains minnow			Common shiner		
Ecohydrological Index	Absent	Present	t-value[1]	Absent	Present	t-value [1]
Mean summer daily discharge	-0.181	-0.021	**2.571***	-0.080	0.011	2.262
Mean spring daily discharge	-0.125	0.052	4.303	0.110	0.005	2.447
Zero-flow days	0.079	0.025	2.160	-0.032	0.048	2.262
High pulse count	-0.256	-0.029	**2.776***	-0.163	-0.015	**2.365****
High pulse duration	0.033	0.013	4.303	-0.024	0.014	2.447

[1]critical “t” value between “Absent” and “Present” (using t test assuming unequal variances) significant at *(p=0.10) and **(p=0.05) levels.

Figure 2.16 Box plots of ecohydrological indicators' trend for 16 streamflow stations in the Kansas River Basin over the study period (1962 to 2012) in which Plains minnow (*Hybognathus placitus*) went from being present historically (1860-1950) to being either absent or present currently (2000-2012). Test significance is indicated by ** (p=0.05 or 95% confidence) and* (p=0.10 or 90% confidence)

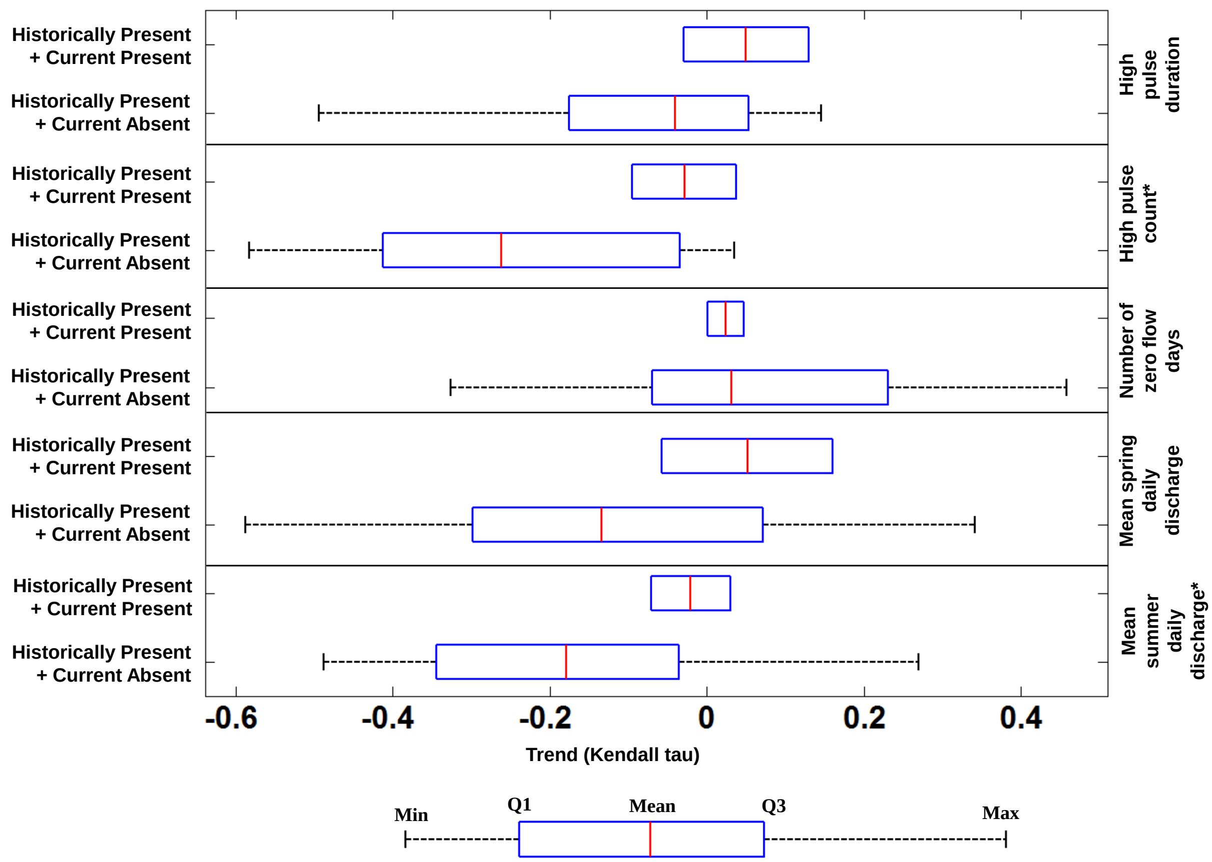
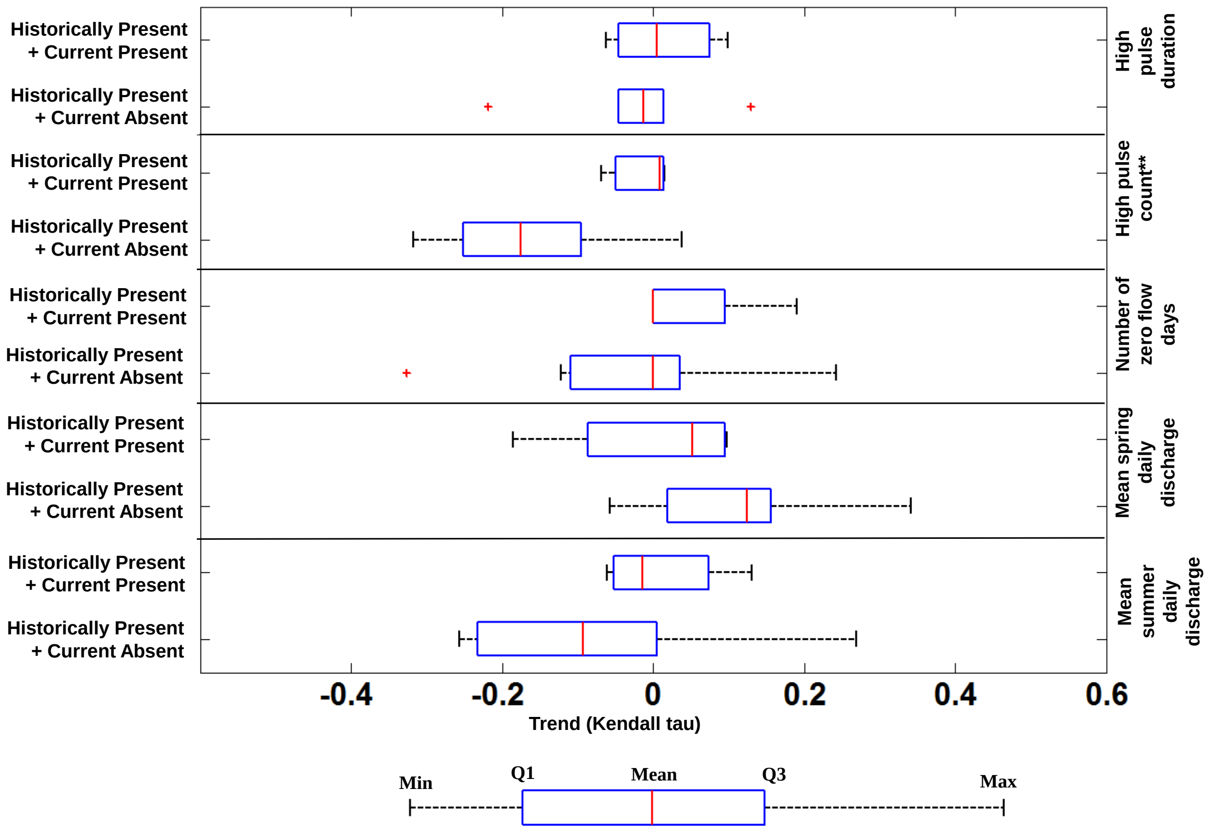


Figure 2.17 Box plots of ecohydrological indicators' trend for 16 streamflow stations in the Kansas River Basin over the study period (1962 to 2012) in which common shiner (*Luxilus cornutus*) species went from being present historically (1860-1950) to being either absent or present currently (2000-2012). Test significance is indicated by * (p=0.05 or 95% confidence) and (p=0.10 or 90% confidence)**



Another possible cause could be change in hyporheic zone. Hyporheic zone is the zone where shallow groundwater and surface water mixes. It located beneath and alongside a stream bed. This zone is important region of biogeochemical cycling and active biologically. Also it regulates temperature, especially in small streams, and acts as natural treatment plants. Plains minnow is mostly abundant in streams with shallow, braded flow over broad beds of shifting sand, where they get their diet (diatoms and other algae). When there are no seasonal scouring discharges and diminished summer flows, those diatoms and algae may be eliminated due to insufficient water to maintain the hyperic zone. This change has led to declines in Plains minnow species (Distler et al., 2014). In addition, a shallow water column depth can cause additional stress by altering secondary physical variables. Plains minnow species also disappeared in the present time period (2000-2012) in the streams that have greater variability and magnitude of trend reduction of mean spring daily discharge, high pulse duration, and high pulse count. This species also disappeared when the streams showed an increasing trend in number of zero-flow days. Gido et al. (2010) also showed a pronounced pattern of decline for Plains minnow.

A special condition is observed between Common shiner distribution and mean spring discharge. Common shiner is absent currently in the streams that have greater mean spring discharge trend. As Common shiner is a silt intolerant species, increasing turbidity may be a possible reason for their absence in streams with increasing trends in spring flow (Cathcart, 2014). Similarly, the trend in high-flow pulses (count and duration) can be related to the loss of spawning cue.

Trends in other ecohydrological indicators other than mean summer daily discharge and high pulse count for Plains minnow and high pulse count for Common shiner, were “small” and not enough to show statistically significant difference (Table 2.10, Figures 2.16 and 2.17). However, it seems those difference might be extremely rapid in an ecological sense where the species could not develop an adequate survival response or the environmental change exceeds the phenotypic plasticity of the species.

Other than streamflow alteration, other anthropogenic stressors, including increasing row-crop agriculture sediment supply (beginning in 1880), habitat fragmentation caused by impoundments (beginning in 1950s), and reduced return flow caused by groundwater withdrawal (beginning in the 1960s) can also play role in fish distribution. However the effects on those factors were not tested in this study.

2.3.8 Future climate change and possible change in fish species distribution

Brunsell et al. (2010) and Logan et al. (2010) reported increasing temperature in all seasons by an average of 2-4 ^{o}F and highly variable precipitation with longer dry weather periods. These changes expected to cause warmer and drier western Kansas and warmer and wetter eastern Kansas. Water need is expected to be increased during the summer. This may lead an additional pressure on irrigation. These future predicted precipitation and temperature changes show that deterioration of habitat with increasing stressors, especially decreasing summer flow, over future and may cause drastic shifts or even extirpation of fish species. The effect of change in mean summer in species distribution, coupled with the observed species loss may define potential loss of many future species in this region. Increasing pressure on irrigation may lead additional groundwater water pumping which will ultimately lead a detrimental effect on streamflow. Highly variable precipitation with less frequent, intense storms and longer dry spells might cause additional stress by changing pulses and count (low and high), increasing zero flow days and affecting spawning cues, migrating patterns/ recruitment and introducing invasive species.

2.4 Conclusion

Trends of WRIs and IHAs have been observed for KRB stations using 50-year streamflow records. Across entire KRB a decreasing trend is evident for annual mean runoff, summer and autumn mean runoff, 30-day, 90-day minimum flows, and 1-day, 3-day, 7-day, 30-day and 90-day maximum flows. The potential causes of observed variability in trend include fluctuations in precipitation, temperature, shifts in land uses and management practices. Most significant negative trends observed in High Plains. The results also show that changes in streamflow have altered the habit of this region. Two species (Plains Minnow [*Hybognathus placitus*] and Common Shiner [*Luxilus cornutus*]) were not present ($p = 0.05$) during the sampling period (2000-2012) in streams with greater decreasing trends of mean summer daily flows, high-flow (> 75^{th} percentile) pulse count, and median duration of high-flow pulses. These results demonstrate the importance of changes in these ecohydrological indices on distributions of these faunal species and suggest factors that could be targeted in restoration activities. Decreasing trends in all minimum and maximum flows may exhibit an additional habitat threat, especially in the High Plains ecoregion. Also, increasing trend of fall rate and decreasing trends in high and low pulse numbers show higher drought potential and increasingly unsuitable conditions for spawning, migration and survival for aquatic organisms in this region.

If changes in habitat are extensive, rates of fish, survival and reproduction can decline, and the density of their populations may decrease. However, the effect may differ based on ecoregion, climate, and individual species requirements.

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Chapter 3 - Multi- Objective Framework Calibration and Validation of SWAT Watershed Model for Ecohydrological Indicators

Abstract

Rigorous parameterization, calibration and validation are crucial in a distributed hydrological modeling. A multi-objective calibration strategy was used in this study to calibrate the SWAT (Soil and Water Assessment Tool) model. The multi-objective framework included multi-sites, multi-variables and multi-criteria. The proposed strategy was used to calibrate streamflow and crop yield for two different watersheds (Perry Lake and Kanopolis Lake) with different hydrologic conditions and scales within the Kansas River Basin (KRB). The study demonstrated and quantified the benefits of multi-objective calibration protocol for modeling ecohydrological indicators. The results show that SWAT was able to predict streamflow and crop yields for corn, soybean, winter wheat and grain sorghum reasonably accurately and over a range of climatic conditions. Model performance in flow simulation improved with sequential implementation of parameterization and calibration steps. Careful parameterization alone improved model flow predictions significantly. The best combination of model efficiency and bias for flow were achieved after the combination of parameterization, flow calibration, and crop calibration in most cases. Flow calibration with crop calibration helped reduce bias in most cases. SWAT was suitable for simulating high-flow-rate ecohydrologic indicators. SWAT simulated high-flow-ratel ecohydrological indicators without even calibration in one watershed. This shows that SWAT is robust enough that it doesn’t need calibration to be a useful tool for some purposes. However performance of several other ecohydrologic indicators was highly dependent on the level of calibration and parameterization. The effect of calibration level and parameterization on ecohydrologic indicators performance varied between watersheds and among subwatersheds. This study shows that only robust model parameterization and daily streamflow calibration above good level are strong enough for simulating high-flow-rate ecohydrological indicators even without further any variable calibration.

3.1 Introduction

Distributed hydrological models enable model practitioners to simulate the spatial variability of climate and land surface characteristics on the hydrological, physical, and biological process in a watershed (Becker and Braun, 1999). Capturing spatial variability is important to understand watershed hydrological process. This is especially true for large-scale watersheds, which often encompass a diversity of conditions. However, rigorous parameterization, calibration and validation are crucial in a distributed modeling. Model parameterization attempts to represent actual field conditions by careful selection of model input parameter values. Most watershed modeling studies calibrate and validate model performance solely at the watershed outlet using discharge measurements, which may lead to the model not performing well for other variables (such as groundwater recharge, water-table level, crop growth and development, etc.).

A multi-objective calibration and validation framework (multi-site, multi-variables and multi-criteria) is recommended for distributed hydrological modeling (Ambroise et al., 1995; Andersen et al., 2001; Moussa et al., 2007; Khu et al., 2008; Dai et al., 2010). Calibration at multiple sites introduces more constraints on the calibration process and helps indicate how well the model predicts watershed response at other locations (White and Chaubey, 2005). When a model is calibrated against more variables than streamflow, it increases confidence in the physical relevance of the model (Bergstrom et al., 2002). Similarly, multi-criteria protocol, including statistical, analytical and visual criteria, enhances the physical consistency of model prediction. Altogether, a multi-objective framework helps to reduce the uncertainty and modeling bias and reduces the equifinality of distributed hydrological models to a certain degree (e.g., Mroczowski et al., 1997; Seibert et al., 2000; Andersen et al., 2001; Bergstroom et al., 2002; Khu et al., 2008; Dai et al., 2010). However, little guidance is available for model multi-objective framework calibration protocols for distributed models.

The SWAT (Soil and Water Assessment Tool) is one of the most widely used process-based, distributed watershed-scale hydrologic/water quality models (Arnold and Allen, 1996; Arnold et al., 1999; Abbaspour et al., 2007). It is a continuous-time model that uses spatially distributed data on weather, soil properties, topography, vegetation and land management practices to simulate the impact of land management practices on water, sediment and agricultural chemical yields (Neitsch et al., 2011). It was created in the early 1990s by incorporating several U.S. Department of Agriculture-Agricultural Research Service (USDA-ARS) models and has been used worldwide for over 30 years to study environmental issues of small to large watersheds (Saleh et al., 2000; Romanowicz et al., 2005; Jha et al., 2006; Gassman et al., 2007; Douglas-Mankin et al., 2010a; Srinivasan et al., 2010; Tuppad et al., 2011; Arnold et al., 2012). It has been used in many Kansas studies, from field scale (Anand et al., 2007; Maski et al., 2008; Douglas-Mankin et al., 2010b) to watershed scale (Parajuli et al., 2009a,b,c; Tuppad et al., 2010a,b; Daggupati et al., 2011; Nejadhashemi et al., 2011; Sheshukov et al., 2011a,b,c; Lee and Douglas-Mankin, 2011; Gali et al., 2012; Douglas-Mankin et al., 2013). The model is often used to examine the effects of agricultural practices on water quality, quantify environmental benefits of conservation practices, perform Total Maximum Daily Load (TMDL) analyses, and quantify the impacts of climate change (Gassman et al. 2007). However, there is very little work done with SWAT regarding its ecohydrological applications.

Multi-site calibration is becoming more common in SWAT applications (Santhi et al., 2001; Liew and Garbrecht, 2003; White and Chaubey, 2005; Cao et al., 2006; Bekele and Nicklow, 2007). However, multi-objective calibration protocols that combine multiple performance metrics (e.g., Nash-Sutcliffe efficiency [NSE], percent bias [PBIAS], and ratio of the root mean square error to the standard deviation of measured data [RSR]), multiple variables (e.g., surface flow, baseflow, soil moisture, sediment and nutrients), and multiple sites is not common for SWAT studies.

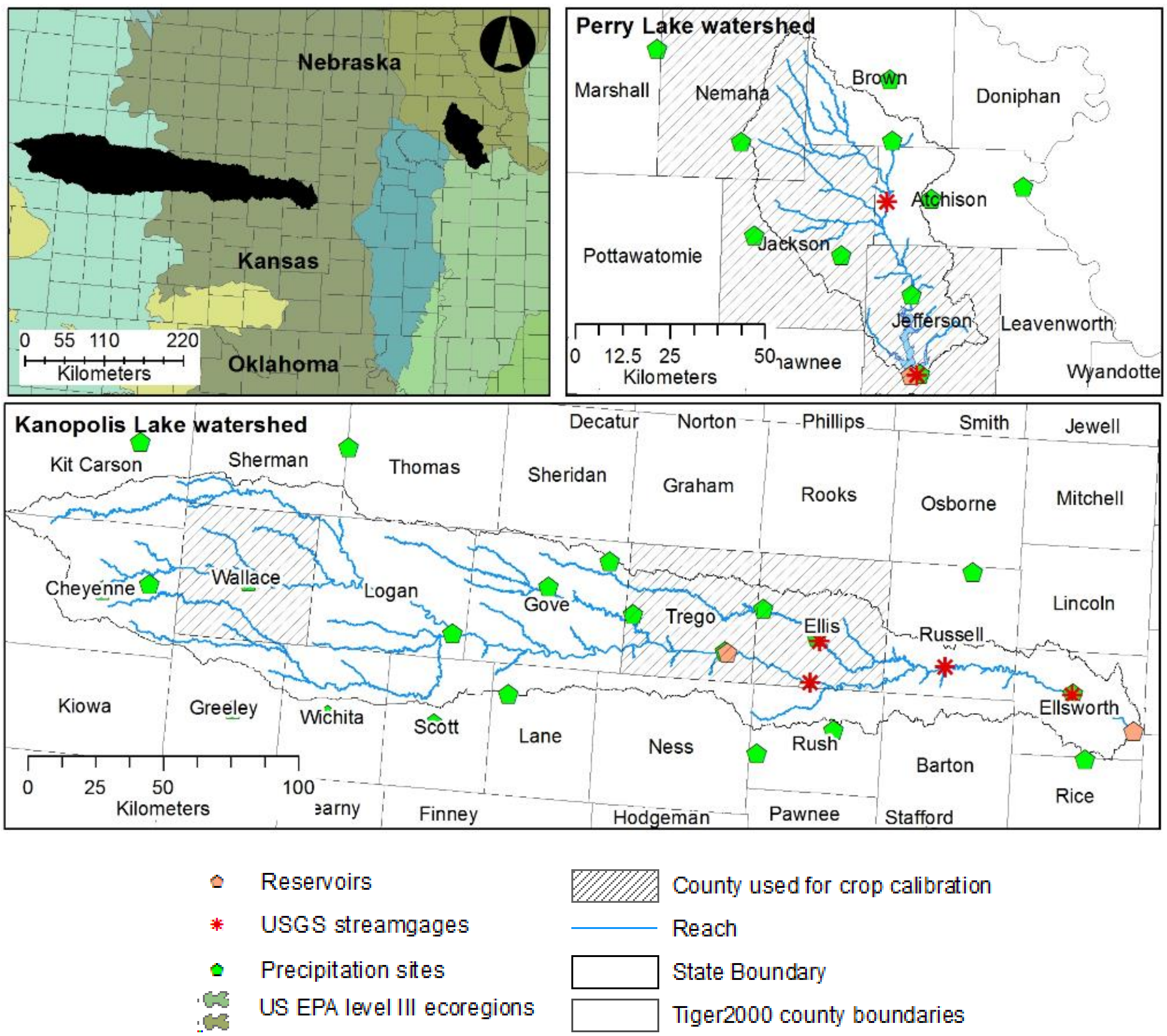
Therefore, the goal of this study is to compare and evaluate the effect of multi-objective protocol for accurate ecohydrological simulation. The specific objectives of this study are to: 1) develop a biophysical model of current conditions using a distributed parameter watershed model (Soil and Water Assessment Tool, SWAT) for two different watersheds (Perry Lake watershed and Kanopolis Lake watershed) with different hydrologic conditions and scales within Kansas River Basin (KRB); 2) assess multiple parameterization, calibration and validation strategies that highlight the model performances at different spatial scales, which are essential for accurate ecohydrological indicator simulation; and 3) demonstrate and quantify the benefits of a multi-objective calibration protocol for modeling ecohydrological indicators.

3.2 Methods

3.2.1 The study sites

The study used two diverse watersheds, with different hydrologic conditions and scales located within Kansas River Basin (KRB; Figure 1).

Figure 3.1 Two watersheds within the Kansas River Basin (KRB), the Perry Lake watershed (HUC-8: 10270103) and the Kanopolis Lake watershed (HUC-8s: 10260001-10260007) located in northeast, north-central northwestern central and Kansas are used in this study.



Perry Lake watershed: The Perry Lake watershed is located in the northeastern part of KRB and has 2,924 km^2 drainage area. The Perry Lake watershed is an 8-digit hydrologic unit code (HUC) (10270103) watershed and drains into Perry Reservoir. Perry Lake is a federal reservoir and maintained by the U.S. Army Corps Engineers. Outflow from Perry Lake continues south until its confluence with Kansas River. The watershed covers parts of 2 eco-regions: Western Corn Belt Plains (85.5%) and Central Irregular Plains (14.5%). This region has an average annual total precipitation of 762 mm and 82% of the annual total (about 625 mm) falls during the six-month growing season, April to September. The annual mean temperature for this region ranges from 11.1 ^{o}C to 12.2 ^{o}C (Sophocleous, 1998).The temperature range shows the effect of the center of a continent and latitude. Elevation of the Perry Lake watershed ranges from 252 m to 428 m with an average slope of 5.2%. Soils in the watershed are mostly (≈77%) fine-textured (silt and clay), have moderately high (C hydrologic soil group) and high (D hydrologic soil group) runoff potential, and consist primarily of Pawnee clay (30.5%), Grundy silt clay (30.0%), and Kennebec silt (16.1%) soil groups. Agriculture is the dominant land use (63.7%), followed by rangeland (15.4%) and forest land (12.4%). The primary agricultural crops are hay (32.3%), dry-land corn (14.0%) and soybean (13.4%).

Analysis of 50 years (1962-2012) of stream flow from Delaware R NR Muscota (USGS 06890100), draining 38.7% of the watershed north of Perry Lake, indicated that this watershed had slight (not significant at p=0.10) decreasing trends annual, winter, spring, autumn, and 1- to 90-day minimum and maximum flows (Sinnathamby et al., 2014a). Analysis also indicated a slight increasing trend in the number of zero-flow days and slight decreasing trend in baseflow index, though both were not significant at p=0.10.

Kanopolis Lake watershed: The Kanopolis Lake watershed is located in north-central to northwestern central Kansas and covers about 20,291 km^2 drainage area. It includes Smoky Hill River and its major tributary, the Saline River, which drain into Cedar Bluff Reservoir in Trego County and ultimately Kanopolis Reservoir in Ellsworth County. Both reservoirs are maintained by the U.S. Army Corps Engineers. The Kanopolis Lake watershed has an elongated drainage area with flat to gently rolling topography with narrow, shallow valley and low relief. The Kanopolis Lake watershed includes subbasins with HUCs 10260001 through 10260007. It lies within the High Plains (46.5%) and Central Great Plains (53.5%) ecoregions. Highly variable precipitation with extremes and temperature are common in this watershed. Normal annual precipitation of this region ranges from 381 mm (15 in.) to 635 mm (25 in.). This region has an average annual mean temperature between 50 to 54 ^{o}F based on its latitude (Goodin et al., 1995).

The elevation of watershed ranges from 428 m to 1470 m. The average watershed slope is 2.8%. Soils in the watershed are mostly silty, with moderate infiltration rates (B hydrologic soil group). The primary agricultural crop is winter wheat (32.3%). Other land uses include range land (39.5%), general agriculture (10.6%), CRP (5.7%), grain sorghum (4.6%), dry land corn 2.7%) and irrigated corn (2.7%).

The surface and ground water interactions are more complex in this region due to alluvial and ground-water pumping associated with public water supply (e.g., city of Hays, Rural Water Districts), agricultural irrigation and ongoing agricultural practices (Sophocleous and Wilson, 2000). Groundwater is the major source of freshwater in this area. Extreme groundwater pumping has resulted due to the shift toward irrigated crop production, can cause streams to lose water to the underlying aquifers through seepage, and has resulted in many losing streams in this region (Sophocleous and Wilson, 2000). This also resulted in significantly reduced baseflow contributions to stream from shallow aquifers. Results of Sinnathamby et al. (2014a) show many streams in this region have experienced reduction in flow through last five decades (1962 to 2012). Significantly decreasing trend in annual surface flow (-2.05 mm/ 50 years; p=0.05), summer flow (p=0.05), autumn (p=0.10), and 30- and 90 day minimum flows (p=0.10) has been documented (Sinnathamby et al., 2014a). In addition increasing number of zero-flow days (p=0.05), slight (not significant at p=0.10) decreasing trend in baseflow index, and slight (not significant at p=0.10) decreasing trend in center of timing (i.e., centroid displays annual streamflow shift towards earlier) show additional changes in hydrologic regime for this watershed.

3.2.2 Model parameterization, calibration and validation procedure

Parameterization has been defined as the process of defining the spatial pattern of model parameter values (Refsgaard and Storm, 1996), although some models have a temporal pattern that must be parameterized as well. Model parameterization, calibration and validation are difficult and crucial steps in hydrological modeling (Ajami et al., 2004). An accurately parameterized model can be used to investigate the sensitivity and extent of watershed hydrological response to distributed inputs. However, the capabilities of a parameterized model are difficult to characterize without calibration (Hernandez et al., 2000). A rigorous parameterization minimizes problems during model calibration and validation and reduces the number of parameters that need to be adjusted during the calibration procedure (Refsgaard and Storm, 1996).

A three-step approach was adopted in the parameterization procedure of the SWAT model. First, some parameters were estimated based on the catchment's physical characteristics without any model calibration. Then, a multi-objective calibration procedure was carried out to adjust other parameters so that the model response approximated observed data for a defined criterion. The last step was the validation procedure, which consisted of applying the model with the calibrated parameters to other hydrological data.

3.2.2.1 SWAT model setup and parameterization

The SWAT ver.2010-beta was used to build models of Perry Lake and Kanopolis Lake watersheds. The 30 m digital elevation model (DEM) was used to delineate sub-watersheds, channel network reaches, the topological linkage between sub-watersheds and the channel network, and to determine the geometric characteristics of sub-watersheds (area, mean slope, time of concentration) and reaches (length and slope). A total of 38 sub-watersheds were delineated for Perry Lake watershed. In the case of Kanopolis Lake watershed, 148 sub-watersheds were delineated. For both watersheds, SWAT hydrological response units (HRUs) were distributed based on 30 m DEM derived slope, 2005 Kansas Level IV map land cover (Kansas Applied Remote Sensing (KARS) Program) and STATSGO soil dataset from the SWAT database. A total of 3,839 HRUs in Perry Lake watershed and 14,353 HRUs in Kanopolis Lake watershed, each representing specific combinations of soil, slope, and land-use, were generated from these data. No thresholds to reduce HRU numbers were used in this study. In addition, point sources and reservoirs were also placed in the watershed.

Nutrient point-source locations and data were gathered from the Kansas Department of Health and Environment, the EPA Clean Watersheds website, and the EPA ECHO online tool. Data for reservoirs were obtained by request from the USACE Kansas City office. Reservoir data includes reservoir structural information, such as volume and surface area of the reservoir at the emergency spillway (maximum reservoir operating conditions) and principal spillway (normal reservoir operating conditions), initial sediment concentration and equilibrium sediment concentration in the reservoir. Daily discharges for these reservoirs were available from 1975 to

2011. The average suspended sediment concentration of the reservoir over the period of record, obtained from the EPA STORET database, was used as the initial sediment concentration.

Weather data (daily maximum and minimum temperature and precipitation) for this study were obtained from the National Climatic Data Center (NCDC) Interactive Map Application for daily datasets accessing the Global Historical Climatology Network (GHCN) for the period starting from January 1975 to December 2011. GHCN daily is a composite of climate records from numerous sources that were merged and then subjected to a suite of quality assurance reviews. Crop Data Layer (CDL) data from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Services (NASS) from 2008-2010 and National Land Cover Database (NLCD) layer from 2006 were overlaid to determine dominant crop rotations (Srinivasan et al., 2010). Continuous corn, continuous soybean and corn-soybean rotation are the major cropping pattern observed Perry Lake watershed. Winter wheat and grain sorghum are the dominant crops in Kanopolis Lake watershed. Other cropland management schedules including tillage practices and fertilizer application rates (Table 3.1) were obtained through conversations with K-State Agronomist Dr. Nathan Nelson and with the use of K-State Extension documents. Applications of nitrogen (lb ac^{-1} yr^{-1}) and P_2O_5 (lb ac^{-1} yr^{-1}) fertilizer rates were estimated using recommended rates per acre corresponding to a bushel yield goal (Leikam et al., 2003). During calculations the soil organic matter content was assumed as 2.5%. The NASS county-level yield averages (bushel ac^{-1} yr^{-1}) from 2005 – 2010 (+10% to be conservative) were used to calculate yield goal to determine nutrient application rates per acre for both irrigated and non-irrigated corn, soybeans, sorghum and winter wheat. Thirty percent of fertilizers were applied to the top 10 mm of soil in SWAT. Auto-irrigation management was applied at an efficiency of 0.7 to land-use classes identified as irrigated cropland and 0.9 plant stresses. Herbicides were used on crops but were not included in management practices, because pest or pesticide impacts were not modeled. Time-based management operations were used instead of the default method, which used the fraction of PHU. Potential evapotranspiration (PET) was calculated using the Penman/Monteith Method.

Table 3.1 Plant and harvest dates and N and P fertilizer application amounts (kg ha^{-1}) and tillage practices for corn, soybean, winter wheat and grain sorghum

Perry Lake watershed	
Corn	
Planting Date	April 30
Harvesting Date	October 10
Fertilizer (Date, Amount)	
Nitrogen[1]	May 1, 170 kg ha^{-1}
Phosphorus[2]	May 1, 45 kg ha^{-1}
Tillage	Conventional fall tillage, disc + 3-4 field cultivators
Soybean	
Planting Date	May 15
Harvesting Date	October 10
Fertilizer (Date/Amount)	
Nitrogen	None
Phosphorus[3]	May 18, 23 kg ha^{-1}
Tillage	Disc + 4 field cultivators
Kanopolis Lake watershed	
Winter wheat	
Planting Date	September 10
Harvesting Date	June 30
Fertilizer (Date, Amount)	
Nitrogen[4]	September 10, 75 kg ha^{-1}
Phosphorus[5]	September 10, 22 kg ha^{-1}
Tillage	after wheat is harvested disc + 5-7 field cultivations (5 if next crop is winter wheat, 7 if next crop is planted in spring) When grown in a rotation, no till conventional till for continuous wheat
Grain Sorghum	

Planting Date	June 1
Harvesting Date	October 15
Fertilizer (Date, Amount)	
Nitrogen[6]	June 2, 59 kg ha^{-1}
Phosphorus[7]	June 2, 16 kg ha^{-1}
Tillage	7 field cultivator (after wheat)
Corn/ Irrigated corn	
Planting Date	April 25
Harvesting Date	October 1
Fertilizer (Date, Amount)	
Nitrogen[1]	April 26, 101 kg ha^{-1}
Phosphorus[2]	April 26, 27 kg ha^{-1}
Tillage	Conventional fall tillage, disc + 3-4 field cultivations

[1] 1.25 lb-N bu^{-1} corn × (county average corn yield [bu ha^{-1}] + 10% for yield goal)

[2] 0.33 lb-P_2O_5 bu^{-1} corn × (county average corn yield [bu ha^{-1}] + 10% for yield goal)

[3] 0.5 lb-P_2O_5 bu^{-1} soybean × (county average soybean yield [bu ha^{-1}] + 10% for yield goal)

[4] 1.7 lb-N bu^{-1} corn × (county average winter wheat yield [bu ha^{-1}] + 10% for yield goal)

[5] 0.5 lb-P_2O_5 bu^{-1} corn × (county average winter wheat [bu ha^{-1}] + 10% for yield goal)

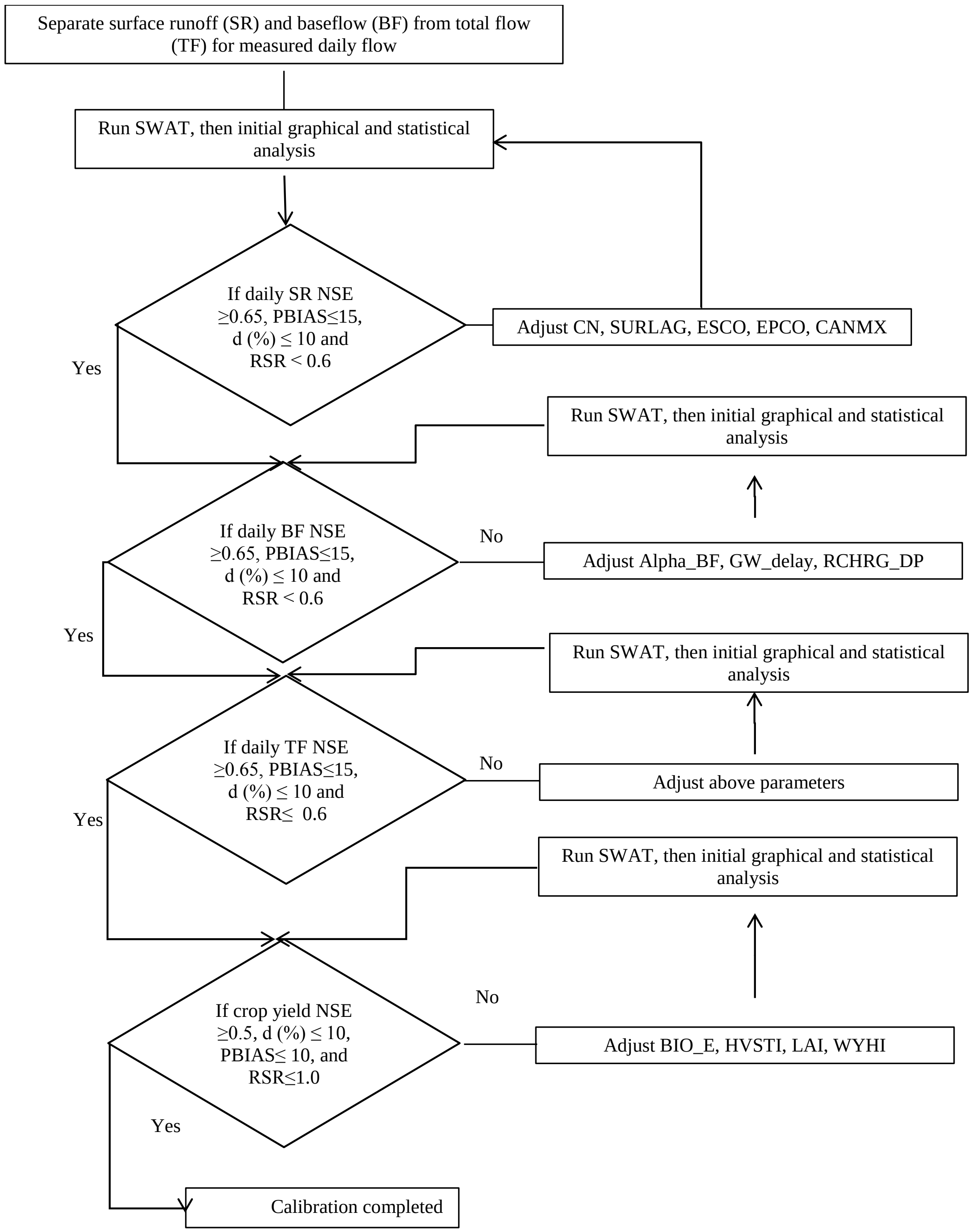
[6] 1.25 lb-N bu^{-1} corn × (county average grain sorghum yield [bu ha^{-1}] + 10% for yield goal)

[7] 0.33 lb-P_2O_5 bu^{-1} corn × (county average grain sorghum [bu ha^{-1}] + 10% for yield goal)

3.2.2.2 Model calibration and validation

Model calibration improves model performance by adjusting model parameters within acceptable range to obtain good agreement between observed and simulated values. Model outputs (flow components and crop yield) were calibrated to fall within 10% of average measured values and then evaluated with three quantitative statistics: Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR) (Figure 3.2). These statistics are commonly used in SWAT applications (Moriasi et al., 2007; Douglas-Mankin et al., 2010a).

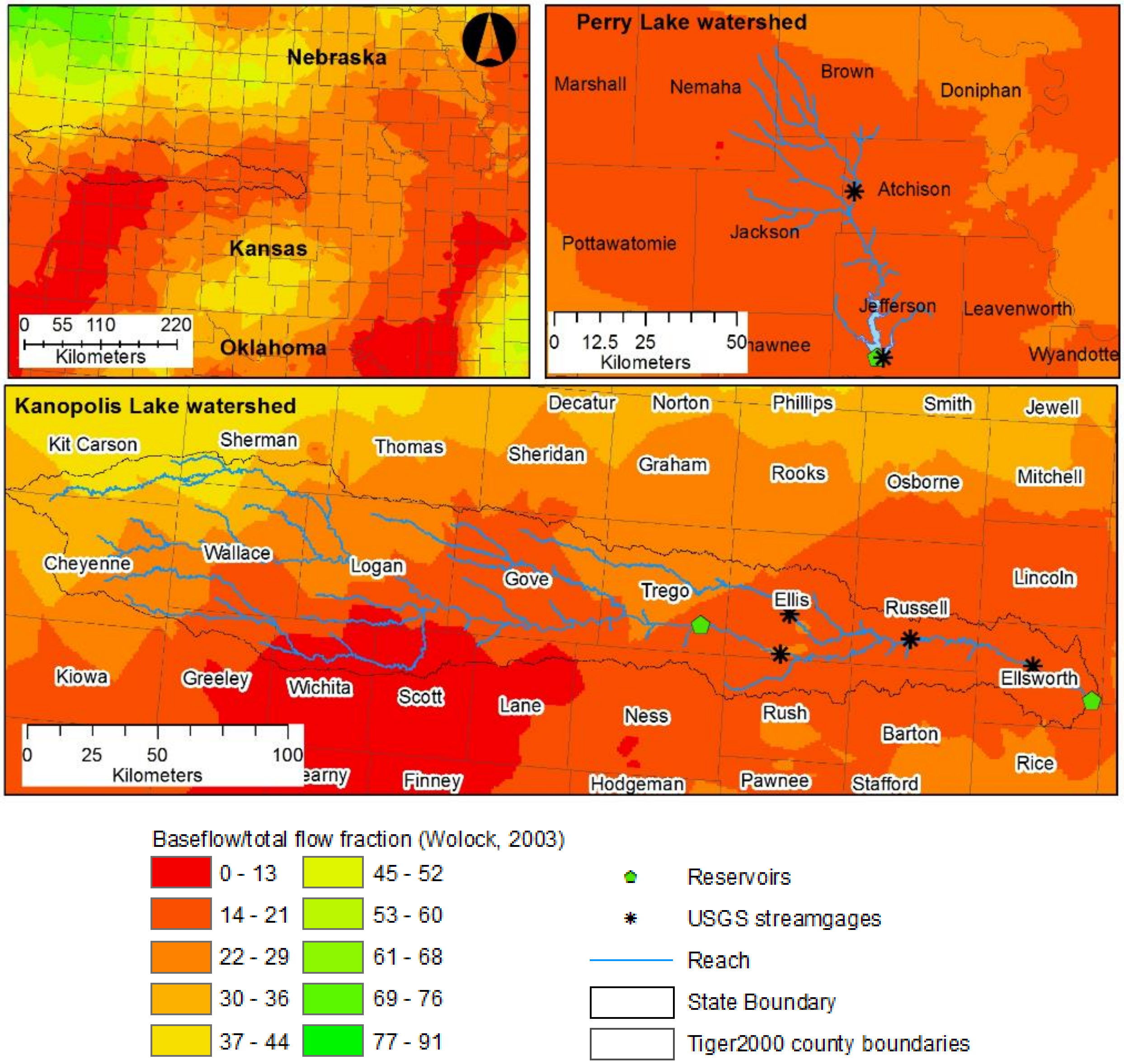
Figure 3.2 Calibration procedure for flow and crop yield (based on calibration chart for SWAT from Santhi et al., 2001).



NSE=Nash-Suttcliffe efficiency
RSR=RME/OBSTDEV ratio
d=percent difference between measured and simulated values
pBias=Percent bias

A multi-step manual calibration procedure for flow components (baseflow, streamflow and total flow) and crop yield is shown in Figure 3.2. Initially, baseflow was separated from surface flow for both observed and simulated streamflow using an automated digital filter technique (Nathan and McMahon, 1990; Arnold and Allen, 1999). A second iteration in the baseflow filter program was used in this study to ensure the baseflow/total flow fraction was matched with the watershed's baseflow/total flow fraction presented in Figure 3.3 (Wolock, 2003). During calibration, a minimum number of parameters were used to avoid over-parameterization (Beven, 1996). From literature (White and Chaubey, 2005; Zhang et al., 2009; Schmalz and Fohrer, 2009; Cibin et al., 2010; Guse et al., 2014) and experiences with the SWAT model in this region, ten parameters for flow and four parameters for crop yield were selected for calibration. These parameters affect major hydrological process, such as evapotranspiration, surface flow and groundwater flow. More detail on relationships of parameters and corresponding hydrological process are discussed in Neitsch et al. (2011) and Guse et al. (2014). Thereafter the sensitivity parameter range for each parameter was identified by adjusting them one at a time. The combination of model parameters were adjusted within sensitive ranges until the daily model output fell within 10% of average measured values and acceptable statistics were reached. If model output fit the criteria, other conditions such as baseflow/ total flow fraction and basin average evapotranspiration were checked. If all the conditions met at one station and the calibration procedure was continued until other station meet the criteria. Finally a local optimum parameter set which yielded the higher NSE, lower RSR and PBIAS at both stations was used in the model. If all model parameters were adjusted to the limit and the calibration criteria were still not met, then calibration was stopped for that output and better statistical performance with higher NSE, lower RSR and PBIAS of parameters until then were used in the model.

Figure 3.3 Baseflow/ total flow fraction (Wolock, 2003)



3.2.2.2.1 ***Flow***

As SWAT is a deterministic hydrologic model that simulates interacted process, many parameters may be involved in multiple processes. When surface-runoff related parameters are adjusted, they directly change surface runoff and indirectly change other hydrological and related process. Therefore, streamflow was calibrated first (Figure 3.2).

Two USGS gage stations within the Perry Lake watershed (Delaware R NR Muscota [USGS 06890100] and Delaware R at Perry Dam [USGS 06890900]) and 4 gage stations within

Kanopolis Lake watershed (Big Creek NR Hays [USGS 06863500], Smoky Hill R BL Schoenchen [USGS 06862850], Smoky Hill R NR Bunker Hill [USGS 06864050], and Smoky Hill R Ellsworth [USGS 06864500]) were used for streamflow calibration (USGS, 2014). All the stations, except Smoky Hill R BL Schoenchen, have discharge data from 1975-2011. Smoky Hill R BL Schoenchen has discharge data only from 01-10-1981. For all stations, data from 1975-1996 were selected for calibration and 1997-2011 were used for validation. A three year period was used as spin-up period. Both calibration and validation periods include wet, moderate and dry periods (Arnold et al., 2012).

During flow calibration in both watersheds, surface runoff and baseflow were continued at daily time step until average measured and simulated surface flow was within 15% and daily NSE reached a threshold of ≥ 0.65 (good level), PBIAS is ≤ 15% (good level) and RSR is ≤ 0.60 (good level). While calibrating baseflow, surface flow was continually rechecked, as the baseflow calibration variables also affect surface flow. At the end of baseflow and surface flow calibration, the total streamflow statistics were checked with the same criteria. Once flow was calibrated, crop calibration was continued until average measured and simulated crop yield was within ≤ 10%, NSE ≥ 0.50, RSR ≤ 1 and PBIAS ≤ 10%. The tested ranges and final parameter values after each calibration for both watersheds are presented in Tables 3.2 and 3.3.

Table 3.2 SWAT parameters adjusted during the streamflow and crop calibration procedure within Perry watershed

Parameters	Definition	Default value	Tested range		Magnitude Of tested value	Final value
Flow						
ICN	Daily curve number calculation method	antecedent soil moisture condition			0 or 1	plant evapotranspiration
CNCOEF	Plant ET CN Coefficient	1	0.5	-1.5	±0.1	1.3
CN2.mgt	SCS runoff curve number for moisture condition 2	35-98	-15% ×CN2[1]	15% ×CN2[1]	±1%	-5% ×CN2 for all sub-watershed above Perry at

						Delaware +12% ×CN2 for all sub-watershed below Perry at Delaware
ESCO.hru	Plant evaporation compensation factor	0.95	0	1	±0.05	0.6 all HRU
SURLAG.bsn	Surface runoff lag coefficient	4	0	10	±1	1
ALPHA_BF.gw	Baseflow alpha factor (days)	0.048	0	1	±0.001	0.10 all HRU
GW_DELAY.gw	Groundwater delay (days)	31	0	500	±5	0 all HRU
RCHRG_DP	Aquifer fraction coefficient	0.05	0	0.5	±0.01	0
CANMX	Maximum canopy storage	0				Agricultural and pasture areas 3 Forests 8 Urban 1.5
Crop						
BIO_E	Biomass-energy ratio					
	Corn	39	40	25	±1	35
	Soybean	25	28	20	±1	20
HVSTI	Harvest index					
	Corn	0.50	0.6	0.2	±0.01	0.46
	Soybean	0.31	0.3	0.2	±0.01	0.31
WYHI	Lower limit of harvest index					
	Corn	0.3	0.35	0.4	±0.01	0.35
	Soybean	0.01	0.3	0.01	±0.01	0.20
LAI	Leaf area index					
	Corn	5	4	6	±0.5	5
	Soybean	3	2	5	±0.5	2

[1]Tested a range based on a percentage of the baseline CN2 (SCS, 1972)

Table 3.3 SWAT parameters adjusted during the streamflow and crop calibration procedure within Kanopolis Lake watershed

Parameters	Definition	Default value	Tested Range		Magnitude Of tested value	Final value
Flow						
CN2.mgt	SCS runoff curve number for moisture condition 2	35-98	-20% ×CN2[1]	20% ×CN2[1]	±1%	-20% ×CN2 for all sub-watersheds
ESCO.hru	Soil evaporation compensation factor	0.95	0	1	±0.05	0.5 for all HRUs above Big C NR Hays 0.8 all other HRUs
EPCO	Plant evaporation compensation factor	1	0	1	±0.01	0.01 all HRU
SURLAG.bsn	Surface runoff lag coefficient	4	0	10	±1	2
ALPHA_BF.gw	Baseflow alpha factor (days)	0.048	0	1	±0.001	0.001 all HRU
GW_Delay.gw	Groundwater delay (days)				±5	0 all HRU
RCHRG_DP	Aquifer fraction coefficient	0.05	0	0.5	±0.01	0.75 all HRU
CANMX	Maximum canopy storage	0				Agricultural and pasture areas 3 Forests 8 Urban 1.5
Crop						
BIO_E	Biomass-energy ratio					
	Winter wheat	30	20	30	±1	30
	Grain sorghum	33.5	30	37	±1	36.5
HVSTI	Harvest index					
	Winter wheat	0.40	0.3	0.4	±0.01	0.41
	Grain sorghum	0.45	0.40	0.46	±0.01	0.46
WSYF	Lower limit of					

	harvest index	0.3	0.2	0.3	±0.01	0.3
	Winter wheat					
	Grain sorghum	0.25	0.25	0.36	±0.01	0.4
LAI	Leaf area index					
	Winter wheat	4	4	5	±0.5	4
	Grain sorghum	3	3	5	±0.5	5

[1]Tested a range based on a percentage of the baseline CN2 (SCS, 1972)

Perry Lake watershed flow calibration: First the runoff curve number (CN2) was reduced within 5% from the default values to reflect conservation tillage practices and soil residue cover conditions in the sub-basins above Delaware River NR Muscota (Arabi et al., 2007; Table 2). The CN2 value was increased in downstream watersheds to reflect improved landuse through CRP. Second, the surface runoff lag coefficient (SURLAG) was adjusted to allow the surface runoff to reach the river in a day. Third, the baseflow recession factor (ALPHA_BF) and the groundwater delay (GW_DELAY) were adjusted so that there was no delay for recharging aquifer and to increase groundwater flow to the reach. Finally, other flow-related parameters, such as maximum canopy storage (CANMX), soil evaporation compensation factor (ESCO), daily curve number calculation method (ICN) and plant ET CN Coefficient (CNCOEF), were adjusted to match the simulated and observed flows (Table 3.2). Values of CANMX reported by Guse et al. (2014) were used to represent the water capacity of the canopy storage. Reducing ESCO reduces water yield by increasing evapotranspiration from the deeper soil layers. Changing ICN method to plant evapotranspiration, rather than available moisture capacity, was used to adjust antecedent soil moisture condition. Increasing CNCOEF reduced evapotranspiration and decreased runoff to within an acceptable range. The default potential evapotranspiration (PET) method, Penman-Monteith, provided better flow results in this study. Kannan et al. (2007) also found Penman-Monteith method (energy balance) to be better than Hargreaves (simple empirical method) in a study using SWAT for a watershed in New England, South Atlantic Gulf, Texas Gulf and Upper Colorado.

Kanopolis Lake watershed flow calibration: Same parameters (Table 3.3) were used, other than ICN and CNCOEF, in Kanopolis Lake watershed. Initial simulated baseflow in Kanopolis Lake watershed was almost zero in all subwatersheds. To increase baseflow, the CN was reduced by 20% relative to the baseline CN2. Thereafter, ESCO, EPCO, SURLAG were adjusted to reduce peak flows. Lowering ESCO increases the evaporative demand and reduces the surface runoff. Following that, ALPHA_BF and GW_DELAY were adjusted. Deducing GW_DELAY allows faster recharge process. Also ALPHA_BF was reduced to model slower groundwater response. Increased RCHRG_DP allow higher percolation to the deep aquifer. Since Cedar Bluff Reservoir daily outflow was used, the subbasins above this reservoir were not included in calibration.

3.2.2.2 .1 Crop Yield

After flow calibration, Four plant parameters crop parameters were adjusted one at a time within acceptable ranges to identify their sensitivity range. The plant parameters modified in this study included lower harvest index (WYSF), harvest index for optimal growing condition (HVSTI), radiation use efficiency (BIO_E), and maximum leaf area index (BLAI). Sinnathamby et al. (2014b) also used all these four parameters in field-level crop calibration and Nair et al. (2011) used crop parameters HVSTI, BIO_E, and BLAI in watershed-level calibration. Thereafter, several combinations of four parameters were tested within identified sensitive ranges to achieve a high NSE and low bias (at least NSE $\geq$ 0.50 and PBIAS $\leq$ 5%) for both watersheds. When crop yield met criteria (average measured and simulated crop yield was within $\leq$ 15%, NSE $\geq$ 0.50, RSR $\leq$ 1and PBIAS $\leq$ 10%, Figure 3.2) the crop calibration was stopped. If all four crop parameters were adjusted to the limit and the calibration criteria were still not met, then calibration was stopped and optimum parameter set which yields higher NSE and lower RSR and PBIAS was selected. Following crop calibration, crop-specific ET and annual-basin ET values were verified, as plant growth and biomass production can have an effect on water balance (Nair et al., 2011). Dry land corn and soybean for Perry Lake watershed and winter wheat and dry land grain sorghum for Kanopolis Lake watershed are the primary agricultural crops and were selected for county-level calibration. Corn and soybean crop yields for Jackson and Brown Counties from 1996 to 2009 were used for calibrating the crop sub-model of Perry Lake watershed, and winter wheat and grain sorghum crop yields for Wallace and Trego Counties were used for Kanopolis Lake watershed crop calibration (Figure 3.1).

Initially, simulated corn and soybean crop yields were much higher, and winter wheat and grain sorghum yields were lower than USDA-NASS published county values. Corn crop yields were calibrated by adjusting each crop's biomass energy factor (BIO_E), harvest index for optimal growing condition (HVSTI), and the lower limit of harvest index (WYHI) in the SWAT crop database file. BIO_E for corn was reduced from 39 to 35 to correspond more closely with published crop yields for Jackson and Brown counties. In the case of soybean, BIO_E was also reduced from the default value. This adjustment was made mainly to accommodate potential impacts of climate and management stress factors on yields (Baumgart, 2005). In addition, corn HVSTI was reduced from 0.50 to 0.46 to account for generally less production from dry land (non-irrigated) corn production systems. Finally, WYHI was increased to improve the yield results based on SWAT water stress (Table 3.2). Similar changes were made in soybean. The WYHI was increased from default values to 0.20. HVSTI was kept same as the default value. For winter wheat calibration only HVSTI was slightly modified. During grain sorghum calibration, all these parameters were increased in addition to LAI. Final, HVSTI and WSYF used in winter wheat modeling are closely matched with the values reported in Dorsey (2014) and agree with values suggested by Dr. Nathan Nelson, Kansas State University (personal comm., 2013). Dorsey (2014) analyzed lower and upper harvest index ranges of wheat verities commonly grown in the Great Plains, USA.

3.2.3 Model validation

During the validation process, the model parameters were set to the final calibrated values without any change, and the results compared to the remaining observational data to evaluate model performance. The streamflow measurements from 1996 to 2011 were selected for validation measurements. The same statistical measures used in calibration also were used to evaluate the model simulations during validation. Nemaha and Ellis County yields were used for crop yield validation.

3.2.4 Evaluating ecohydrological indicators

The benefit of multi-objective calibration protocol for modeling ecohydrological indicators was evaluated using 32 Indicators of Hydrologic Alteration (IHA) (Richter et al., 1996; The Nature Conservancy, 2009). Each IHA parameter was calculated based on observed data and modeled results, and NSE was calculated to quantify model performance in simulating the IHA value. Detailed descriptions of IHA can be found in Sinnathamby et al. (2014a) and elsewhere (Richter et al., 1996; The Nature Conservancy, 2009). SWAT-generated streamflow values at all station used in calibration were used in this analysis. NSE was used in ecohydrological indicator evaluation, as it is a very commonly used statistics in SWAT application. The NSE values ≥ 0.5 were considered as acceptable for this purpose (Moriasi et al., 2007).

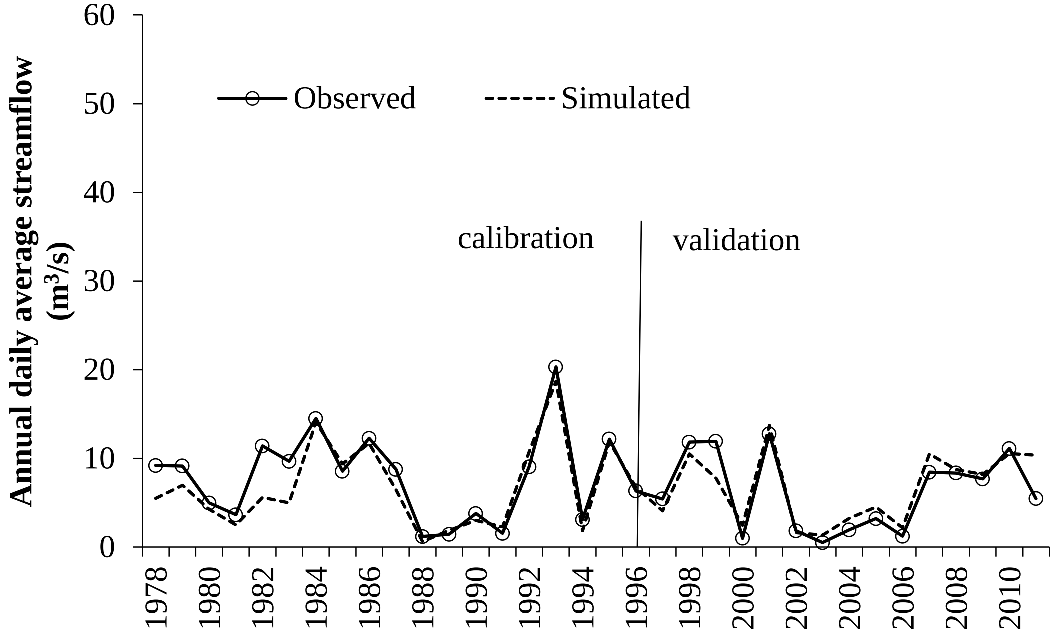
3.3 Results and Discussion

3.3.1 Model calibration and validation

SWAT-predicted annual, monthly, and daily average flows at Delaware R NR Muscota and Delaware River at Perry Lake appear to follow the measured hydrograph (Figures 3.4, 3.5) over the calibration (1978-1996) and validation (1997-2011) periods. Slight discrepancies in peak flow predictions were noted for both periods, especially at Delaware R NR Muscota (Figure 3.4). The model performance statistics showed that the calibrated model met commonly-accepted metrics for all model evaluation criteria (Table 3.4). The NSE in both conditions was greater than 0.60. Additionally, monthly average flow intercepts of regression (Figure 3.6) were not significantly different from zero and the coefficients of determination (R^2) in all conditions were greater than 0.5, which is above acceptable range (Santhi et al., 2001; Moriasi et al., 2007). However, flow intercepts and R^2 were not considered as criteria in this study. The results also showed that simulated surface flow, baseflow and total streamflow matched well with the observed values (Table 3.4).

Figure 3.4 Observed and simulated annual average of daily streamflows at a) Delaware R NR Muscota and b) Delaware River at Perry Lake over calibration (1978-1996) and validation (1997-2011) periods.

a



b

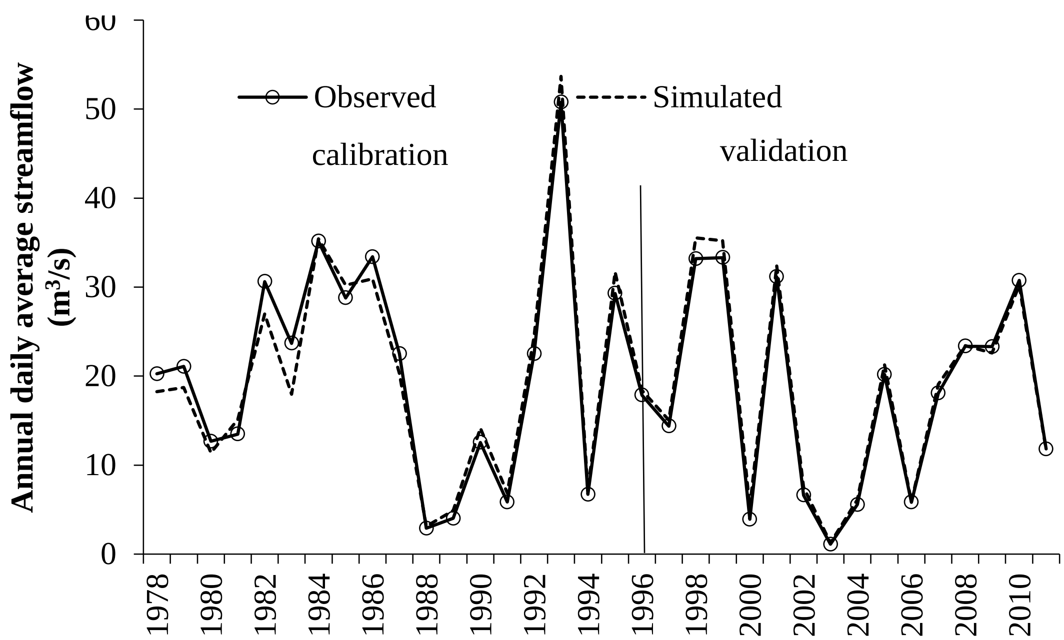
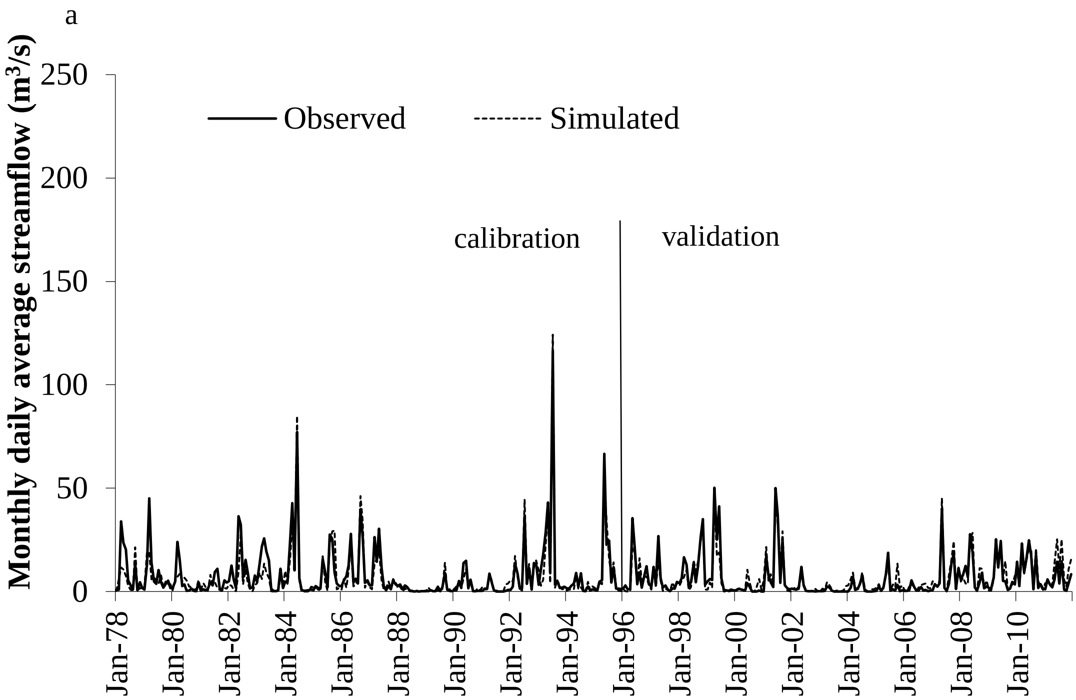


Figure 3.5 Observed and simulated monthly average of daily stream flows at a) Delaware R NR Muscota and b) Delaware River at Perry Lake over calibration (1978-1996) and validation (1997-2011) periods.



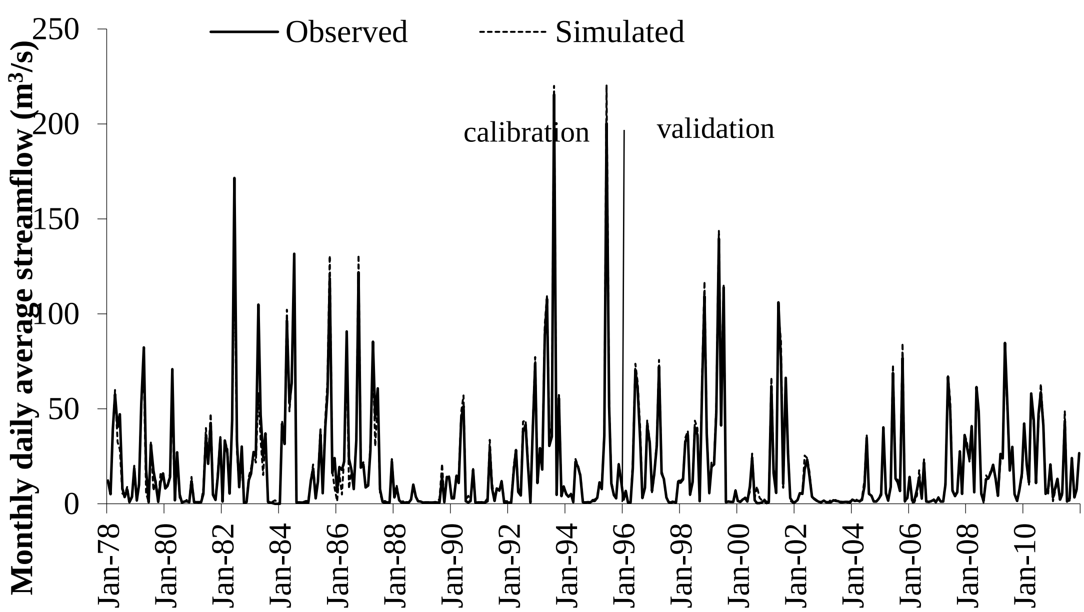


Figure 3.6 Observed and simulated monthly average of daily streamflows at Delaware R NR Muscota (upper panel) and Delaware River at Perry Lake (down) for calibration period (1978-1996; right side) and validation period (1997-2011; left side)

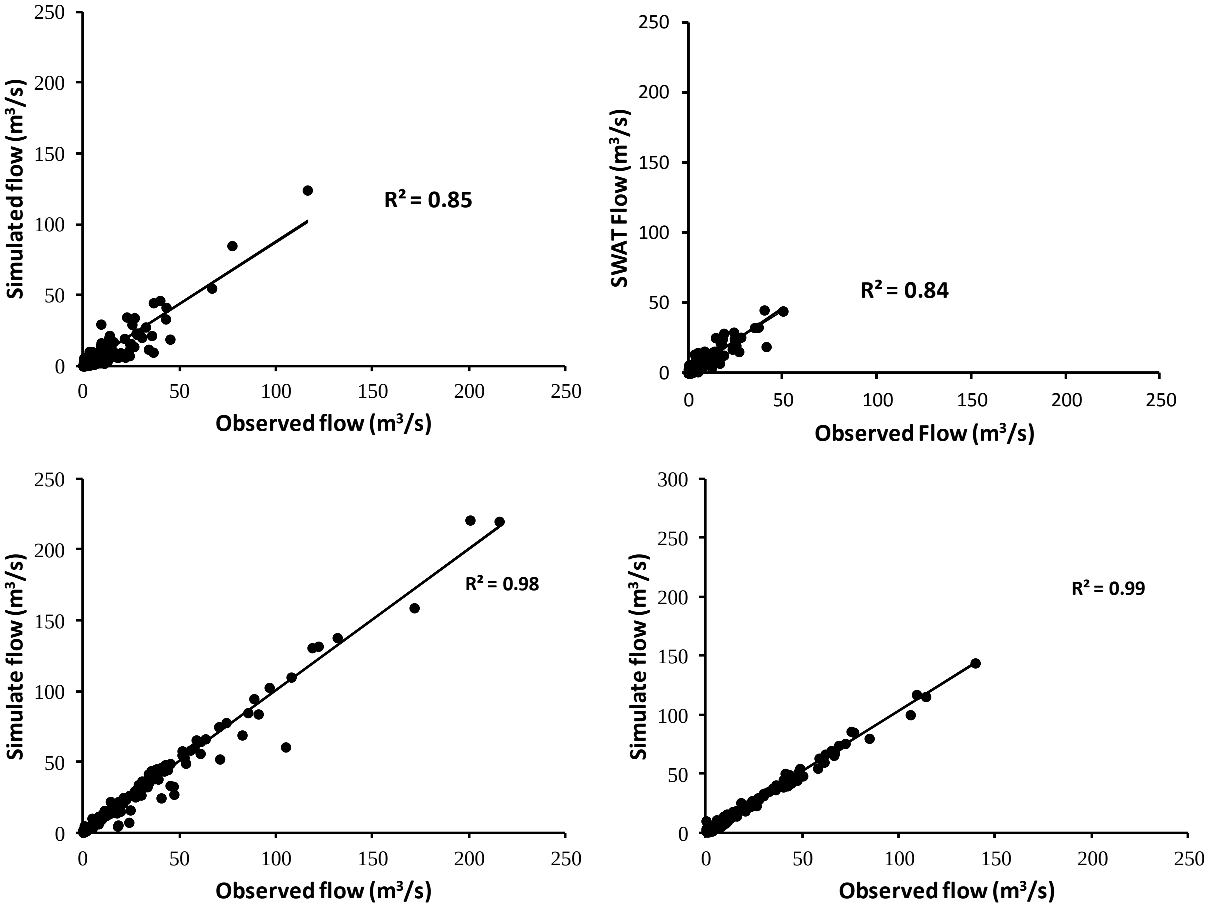


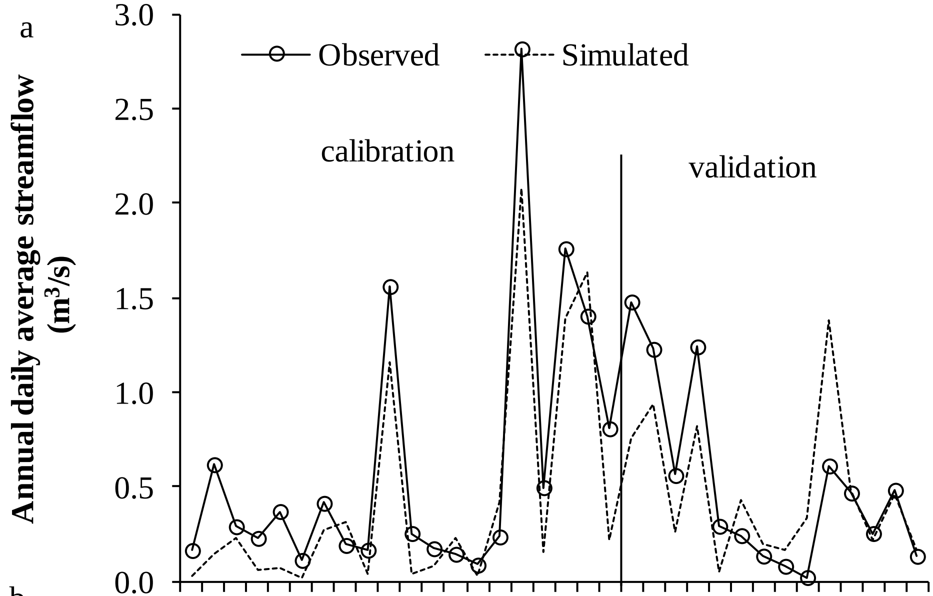
Table 3.4 Stream flow calibrated statistics at Delaware River near Muscota and Delaware River at Perry Lake

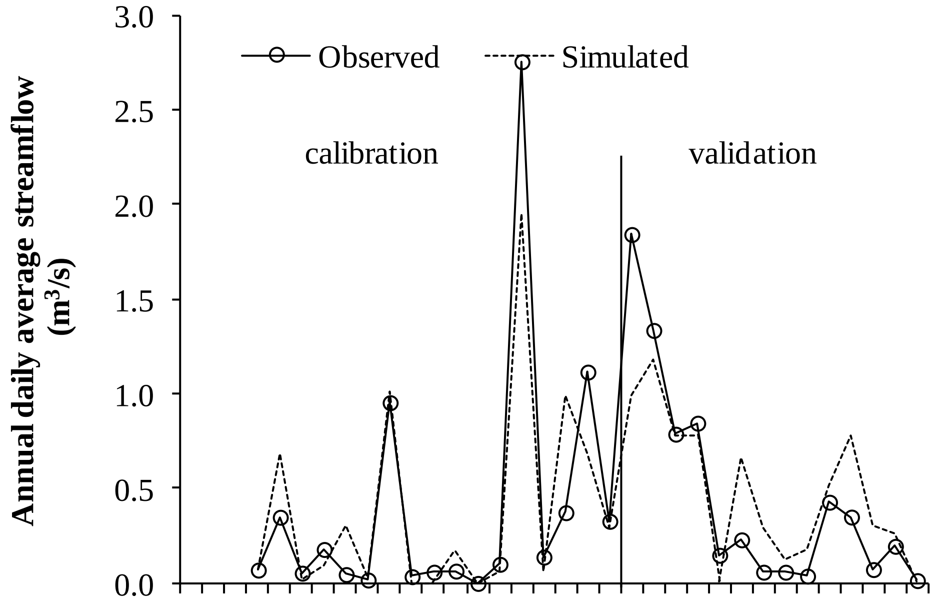
	NSE		PBIAS (%)		RSR	
	After parameterization	Final	After parameterization	Final	After parameterization	Final
Delaware River near Muscota						
Annual Calibration (1978-1996)	0.82	0.80	14.41	-3.75	0.43	0.19
Monthly Calibration	0.80	0.84	12.97	-15.66	0.44	0.26
Daily Calibration	0.37	0.65	-12.85	5.68	0.79	0.59
Surface flow	0.25	0.57	-4.67	-15.03	0.86	0.65
Baseflow Calibration	0.22	0.69	5.54	28.99	0.88	0.85
Annual Validation (1997-2011)	0.51	0.79	40.05	7.46	0.70	0.46

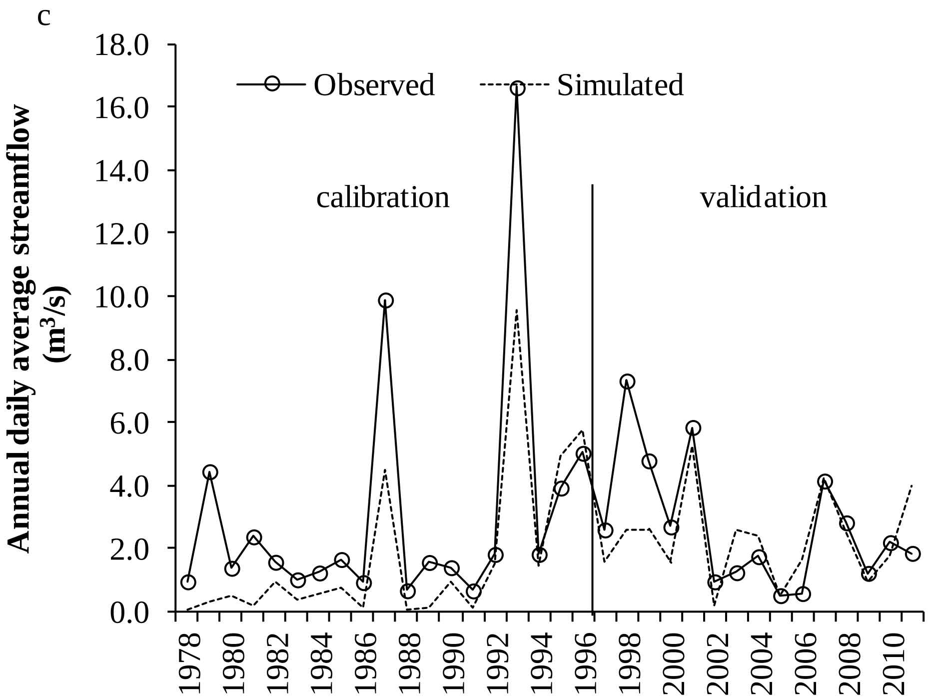
Monthly Validation	0.73	0.84	40.05	7.46	0.51	0.40
Daily Validation	0.15	0.74	25.84	0.13	0.92	0.51
Surface flow	0.21	0.76	45.99	3.00	0.74	0.49
Baseflow Validation	0.15	0.47	-17.36	-20.55	0.91	0.72
Delaware River at Perry Lake						
Annual Calibration (1978-1996)	0.99	0.99	2.45	1.13	0.11	0.08
Monthly Calibration	0.98	0.98	5.27	4.70	0.13	0.09
Daily Calibration	0.91	0.90	5.04	1.44	0.31	0.32
Surface flow	0.86	0.84	5.51	1.15	0.37	0.40
Baseflow Calibration	0.72	0.93	-22.98	-1.44	0.52	0.25
Annual Validation (1997-2011)	0.99	0.99	7.22	1.14	0.10	0.10
Monthly Validation	0.99	0.99	4.73	3.96	0.10	0.10
Daily Validation	0.87	0.87	0.75	-1.75	0.36	0.36
Surface flow	0.83	0.86	0.37	-0.10	0.41	0.38
Baseflow Validation	0.83	0.84	-1.56	-6.39	0.40	0.40

The SWAT model flow performance after calibration at Big C NR Hays, Smoky Hill R BL Schoen, Smoky Hill R NR Bunker Hill and Smoky Hill R at Ellsworth is given in Figures 3.7 through 3.9 and Table 3.5. Based on the statistics (Table 3.5) the overall the model performed well. However, the low and high flow conditions were not able to model in most cases (Figure 3.7 to Figure 3.9). The watershed baseflow/ total flow fraction after calibration was 0.29 compared to grid averaged values for the watershed 0.21 reported by Wolock (2003).

Figure 3.7 Observed and simulated annual average flows at a) Big C NR Hays b) Smoky Hill R BL Schoen c) Smoky Hill R NR Bunker Hill and d) Smoky Hill R at Ellsworth over calibration (1978-1996) and validation (1997-2011) periods.






c
Annual daily average streamflow (m³/s)
18.0
16.0
14.0
12.0
10.0
8.0
6.0
4.0
2.0
0.0
Observed
Simulated
calibration
validation
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010

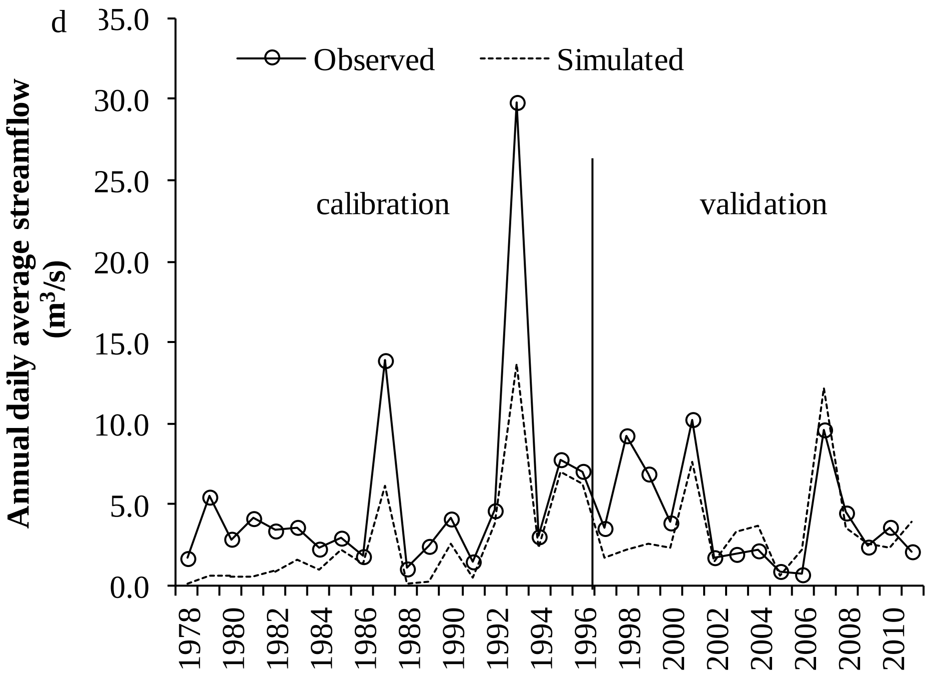
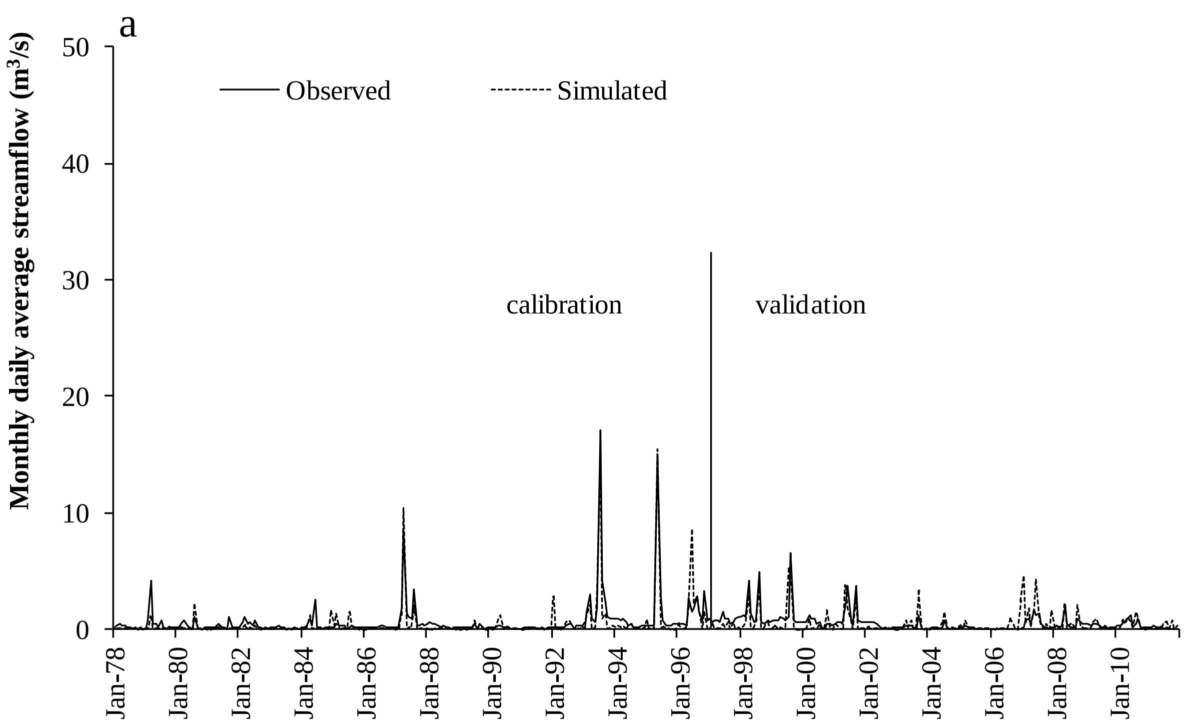
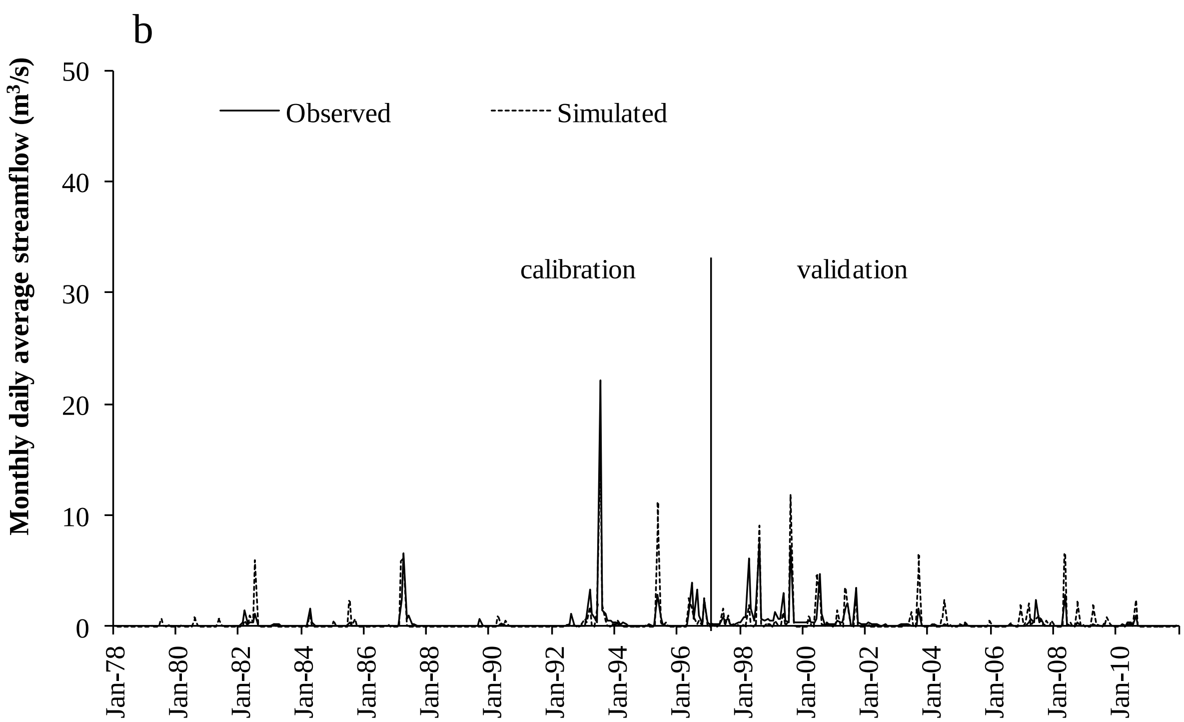
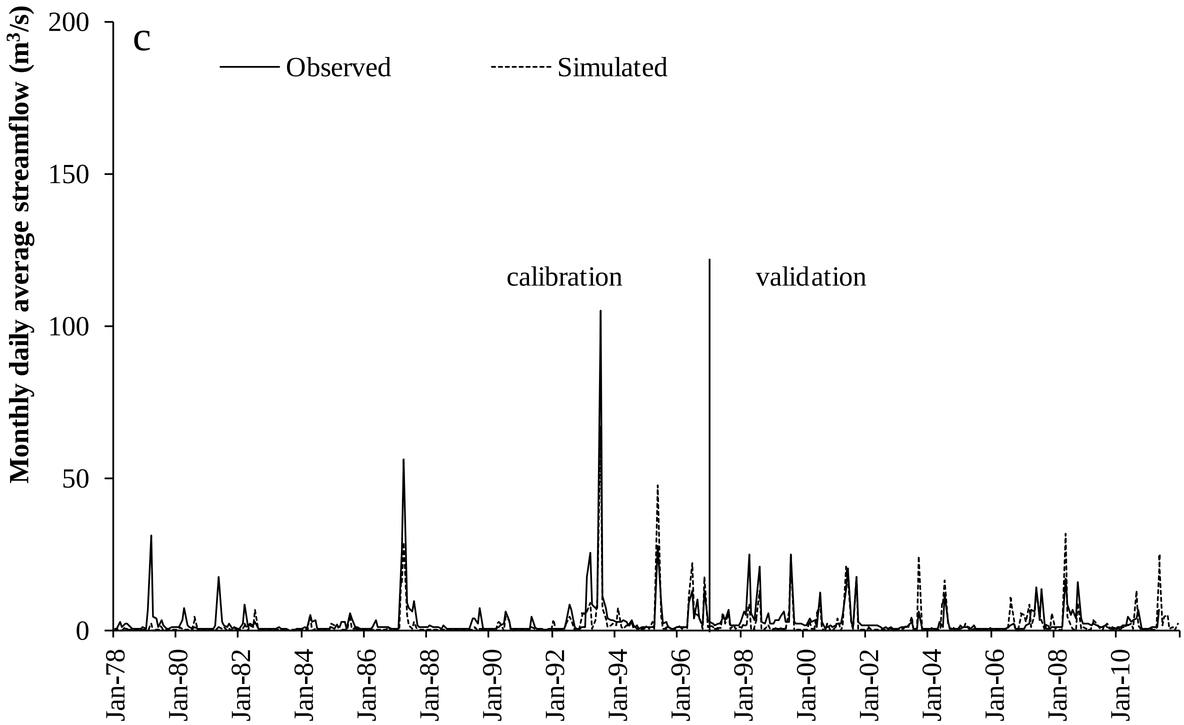

d
Annual daily average streamflow (m³/s)
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
Observed
Simulated
calibration
validation
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010

Figure 3.8 Observed and simulated daily average (monthly) flows at a) Big C NR Hays b) Smoky Hill R BL Schoen c) Smoky Hill R NR Bunker Hill and d) Smoky Hill R at Ellsworth over calibration (1978-1996) and validation (1997-2011) periods.






c
Observed
Simulated
calibration
validation
Monthly daily average streamflow (m3/s)
200
150
100
50
0
Jan-78
Jan-80
Jan-82
Jan-84
Jan-86
Jan-88
Jan-90
Jan-92
Jan-94
Jan-96
Jan-98
Jan-00
Jan-02
Jan-04
Jan-06
Jan-08
Jan-10

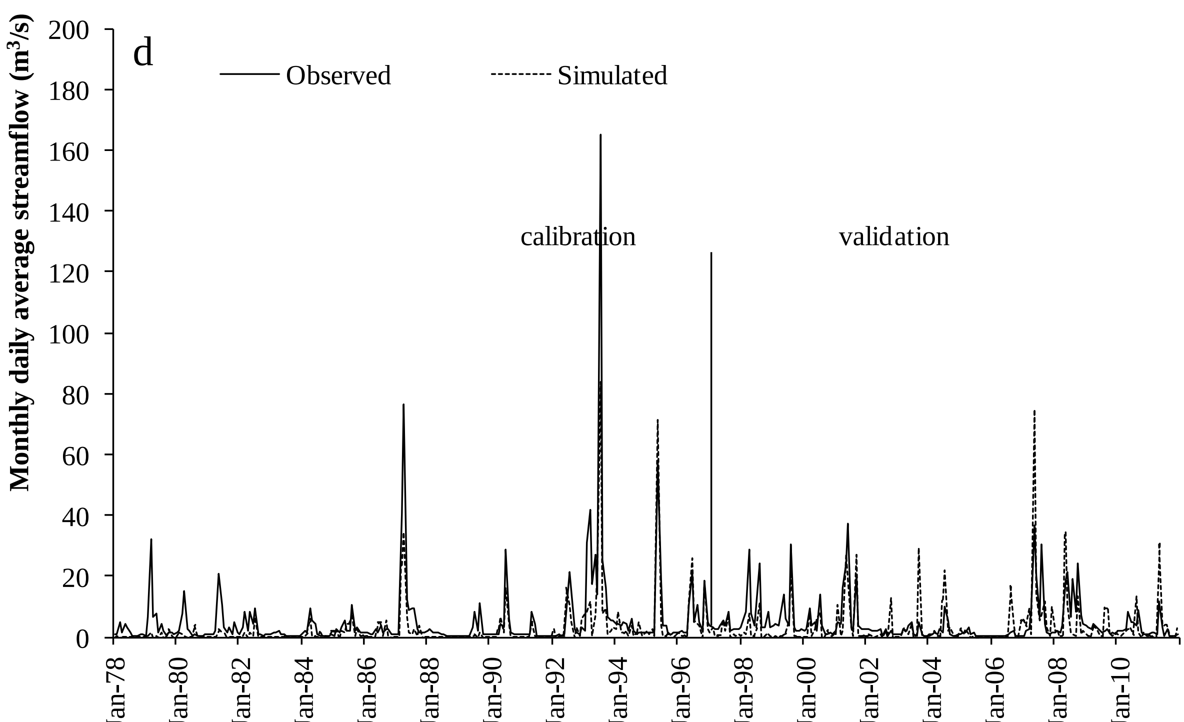
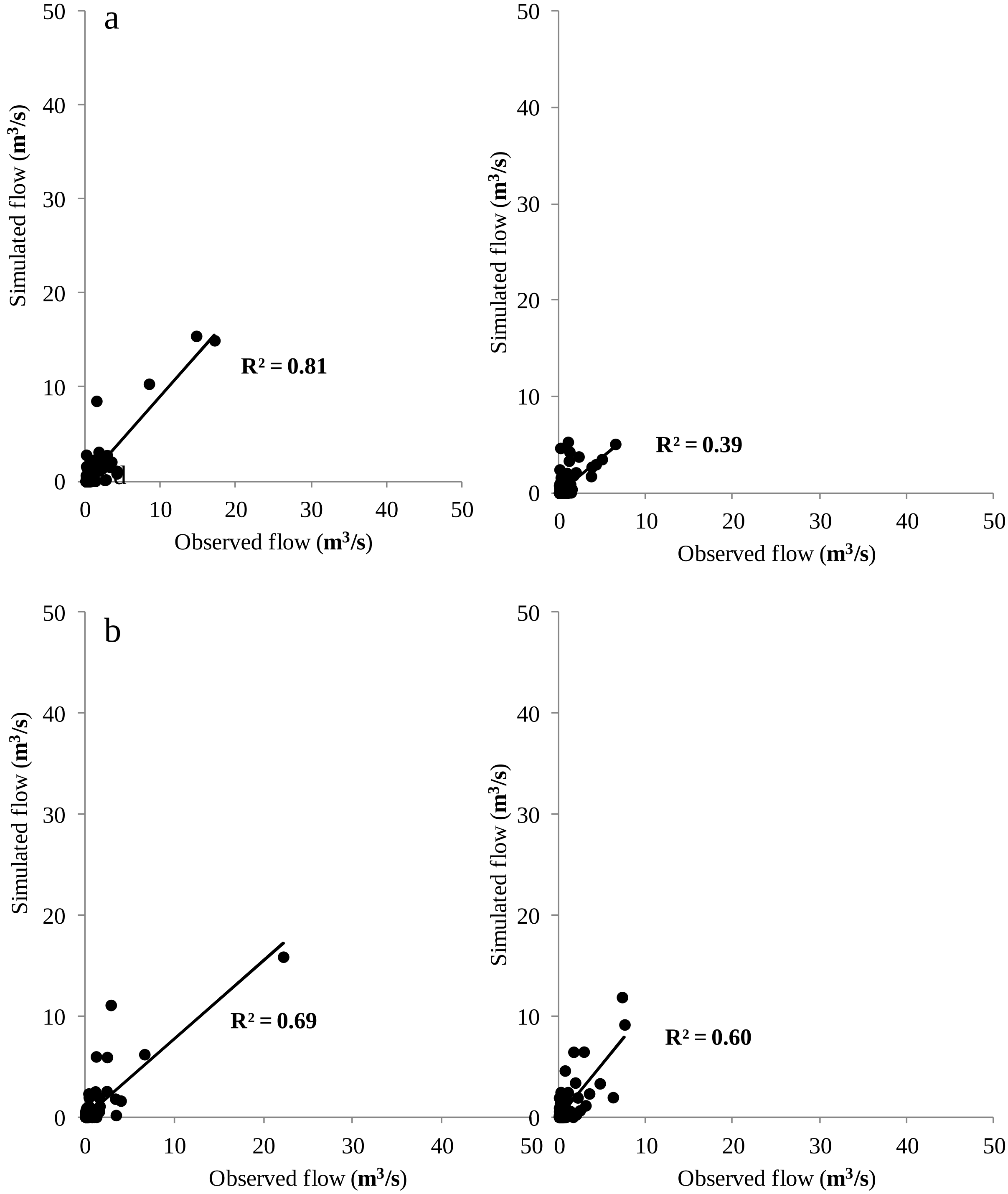

d
Observed
Simulated
calibration
validation
Monthly daily average streamflow (m3/s)
200
180
160
140
120
100
80
60
40
20
0
Jan-78
Jan-80
Jan-82
Jan-84
Jan-86
Jan-88
Jan-90
Jan-92
Jan-94
Jan-96
Jan-98
Jan-00
Jan-02
Jan-04
Jan-06
Jan-08
Jan-10

Figure 3.9 Observed and simulated daily average (monthly) flows at a) Big C NR Hays b) Smoky Hill R BL Schoen c) Smoky Hill R NR Bunker Hill and d) Smoky Hill R at Ellsworth over calibration (1978-1996; right side) and validation (1997-2011; left side) periods.



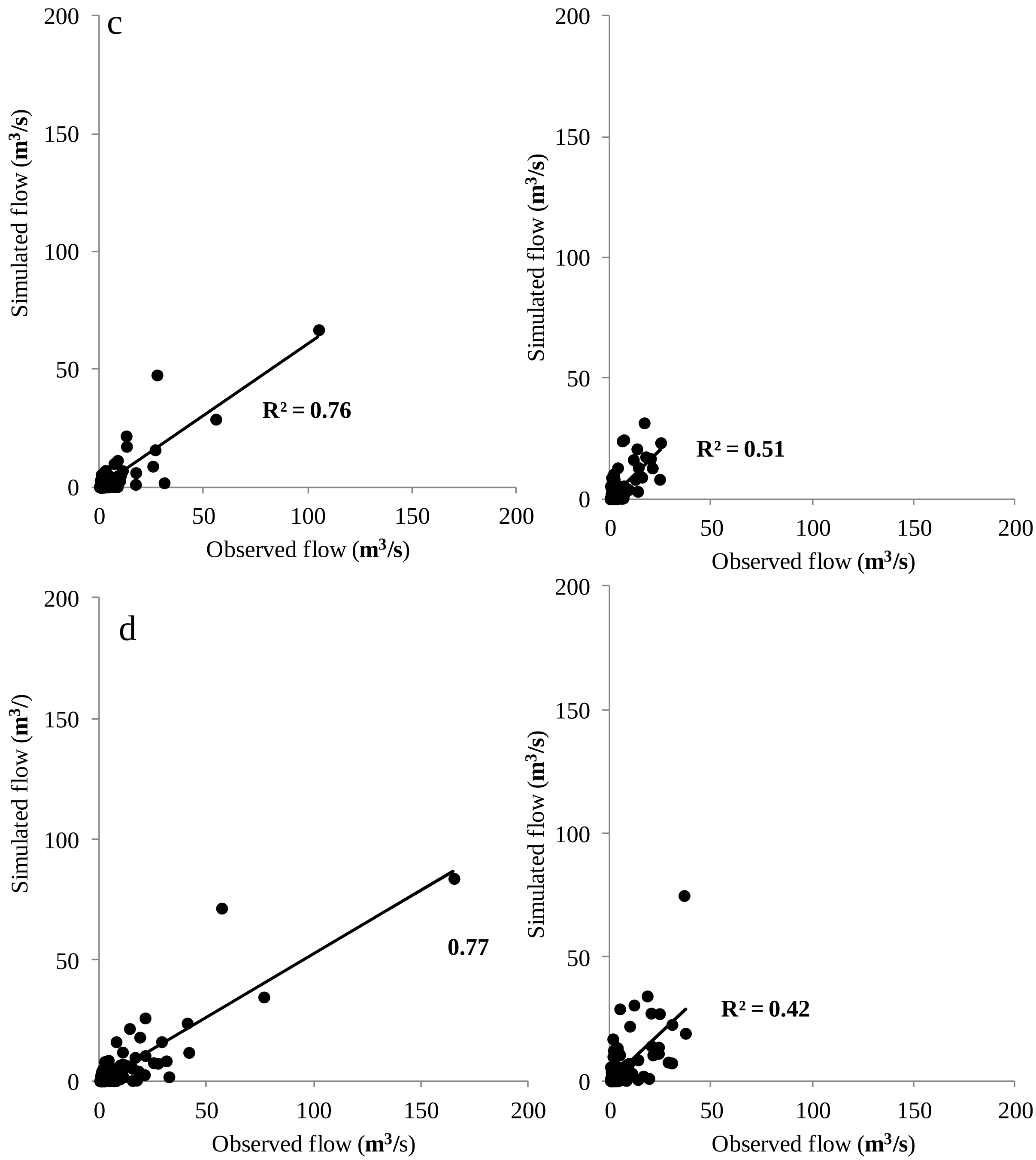


Table 3.5 Stream flow calibrated statistics for Kanopolis Lake watershed

	NSE		PBIAS (%)		RSR	
	After parameterization	Final	After parameterization	Final	After parameterization	Final
Big C NR Hays						
Annual Calibration (1978-1996)	-11.71	0.85	330.83	-27.20	3.56	0.39

Monthly Calibration	-3.98	0.87	330.83	-27.19	2.23	0.36
Daily Calibration	-15.57	-0.62	337.20	-27.90	4.00	1.79
Annual Validation (1997-2011)	-37.23	0.31	81.26	-10.43	6.18	0.83
Monthly Validation	-20.50	-0.17	414.06	-14.07	4.63	1.08
Daily Validation	-53.91	-8.25	317.48	0.10	7.40	3.04
Smoky Hill R BL Schoenchen						
Annual Calibration (1978-1996)	-8.44	0.83	445.04	-2.97	3.07	0.42
Monthly Calibration	-2.76	0.69	401.76	-0.91	1.94	0.56
Daily Calibration	-3.64	0.30	400.69	-2.90	2.15	0.83
Annual Validation (1997-2011)	-16.72	0.66	375.34	-0.38	4.21	0.58
Monthly Validation	-7.76	0.28	375.00	-1.26	2.96	0.85
Daily Validation	-0.19	-0.08	-72.87	-97.17	1.09	1.03
Smoky Hill R NR Bunker Hill						
Annual Calibration (1978-1996)	-3.44	0.60	180.38	-50.62	2.10	0.63
Monthly Calibration	-0.61	0.71	179.26	-50.40	1.27	0.54
Daily Calibration	-3.73	0.03	66.07	-44.45	2.17	0.98
Annual Validation (1997-2011)	20.85	0.36	283.37	-17.35	4.67	0.80
Monthly Validation	-7.69	0.32	275.00	-18.70	2.95	0.82
Daily Validation	-17.80	-1.57	63.38	-40.60	4.33	1.60
Smoky Hill R at Ellsworth						
Annual Calibration (1978-1996)	-1.60	0.49	141.19	-53.80	1.61	0.71
Monthly Calibration	-0.10	0.65	142.02	-51.19	1.05	0.59
Daily Calibration	-3.12	-0.15	152.59	-51.13	2.03	1.04
Annual Validation (1997-2011)	-6.68	0.34	-18.69	-15.75	4.44	0.81
Monthly Validation	-6.68	0.14	248.00	-21.00	2.77	0.92
Daily Validation	-6.07	-0.62	213.80	-57.34	2.66	1.27

The above observed results show that calibration process was more successful in Perry Lake watershed than Kanopolis Lake watershed. In most cases Kanopolis Lake watershed flow was more difficult to predict. This is mainly due to its geographic location, where there is highly variable precipitation with extremes, complex surface and groundwater interactions because of its underlying aquifer, extreme groundwater pumping and ongoing agricultural practice. Western Kansas has lower magnitude of precipitation compared to north-eastern Kansas. The potential evaporation excessed the annual precipitation and leading moisture deficit in most seasons in this region (Sophocleous, 1998). These natural conditions are leading the streams in western half to have lower magnitude of discharge than the north-eastern part. The average runoff ranges from approximately 2.54 mm to 254 mm (0.1 to 10 in.) from west to east (Sophocleous and Wilson, 2000). This shows a 100-fold change in the runoff across the State. Due to this reason agricultural, domestic/municipal and industrial fresh water needs in western Kansas mainly meet by groundwater. In addition, many Kansas streams have groundwater contribution (known as baseflow). To have contribution from groundwater, the water table in the vicinity should have higher elevation than the stream-water surface. When the elevation of water table decreases due to groundwater pumping, the stream will lose water to the underlying aquifer and become as a losing (leaking) stream. Sophocleous and Wilson (2009) reported this condition for many western Kansas streams. These all situations have led most of the western region perennial streams into intermittent streams (Perry et al., 2004).

The above mentioned complex groundwater interactions, climate variations and agricultural practices made calibration as a challenging process for Kanopolis Lake watershed. Discrepancies in low and high flows were observed in all four stations. Naturally, Kanopolis Lake watershed has lower flows due to lower western gradient of precipitation and seasonal moisture deficit (more potential evapotranspiration than precipitation). The uncertainty in measuring low flows is higher than the regular flows. Especially, reliable low discharge measurements are difficult to record and have considerable uncertainties due to hyporheic flow exchange (in channel water exchange with groundwater) and the presence of ice and vegetation (Hamilton, 2008 and Shrestha et al., 2013). Also the number of precipitation gages (20 gages/ 20,291 km^2) may not be sufficient to represent the variability. In addition, lack of explicit consideration of smaller impoundments and wells can be also defined as a limitation of this study.

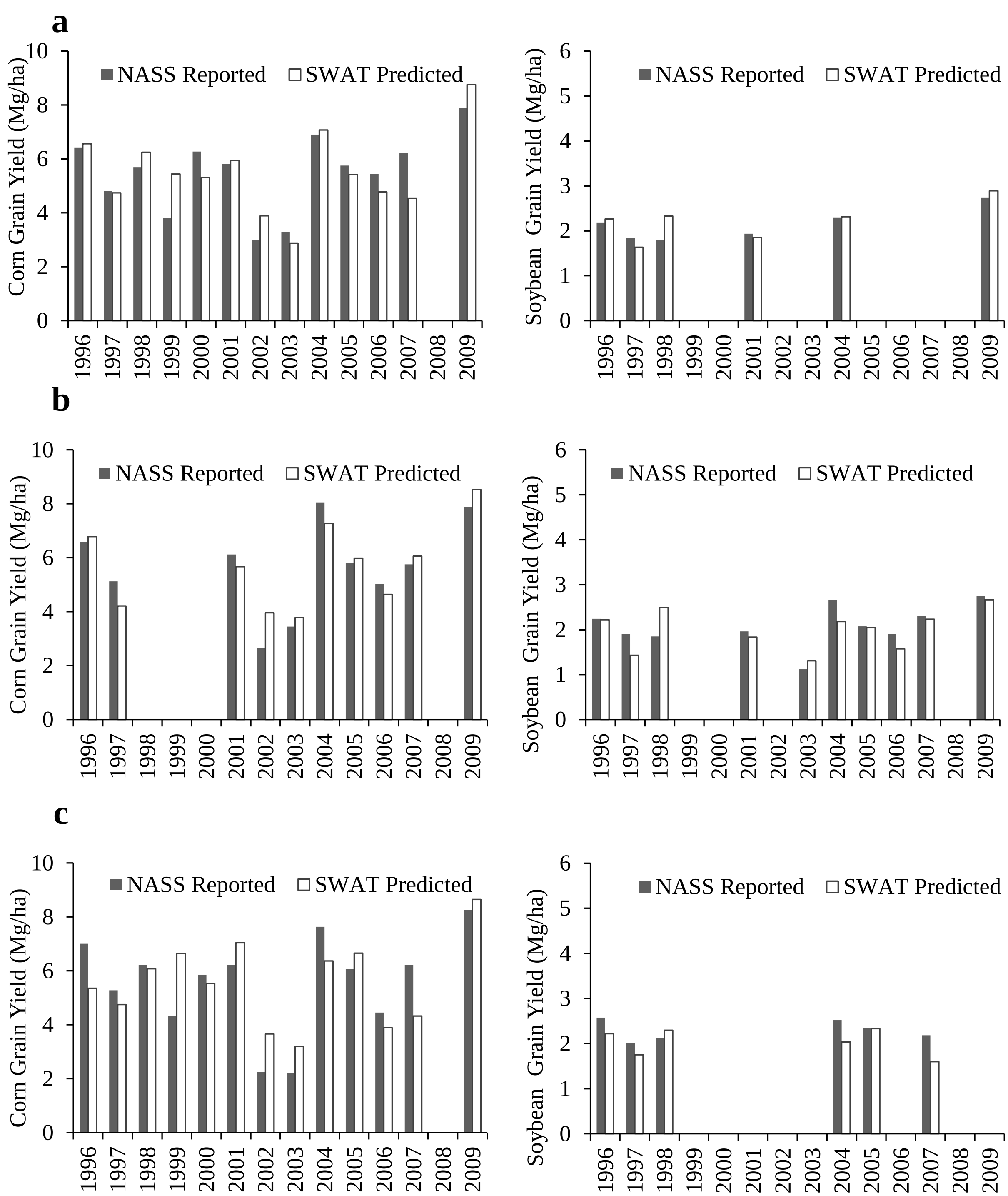
3.3.2 Crop yield calibration and validation

The calibrated SWAT model performaed well in simulating corn and soybean annual yields at Delaware watershed, with NSE above 0.40 and PBIAS less than 5%, except for soybean in Nemaha County (Table 3. 6 and Figure 3.10). Nemaha County has NSE of -0.57 and PBIAS of -11.2% for soybean simulation. Corn yield simulations were reasonable except during 1999. Higher precipitation observed in 1999 may have removed a portion of the applied nitrogen fertilizer (Roozeboom et al., 1999-2008). SWAT may have underestimated fertilizer runoff/removal, resulting in overestimated yield predictions. Bora and Bera (2004) found SWAT suitable for predicting sediment and nutrient loads on a monthly time scale, except for months with extreme storms and hydrologic conditions. Fewer available observed data limited soybean calibration. However for both corn and soybean model, average crop yields were within ± 15% of reported values.

Table 3.6 Average reported and SWAT predicted crop yields and calibration statistics for Delaware River watershed

County	Number of Observation	Crop yield (Mg ha^{-1})		NSE		PBIAS (%)		RSR	
		Reported	Modeled	Default	Final	Default	Final	Default	Final
Dry land corn									
a) Jackson	13	5.49	5.56	-13.32	0.55	78.65	1.83	3.80	0.67
b) Jefferson	10	5.65	5.69	-9.18	0.83	90.33	0.83	3.05	0.42
c) Nemaha	13	5.54	5.61	2.48	0.64	62.41	1.35	1.87	0.60
Soybean									
a) Jackson	6	2.13	2.08	-3.46	0.55	30.94	-2.09	2.11	0.67
b) Jefferson	10	2.07	1.87	-1.11	0.37	27.68	-9.85	1.45	0.80
c) Nemaha	6	2.29	1.90	0.38	-0.57	3.50	-11.24	0.76	0.99

Figure 3.10 Simulated and observed (USDA-NASS) reported crop yield for dry land corn (left) and soybean (right) for (a) Jackson, (b) Jefferson, and (c) Nemaha Counties

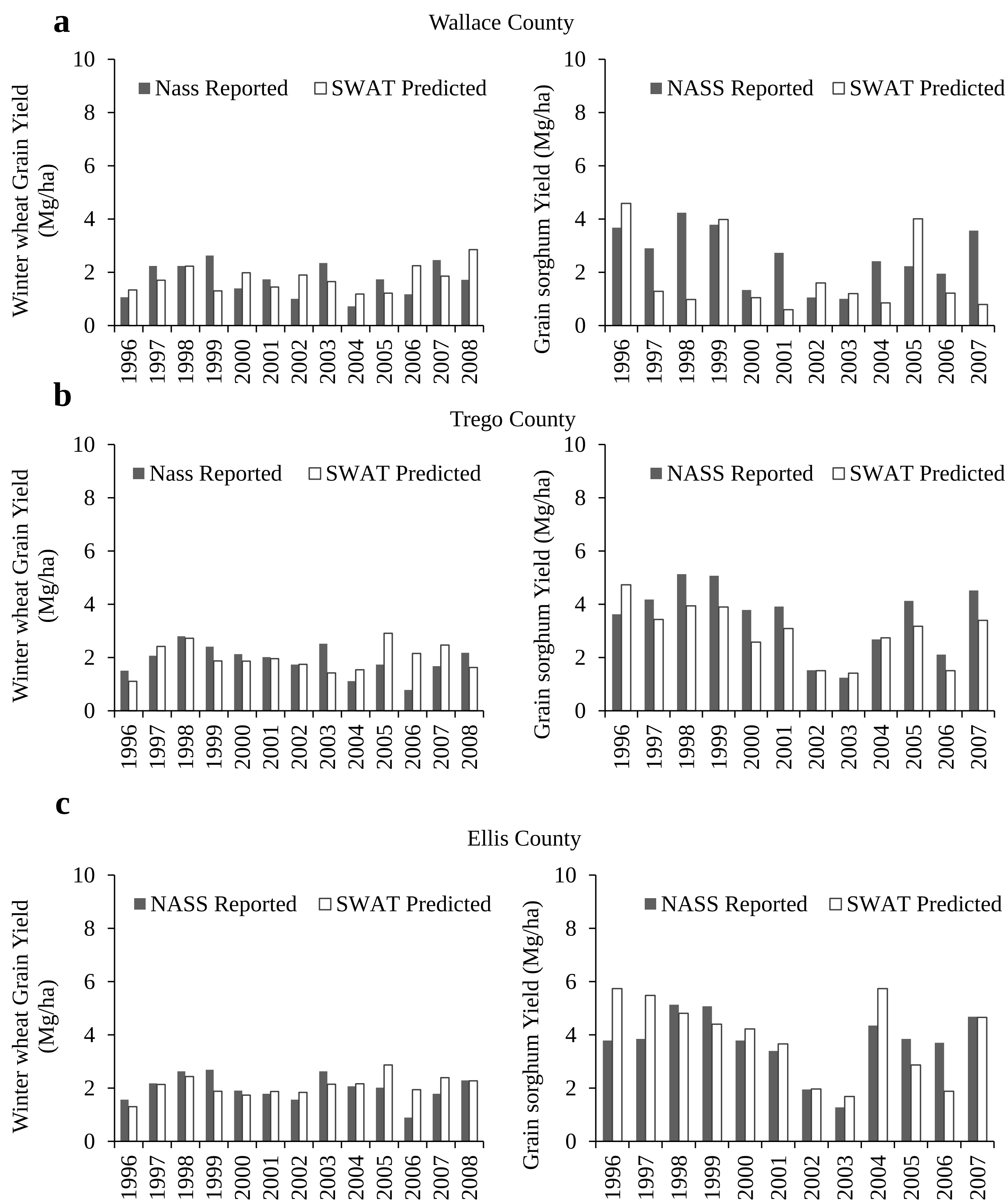


Winter wheat and grain sorghum had PBIAS of less than 15% except in Wallace County, which had under predicted yields for grain sorghum with higher deviations (Table 3.7 and Figure 3.11). Lower streamflow predictions made difficult in predicting crop yields for Kanopolis. However, spatial and temporal trends were predicted reasonably for both crops (Figure 3.11).

Table 3.7 Average reported and SWAT predicted crop yields and calibration statistics for Kanopolis River watershed

County	Number of Observation	Crop yield (Mg ha^{-1})		NSE		PBIAS (%)		RSR	
		Reported	Modeled	Default	Final	Default	Final	Default	Final
Winter wheat									
a) Wallace	13	1.73	1.44	-5.12	-0.53	38.28	-1.91	2.47	1.24
b) Trego	13	1.90	1.86	-17.60	-0.07	87.78	3.70	4.31	1.03
c) Ellis	13	2.00	2.05	-9.15	-0.67	40.18	4.56	3.19	1.29
Grain sorghum									
a) Wallace	12	2.58	1.85	-0.52	-0.40	-36.68	-28.27	1.81	0.85
b) Trego	12	3.50	2.95	-1.51	0.51	-18.0	-15.51	2.10	1.43
c) Ellis	12	3.74	3.93	-0.03	0.10	9.40	5.04	1.99	1.05

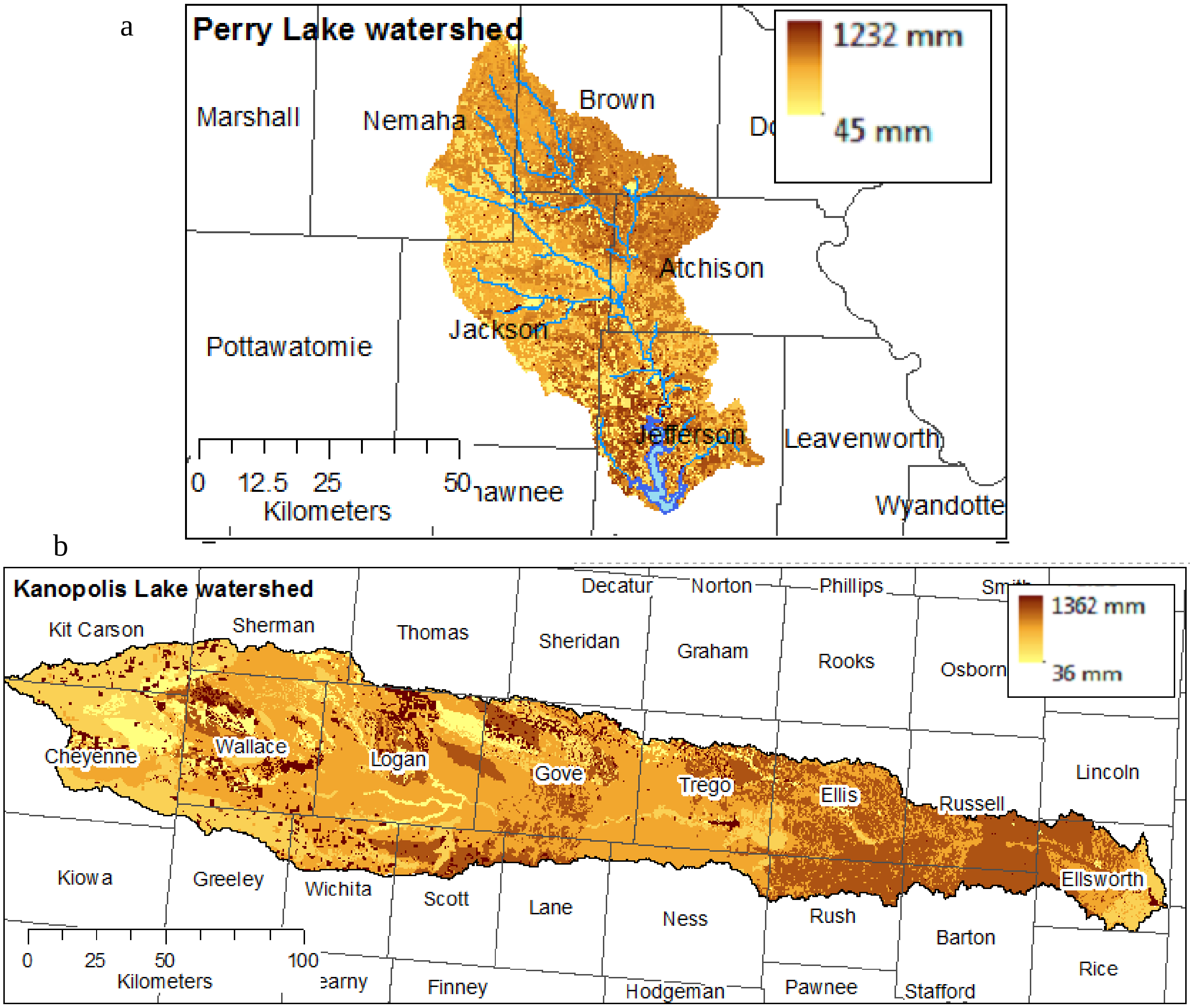
Figure 3.11 Simulated and observed (USDA-NASS) reported crop yield for dry land winter wheat (left) and grain sorghum (right) for (a) Wallace, (b) Trego and (c) Ellis Counties



Corn, soybean, winter wheat and grain sorghum yields were all simulated well by SWAT after adjusting the soil and crop growth parameters. Less precipitation and more evapotranspiration made predicting yield more difficult in Kanpolis Lake watershed. Two of three default values for corn and all three default values for winter wheat were reduced to decrease simulated yields while all three values were increased for soybean and grain sorghum. It was also noticed that the greater drought-tolerance of grain sorghum made it less susceptible to plant stress, and the lesser drought-tolerance of corn made it more susceptible to plant stress than was simulated in SWAT for these regions.

Thirty-seven year average annual modeled ET was 696 mm for Perry Lake watershed and 506 mm for Kanopolis Lake watershed, with values ranging from 45 to 1232 mm (Figure 3.12). Highest ET values were observed in water bodies. Wetter (1987) reported normal ET values from 711 to 762 mm (28 to 30 in.) for Perry Lake watershed area and values from 432 to 635 mm (17 to 25 in.) for Kanopolis Lake watershed. Spatial gradiant of modeled ET was similar to Wetter (1987; Figure 3.12).

Figure 3.12 Thirty seven year average annual modeled ET for Perry Lake watershed, Kanopolis Lake watershed and normal annual ET (precipitation - runoff) reported by Wetter (1987)



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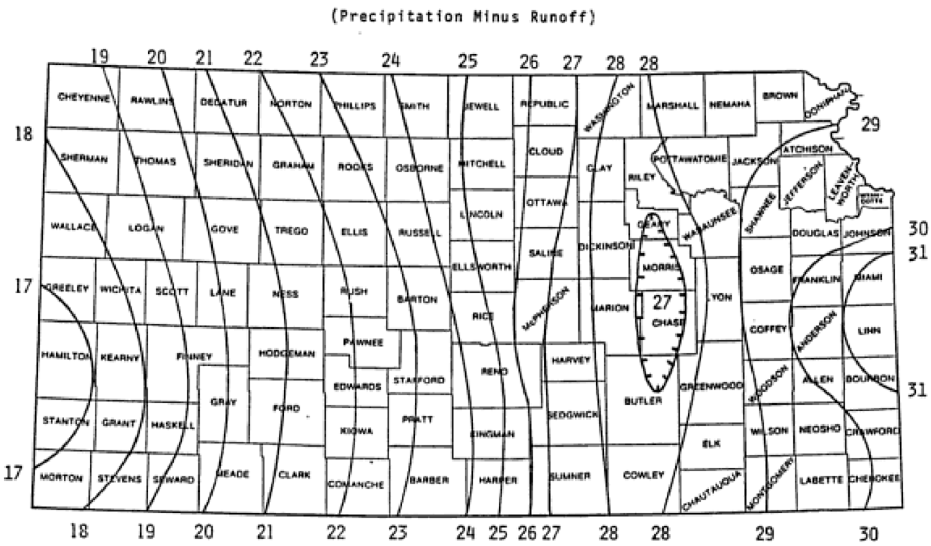

Figure 3.9: Normal Annual Evapotranspiration, Inches (Precipitation Minus Runoff)

SWAT predicted ET using Penman-Monteith method was 697 mm for corn, 661 mm for soybean, 516 mm winter wheat, and 537 mm for grain sorghum compared to 635 mm for corn and 610 mm for soybeans, 610 mm winter wheat and 533 mm for grain sorghum reported by Stone and Schlegel (2006) in western Kansas. Stone and Schlegel (2006) reported ET values for western Kansas under limitted irrigation system. Because there was not any other studies available on dryland cropping system ET for Kansas, Stone and Schlegel (2006) was used as reference in this study.

3.3.3 Progressive change in NSE and PBIAS during each stage of multi-objective protocol

SWAT model performance generally improved with each step of the multi-objective protocol compared to the baseline (with default parameters) for both watersheds (Tables 3.8, 3.9). The greatest NSE and lowest PBIAS were achieved after both flow and crop calibration for most subwatersheds. Flow calibration led to substantial improvements in NSE in both Perry Lake (Table 3.8) and Kanopolis Lake (Table 3.9) watersheds, whereas crop calibration led to improvement in PBIAS in Perry Lake watershed only (Table 3.8). Similar result was observed by Nair et al. (2011). Nair et al. (2011) tested a four stage calibration procedure, parameter selection, hydrology calibration, crop yield calibration and nutrient calibration. They reported slightly improved flow prediction efficiencies with crop yield calibration.

Table 3.8 Improvement in NSE and PBIAS measures at Perry Lake watershed during multi-objective calibration

	NSE			PBIAS (%)		
	Day	Month	Annual	Day	Month	Annual
Delaware River near Muscota						
1978-1996						
Baseline	0.36	0.80	0.77	-17.77	17.90	19.39
Parameterization only	0.37	0.80	0.82	-12.85	12.97	14.41
Flow Calibration	0.65	0.84	0.80	15.74	-15.68	-14.66
Flow+Crop Calibration	0.65	0.84	0.80	5.68	-15.66	-3.75
1997-2011						
Baseline	10.00	0.70	0.39	29.35	17.90	19.39
Flow+Crop Validation	0.74	0.84	0.79	0.13	7.46	7.46
Delaware River at Perry Lake						
1978-1996						
Baseline	-3.01	0.13	0.88	29.34	46.92	46.92
Parameterization only	0.90	0.98	0.99	5.04	5.27	2.45
Flow Calibration	0.90	0.98	0.99	1.44	1.44	1.14
Flow+Crop Calibration	0.90	0.98	0.99	1.43	4.69	1.13
1997-2011						
Baseline	-3.77	0.26	0.36	25.21	21.50	15.46
Flow+Crop Validation	0.87	0.99	0.99	-1.75	4.70	1.14

Table 3.9 Improvement in NSE and PBIAS measures at Kanopolis Lake watershed during multi-objective calibration

	NSE			PBIAS (%)		
	Day	Month	Annual	Day	Month	Annual
Big C NR Hays						
1978-1996						
Baseline	-15.57	-3.99	-13.74	337.20	336.94	336.90
Parameterization only	-15.57	-3.98	-11.71	317.48	330.83	330.83
Flow Calibration	-0.63	0.87	0.84	-27.80	-27.88	-27.80
Flow+Crop Calibration	-0.62	0.87	0.85	-27.19	-27.19	-27.20
1997-2011						
Baseline	-53.91	-21.44	-37.17	317.48	440.31	81.27
Flow+Crop Validation	-8.25	-0.17	0.31	0.10	-14.07	-10.43
Smoky Hill R BL Schoenchen						
1978-1996						
Baseline	-18.21	-178.45	-436.66	-225.00	3118.30	-436.66
Parameterization only	-3.64	-2.76	-8.44	-72.87	401.75	445.04
Flow Calibration	0.30	0.69	0.83	-2.90	-0.93	-2.80

Flow+Crop Calibration	0.30	0.69	0.83	-2.90	-0.91	-2.97
1997-2011						
Baseline	-9.65	-65.97	-190.30	113.82	3333.00	-1443.27
Flow+Crop Validation	-0.08	0.28	0.66	-97.17	-1.26	-0.38
Smoky Hill R NR Bunker Hill						
1978-1996						
Baseline	-3.65	-9.33	-24.67	528.15	495.64	-24.67
Parameterization only	-3.73	-0.61	-3.44	63.38	179.26	180.34
Flow Calibration	0.03	0.71	0.60	-44.53	-50.80	-50.82
Flow+Crop Calibration	0.00	0.71	0.60	-44.82	-50.40	-50.62
1997-2011						
Baseline	-89.58	-700.67	-1443.27	552.32	788.00	856.57
Flow+Crop Validation	-1.57	0.32	0.36	-40.60	-18.70	-17.35
Smoky Hill R at Ellsworth						
1978-1996						
Baseline	-11.21	-3.97	-10.28	345.17	345.16	316.24
Parameterization only	-3.12	-0.10	-1.60	213.80	142.02	141.19
Flow Calibration	-0.10	0.65	0.50	-53.93	-51.19	-53.88
Flow+Crop Calibration	-0.10	0.65	0.49	-51.13	-51.19	-53.88
1997-2011						
Baseline	-18.32	-36.71	-101.06	289.12	604.00	588.34
Flow+Crop Validation	-0.62	0.14	0.34	-57.34	-21.00	-15.76

3.3.4 Evaluating ecohydrological indicators performance

The SWAT model demonstrated satisfactory prerformance (i.e., NSE $\geq$ 0.5) in simulating 8 of 32 ecohydrologic indicators for the upper portion of Delaware River watershed (NR Muscota; Table 3.10(a)) using default model parameters (baseline scenario). Mean flows for four months (June, July, October, and November) and 3-, 7-, 30-, and 90-day maximum flow rates were adequately simulated even without parameretization (highlighted in gold). Parameterization did not improve the number of ecohydrologic indicators with satisfactory performance. After flow calibration, SWAT improved to satisfactory performance for April, May and August mean monthly flows, annual 90-day minimum and 1-day maximum flow rates, and median fall rate (Table 3.10(a)). Four other indicators (September, November, and Decemeber monthly flows and date of maximum flow) improved performance after flow calibration, but only to NSE $\geq$ 0.35. The uncalibrated, unparameterized SWAT model performed adequately in simulating flow rates for longer time periods (e.g., monthly flows, 90-day minimum and maximum flow rates), months in seasons with higher flow rates (early spring and fall), and for most durations of sustained maximum levels (3 to 90 days). In this watershed, the SWAT model provided robust performance in simulating high-flow-rate ecohydrologic indicators.

The uncalibrated, unparameterized (baseline) SWAT model of Delaware River watershed at Perry Lake produced satisfactory performance only in simulating 30- and 90-day maximum flow rates (highlighted in gold; Table 3-10(b)). After parameterization, the SWAT model had satisfactory performance for 13 additional ecohydrologic indicators, including all monthly flows (except January), 7-day maximum flow rate, and date of maximum flow. After flow calibration, SWAT improved to satisfactory performance for January mean monthly flow, annual 90-day minimum and 1- and 3-day maximum flow rates, and baseflow index (Table 3.10(b)). Again, the SWAT model provided robust performance in simulating high-flow-rate ecohydrologic indicators, but in this watershed parameterization was needed to achieve this level of performance.

Table 3.10 SWAT model performance (NSE) in simulating 32 ecohydrologic indicators at four levels of model calibration for a) Delaware R NR Muscota and b) Delaware River at Perry Lake. Highlighted cells show ecohydrologic indicators modeled with satisfactory performance (NSE ≥ 0.5) using default model parameters (gold), after parameterization (green), or after flow calibration (blue).

a)

	Baseline	After parameterization	After flow calibration	After flow+crop calibration
October	0.68	0.67	0.72	0.72
November	0.56	0.57	0.43	0.44
December	0.06	0.13	0.37	0.37
January	-0.05	0.04	-0.26	-0.24
February	0.06	-0.07	-2.20	-2.20
March	-0.14	-0.21	0.41	0.42
April	0.20	0.11	0.76	0.76
May	0.12	0.05	0.73	0.73
June	0.53	0.52	0.52	0.52
July	0.62	0.61	0.97	0.97
August	-2.12	-1.89	0.58	0.58
September	-0.56	-0.53	0.35	0.35
1-day min	-1.45	-0.49	-0.71	-0.71
3-day min	-1.42	-0.49	-0.74	-0.74
7-day min	-1.37	-0.56	-0.70	-0.70
30-day min	-2.92	-1.77	0.06	0.06

90-day min	-0.37	-0.09	0.52	0.51
1-day max	-0.72	-0.62	0.54	0.54
3-day max	0.63	0.66	0.72	0.72
7-day max	0.68	0.68	0.69	0.69
30-day max	0.81	0.81	0.81	0.82
90-day max	0.88	0.90	0.86	0.86
Baseflow	-0.53	-0.32	-0.82	-0.82
Date min	-8.50	-8.29	-2.47	-2.48
Date max	0.06	0.06	0.37	0.37
Lo pulse #	-6.19	-6.51	-0.61	-0.51
Lo pulse L	-0.19	-0.18	-0.13	-0.12
Hi pulse #	-22.78	-21.85	-1.44	-1.30
Hi pulse L	-1.43	-1.41	-0.48	-0.46
Rise rate	-0.01	-0.07	-11.53	-12.25
Fall rate	0.01	0.01	0.58	0.57
Reversals	-118.96	-124.41	-13.38	-13.38
Number of improved indicators compared to baseline		0	6	6

b)

Year	Baseline	After Parameterization	After flow calibration	After flow+crop calibration
October	0.19	0.94	1.00	1.00
November	0.11	0.64	0.86	0.86
December	0.26	0.75	0.98	0.96
January	0.15	0.26	0.98	0.98
February	0.26	0.66	0.98	0.98
March	-0.19	0.49	0.98	0.95
April	0.06	0.81	0.84	0.83
May	0.31	0.51	0.93	0.93
June	0.11	0.95	0.99	0.97
July	-0.07	0.74	0.94	0.83
August	0.23	0.98	0.99	0.99
September	-0.16	0.77	0.73	0.74
1-day min	-28.90	-9.17	-0.32	-0.20
3-day min	-25.46	-6.84	0.34	0.16
7-day min	-27.76	-8.28	0.36	0.36
30-day min	-33.67	-14.44	0.29	0.31
90-day min	-0.55	0.25	0.94	0.86
1-day max	-56.39	-26.47	0.98	0.98
3-day max	-5.94	-2.56	0.99	0.99

7-day max	0.37	0.73	0.99	0.99
30-day max	0.75	0.89	0.96	0.96
90-day max	0.70	0.82	0.96	0.95
Baseflow	-0.77	0.16	0.77	0.73
Date min	-0.58	-0.53	-0.24	-0.51
Date max	-0.01	0.52	0.72	0.72
Lo pulse #	-5.13	-0.58	-0.11	-0.48
Lo pulse L	-0.30	-0.05	-0.16	-0.22
Hi pulse #	-34.52	-13.20	0.14	0.02
Hi pulse L	-1.93	-1.02	-0.62	-0.50
Rise rate	-0.17	-0.41	-0.48	-0.38
Fall rate	-0.52	-0.91	-1.00	-0.95
Reversals	-4.92	-2.84	-1.66	-1.73
	Number of improved indicators compared to baseline	15	20	20

The SWAT model of Kanopolis Lake watershed produced similar results overall, but had lower model performance for most ecohydrologic indicators and fewer indicators that reached a satisfactory level of performance. For the western three subwatersheds (Table 3.11(a,b,c)), no ecohydrologic indicators were simulated with satisfactory performance using SWAT default parameters or after careful parameterization. Parameterization and flow calibration produced satisfactory model performance for several ecohydrologic indicators in several subwatersheds: mean July monthly flow, and annual 30- and 90-day maximum flow rates in Big Creek near Hays (Table 3.11(a)); annual 3-, 7-, 30- and 90-day maximum flow rates, and fall rate in Smoky Hill River near Bunker Hill (Table 3.11(c)); and mean July monthly flow, and annual 3-, 7- and 30-day maximum flow rates in Smoky Hill River at Ellsworth (Table 3.11(d)). Although the SWAT model simulated fewer ecohydrologic indicators with an adequate level of performance in the Kanopolis Lake watershed, the indicators that were simulated satisfactorily were those associated with higher flow rate periods.

Table 3.11 SWAT model performance (NSE) in simulating 32 ecohydrologic indicators at four levels of model calibration for a) Big C NR Hays b) Smoky Hill R BL Schoen c) Smoky Hill R NR Bunker Hill, and d) Smoky Hill R at Ellsworth. Highlighted cells show ecohydrologic indicators modeled with satisfactory performance (NSE ≥ 0.5) using default model parameters (gold), after parameterization (green), or after flow calibration (blue).

a)

Year	Baseline	After Parameterization	After flow calibration	After flow+crop calibration
October	-13.06	-13.06	-0.42	-0.48
November	-5.50	-5.50	-0.76	-0.79
December	-6.59	-6.59	-0.58	-0.69
January	-0.69	-0.69	-0.80	-0.88
February	-0.73	-0.73	-1.08	-1.15
March	-0.74	-0.74	-1.44	-1.43
April	-0.83	-0.83	-0.74	-0.74
May	-5.21	-5.21	-0.38	-0.40
June	-11.19	-11.19	-0.60	-0.61
July	-0.06	-0.06	0.48	0.49
August	-2.95	-2.95	-0.18	-0.18
September	-16.23	-16.23	-0.32	-0.34
1-day min	-0.43	-0.43	-0.41	-0.41
3-day min	-0.71	-0.71	-0.43	-0.43
7-day min	-0.88	-0.88	-0.47	-0.47
30-day min	-1.30	-1.30	-0.58	-0.59
90-day min	-7.56	-7.56	-0.66	-0.70
1-day max	-36.59	-36.59	-4.42	-4.43
3-day max	-9.54	-9.54	-0.48	-0.48
7-day max	-4.05	-4.05	0.39	0.39
30-day max	-5.75	-5.75	0.61	0.61
90-day max	-10.51	-10.51	0.69	0.69
Baseflow	-1.17	-1.17	-1.17	-1.17
Date min	-2.08	-2.08	-0.65	-0.64
Date max	-1.17	-1.17	-0.19	-0.21
Lo pulse #	-1.45	-1.45	-1.45	-1.45
Lo pulse L	-0.46	-0.46	-0.46	-0.46
Hi pulse #	-18.95	-18.95	-18.06	-20.66
Hi pulse L	-0.31	-0.31	-0.09	0.16
Rise rate	-40.18	-40.18	-5.18	-10.69
Fall rate	-51.05	-51.05	-1.88	-3.08
Reversals	-10.89	-10.89	-6.71	-8.54

Number of improved indicators compared to baseline			3	3

b)

Year	Baseline	After Parameterization	After flow calibration	After flow+crop calibration
October	-3.95	-0.62	-0.22	-0.22
November	-7.10	-0.16	-0.17	-0.17
December	-13.80	-0.34	-0.31	-0.31
January	-1.49	-0.09	-0.39	-0.39
February	-4.29	-0.36	-0.38	-0.38
March	-0.31	-0.32	-0.34	-0.34
April	-0.40	-0.29	-0.28	-0.28
May	-0.81	-0.25	-0.33	-0.33
June	-0.92	-0.38	-0.40	-0.40
July	-0.26	-1.22	-0.37	-0.37
August	-0.18	-9.56	-0.86	-0.86
September	-0.78	-2.36	-0.24	-0.24
1-day min	-0.28	-0.28	-0.28	-0.28
3-day min	-0.28	-0.30	-0.28	-0.28
7-day min	-0.27	-0.30	-0.27	-0.27
30-day min	0.03	-0.34	-0.32	-0.32
90-day min	-4.08	-0.11	-0.36	-0.36
1-day max	-15.79	-0.14	-0.30	-0.30
3-day max	-9.12	0.05	-0.34	-0.34
7-day max	-7.82	0.01	-0.37	-0.37
30-day max	-3.71	-0.08	-0.45	-0.45
90-day max	-1.28	-0.11	-0.43	-0.43
Baseflow	-0.26	-0.28	-0.26	-0.26
Date min	-1.98	-4.44	-0.16	-0.16
Date max	-0.54	-1.19	-0.54	-0.54
Lo pulse #	-0.68	-0.68	-0.68	-0.68
Lo pulse L	-0.04	-0.04	-0.04	-0.04
Hi pulse #	-5.30	-4.51	-1.50	-1.57
Hi pulse L	-0.10	-0.30	-0.31	-0.31
Rise rate	-89.93	-1.65	-21.77	-26.97
Fall rate	-193.01	-1.82	-2.64	-3.16
Reversals	-0.82	-1.73	-1.97	-1.94
Number of improved indicators compared to baseline		0	0	0

c)

Year	Baseline	After Parameterization	After flow calibration	After flow+crop calibration
October	-72.26	-16.95	-0.29	-0.28
November	-59.09	-14.70	-0.42	-0.43
December	-83.05	-25.16	-0.50	-0.49
January	-24.09	-10.37	-0.96	-0.95
February	-3.74	0.36	-0.14	-0.13
March	0.02	0.27	-0.49	-0.50
April	-0.42	0.31	-0.44	-0.44
May	-39.72	-7.29	-0.76	-0.76
June	-71.66	-10.03	-0.54	-0.54
July	-9.42	-0.84	0.76	0.77
August	-16.79	-4.57	-0.22	-0.25
September	-98.10	-24.37	-0.55	-0.55
1-day min	-3.04	-2.97	-0.94	-0.94
3-day min	-3.12	-2.91	-0.93	-0.93
7-day min	-3.77	-3.32	-0.93	-0.93
30-day min	-8.32	-5.24	-0.73	-0.73
90-day min	-100.61	-21.21	-0.80	-0.80
1-day max	-38.50	-8.18	-0.07	-0.05
3-day max	-11.73	-1.02	0.57	0.56
7-day max	-10.76	-0.26	0.60	0.59
30-day max	-12.01	-0.48	0.64	0.63
90-day max	-30.72	-3.41	0.58	0.57
Baseflow	-1.95	-1.91	-2.02	-2.02
Date min	-2.27	-2.11	-0.18	-0.18
Date max	-0.16	-1.22	-0.72	-0.72
Lo pulse #	-1.53	-1.53	-1.53	-1.53
Lo pulse L	-0.62	-0.62	-0.62	-0.62
Hi pulse #	-25.57	-10.92	-7.51	-7.52
Hi pulse L	-0.22	-0.15	-0.17	-0.17
Rise rate	-547.60	-54.78	0.01	0.05
Fall rate	-705.23	-139.11	0.56	0.51
Reversals	-25.26	-20.91	-2.84	-2.86
Number of improved indicators compared to baseline		0	5	5

d)

Year	Baseline	After Parameterization	After flow calibration	After flow+crop calibration
October	-85.91	-29.35	-0.51	-0.50

November	-33.24	-13.19	-0.40	-0.40
December	-36.00	-13.97	-0.22	-0.23
January	-12.28	-7.50	-0.55	-0.55
February	-0.87	0.48	-0.12	-0.14
March	0.34	0.64	-0.44	-0.45
April	-0.31	-0.17	-0.50	-0.50
May	-9.11	-0.80	-0.52	-0.55
June	-47.72	-10.32	-1.12	-1.12
July	-0.80	0.65	0.56	0.54
August	-12.36	-3.68	-0.26	-0.27
September	-35.93	-8.93	-0.23	-0.23
1-day min	-1.98	-1.17	-1.08	-1.08
3-day min	-2.98	-1.15	-1.06	-1.06
7-day min	-8.28	-0.99	-1.11	-1.11
30-day min	-17.91	-5.12	-1.31	-1.31
90-day min	-80.32	-10.70	-0.58	-0.59
1-day max	-25.52	-7.35	-0.04	-0.01
3-day max	-7.32	-1.47	0.51	0.50
7-day max	-5.31	-0.28	0.60	0.59
30-day max	-4.59	-0.43	0.50	0.50
90-day max	-11.77	-1.94	0.30	0.29
Baseflow	-0.76	-0.72	-0.83	-0.83
Date min	-3.68	-3.96	0.27	0.27
Date max	-0.79	-1.07	-0.58	-0.57
Lo pulse #	-7.11	-4.15	-1.08	-1.08
Lo pulse L	-0.14	-0.24	-0.37	-0.37
Hi pulse #	-23.24	-13.87	-5.10	-5.20
Hi pulse L	-0.67	-0.54	-0.35	-0.40
Rise rate	-55.00	-19.11	-0.01	-0.02
Fall rate	-334.14	-84.94	0.39	0.29
Reversals	-39.51	-29.74	-7.53	-7.40
	Number of improved indicators compared to baseline	3	4	4

These results show that the SWAT model adequately simulates most high-flow-rate ecohydrologic indicators. It can be also noted that in some cases, streamflow needs to be calibrated at daily scale at least to the “good” level (NSE $\geq$ 0.65) for adequate high-flow-rate ecohydrological indicator performances. However, the effect of calibration and parameterization varies among subwatersheds. Perry Lake watershed performance on ecohydrological simulation was better than Kanopolis Lake watershed mainly due to its level of calibration. The density of precipitation gages might also have influence the model performances. For Perry Lake watershed 8 precipitation gages were used over 2,924 km2 area and in Kanopolis Lake watershed it was 20 gages over 20,291 km2. In the case of Perry Lake watershed the density of precipitation gages (8 gages/ 2,924 km2) might be strong enough to represent precipitation variation. Especially with higher variation in weather, the number of stations used to model watershed precipitation might not be sufficient to represent precipitation spatial variability of Kanopolis Lake watershed.

3.4 Conclusion

Overall, SWAT was able to predict streamflow and crop yields for corn, soybean, winter wheat and grain sorghum with reasonable accuracy and over a range of climatic conditions. The model performance increased with sequential integration of parameterization, flow and crop calibration. Tedious parameterization helps to improve model performance for flow even without any calibration. However, the greatest NSE and lower PBIAS for flow were achieved with flow and crop calibration in most cases. Greatest changes in PBIAS were observed at daily and annual scale. Adjustment to four streamflow and four groundwater parameters improved SWAT model performance above satisfactory level (Moriasi et al., 2007). For corn, soybean, winter wheat and grain sorghum, four crop parameters required slight modifications over model-default values to allow accurate simulation. Each crop was validated in a separate county to confirm the change in growth parameters.

It can be concluded that SWAT is suitable for simulating high-flow-rate ecohydrologic indicators. However ecohydrologic indicators performance is highly depend on the level of calibration and parameterization. An NSE above good level and PBIAS closer to zero at daily scale appeared to provide the most consistent model performance across watersheds. The effect of calibration and parameterization on ecohydrologic indicators performance varies between watersheds and among subwatersheds.

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Chapter 4 - Evaluating Soil and Water Assessment Tool (SWAT) simulation of hydro-ecologically relevant indicators

Abstract

Hydrological models have been widely used to simulate baseline conditions and the impacts from alternative conditions that result from changes such as climate, management and land use change. The Soil and Water Assessment Tool (SWAT) is a robust watershed model used to assess anthropogenic and climate change influences on water resources worldwide. However, the application of SWAT to simulate ecohydrologic indicators and their suitability for predicting ecological responses has not been assessed. The goal of this study was to assess the suitability of SWAT to simulate ecohydrological indicators. The results show SWAT was able to reproduce water resource indicators (WRIs), such as monthly, seasonal, and annual flows, and center of timing of annual flows, and Indicators of Hydrologic Alteration (IHA), including monthly flows, 90-day minimum flow, 1- to 90-day maximum flows, baseflow, date of maximum flow, high-flow pulse count, and fall rate. However, accurate simulation of winter month flows, 90-day minimum flow, baseflow and fall rate needed an extensive model calibration. The hydrologic model structure and parameter uncertainties caused difficulty in simulating low flows and streamflow changes (fall and rise rates, and reversals). Based on these results, it can be concluded that SWAT model provided robust performance in simulating high-flow-rate ecohydrological indicators and simulation of low-flow-rate ecohydrological indicators is needed extensive calibration.

4.1 Introduction

Hydrological models are commonly used to assess responses of the hydrologic systems to changing stressors. They have been used to address water quality issues, ecological flow assessment, and alterations to streamflow as a result of land-use and climate change. Hydrological models can represent a wide range of environmental processes and temporal and spatial process scales. Hydrological models have been widely used to simulate baseline conditions and the impacts from alternative conditions that result from changes such as climate, management and land use change.

The Soil and Water Assessment Tool (SWAT) is a continuous time, physical, deterministic hydrologic model developed in the early 1990s by the USDA Agricultural Research Service (ARS; Arnold et al., 1998; Neitsch et al., 2004, 2005). Since its development SWAT has undergone continued review and expansion of capabilities. It uses weather, soil properties, topography, vegetation and land management characteristics to predict the impact of land management practices on water, sediment and agricultural chemical yields. The SWAT model has been accepted as a robust watershed model (Arnold and Allen., 1996; Arnold et al., 1999; Abbaspour et al., 2007; Gassman et al., 2007) and has been used to assess anthropogenic and climate change influences on water resources worldwide. The model is often used to examine the effects of agricultural practices on water quality, quantify environmental benefits of conservation practices, perform Total Maximum Daily Load (TMDL) analyses and quantify the impacts of climate change (Gassman et al., 2007). During these applications, SWAT has been used to simulate reference conditions and alternative scenarios, and to simulate the hydrological and water quality response. The monthly, seasonal and annual flows, and magnitude and timing of peak flows are the common water resource indicators assessed in these applications (Eckhardt and Ulbrich, 2003; Franczyk and Chang, 2008; Guo et al., 2008; Jha, 2005; Van Liew et al., 2005). Detailed descriptions of the SWAT model (Neitsch et al., 2011; Arnold et al., 2012) and numerous model applications (Gassman et al., 2007; Douglas-Mankin et al., 2010) are widely available. .

Douglas-Mankin et al. (2010) indicate the need for integration of SWAT with ecological studies. Douglas-Mankin et al. (2010) and Tuppad et al. (2011) introduced two special collections with 35 articles that presented current developments and applications of SWAT. None of those articles nor more than 250 articles reviewed by Gassman et al. (2007) presented ecohydrological or ecosystem services assessments. Siebenmorgen (2010) used SWAT to calculate numerous hydrologic indicators, and then applied them in an assessment of climate-change impacts (Sheshukov et al., 2011a). Logsdon and Chaubey (2013) connected SWAT hydrologic and water quality results with the ecosystem services. They used SWAT output to quantify ecosystem functions that related to five ecosystem services: fresh water provision, food provision, fuel provision, erosion regulation and flood regulation. However, to the author’s knowledge, SWAT has not been rigorously tested for simulation of ecohydrologic indicators and ultimately for application in study of ecohydrological response to land or climate change.

The amount and variability of discharge are considered as most influential variables in the stream ecosystem (Poff and Ward, 1990; Bunn and Arthingtom, 2002) and flow regime alteration threatens river ecological sustainability (Richter et al., 1996). The water resource indicators (WRIs), such as monthly, seasonal, and annual flows, and center of timing of annual flows, and the Indicators of Hydrologic Alteration (IHA) (Richter et al., 1996; The Nature Conservancy, 2009) are considered as the most important hydrological factors to be considered in ecological studies (Risbey and Entekhabi, 1996; Poff et al., 1997; Dibike and Coulibaly, 2005; Merritt et al., 2006; Toth et al., 2006; The Nature Conservancy, 2009; Shrestha et al., 2013). These indicators provide detailed representations of the hydrologic regime and characterize intra- and inter-annual variability in water conditions, including the magnitude, frequency, duration, timing and rate of change of flows. Richter et al. (1996) called these indicators as biologically relevant parameters and described as the commonly used hydrological variables in limnology due to their great hydrological relevance.

Therefore, the current study attempted SWAT model performance in simulating WRIs and IHAs. The goal of this study was to assess the suitability of SWAT to simulate ecohydrological indicators. The objective of this study are to assess the applicability of SWAT model for simulating WRIs and IHAs at subwatershed and watershed scales ; and to evaluate calibration uncertainty in simulating magnitude and timing of flow at subwatershed and watershed settings. The suitability was determined through a comparison of indicators extracted from the observations to the simulated flows.

4.2 Methods

4.2.1 Study area

The Perry Lake watershed (Figure 4.1), located in the northeastern of Kansas River Basin (KRB), was considered appropriate because of its medium area (2,924 km^2) and and spatial variability in biophysical factors (e.g., soil quality, water availability, land use), which provides a range of conditions for hydroecological study. The Perry Lake watershed is an 8-digit HUC (10270103) watershed and drains into Perry Reservoir. Perry Lake is a federal reservoir and maintained by the U.S. Army Corps Engineers for flood control, recreation and water supply. Outflow from Perry Lake continues south until it reaches a confluence with the Kansas River. The watershed covers parts of 2 eco-regions: Western Corn Belt (85.5% and Central Irregular

Palins(145%), in Northeastern part of Kansas State. This region has an average annual total precipitation of 762 mm and around 82% percentage of annual total (about 625 mm) falls during the six-month crop growing months, April to September. The annual mean temperature for this region ranges from 11.1 ^{o}C to 12.2 ^{o}C (52 ^{o}F to 54 ^{o}F) (Sophocleous, 1998). Elevation of the Perry Lake watershed ranges from 252 m to 428 m with an average slope of 5.2%. Soils in the watershed are mostly (≈77%) fine-textured (silt and clay), has moderately high (C hydrologic soil group) and high (D hydrologic soil group) runoff potential and consist primarily of Pawnee clay (30.5%), Grundy silt clay (30.0%), and Kennebec silt (16.1%) soil groups. Agriculture is the dominant land use (63.7%), followed by range land (15.4%) and forest land (12.4%). The primary agricultural crops are hay (32.3%), dry land corn (14.0%) and soybean (13.4%).

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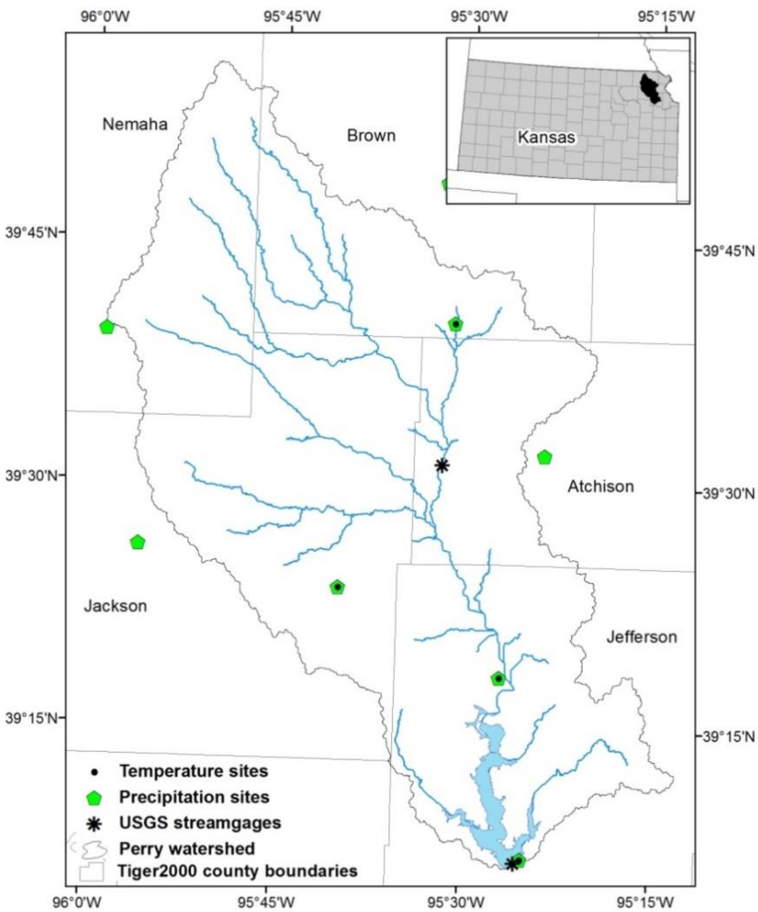
Figure 4.1 Map of Perry Lake watershed with overlay of counties used for crop calibration, weather stations (temperature and precipitation) and USGS gages locations used for flow calibration



4.2.2 Watershed modeling

4.2.2.1 Model set-up

The SWAT 2010 beta version, which is compatible with ArcGIS10, was used to build a model of Perry Lake watershed. The Perry Lake watershed was delineated into 38 sub-watersheds and distributing the SWAT hydrological response units (HRU) based on digital elevation model (30 m DEM), 2005 Kansas Level IV map land cover (Kansas Applied Remote Sensing (KARS) Program) and STATSGO soil dataset from SWAT database. Slope classes were calculated using the DEM. A total of 3,839 HRUs, each representing specific combinations of soil, slope, and land-use, were generated from these data. Weather data (daily maximum and minimum temperature and precipitation) for this study were obtained from the National Climatic

Data Center (NCDC) Interactive Map Application for daily datasets accessing the Global Historical Climatology Network (GHCN) for the period starting from January, 1975 to December, 2011. GHCN daily is a composite of climate records from numerous sources that were merged and then subjected to a suite of quality assurance reviews. Daily values for other three weather variables (Solar radiation, relative humidity, and wind speed) were generated by SWAT. Crop Data Layer (CDL) data from the United States Department of Agriculture (USDA) National Agricultural Statistics Services (NASS) from 2008-2010 and National Land Cover Database (NLCD) layer from 2006 were overlaid to determine dominant crop rotations (Srinivasan et al., 2010). Continuous corn, continuous soybean and Corn-soybean rotation are the major cropping pattern observed in this study area. Other cropland management schedules including tillage practices and fertilizer application rates (Table 4.1) were obtained through K-State Agronomist (Nathan Nelson, Kansas State University, personal comm., 2013) and K-State Extension documents. Applications of nitrogen (lbs) and P_2O_5 (lbs) fertilizer rates were estimated using recommended rates per acre corresponding to a bushel yield goal (Leikam et al., 2003). During calculations the soil organic matter content was assumed as 2.5%. The NASS county-level yield averages (bu ac^{-1}) from 2005 – 2010 (+10% to be conservative) were used to calculate yield goal to determine nutrient application rates per acre for both irrigated and non-irrigated corn, soybeans, sorghum and winter wheat. Thirty percent of fertilizers were applied to top 10 mm of soil. Auto-irrigation management was applied at an efficiency of 0.7 to land-use classes identified as irrigated cropland and 0.9 plant stresses. Plant stresses threshold triggers irrigation and it ranges from 0.0 to 1.0 where 0.0 indicates no plant growth due to water stress and 1.0 indicates no plant growth reduction due to water stress. The recommended plant stress threshold is between 0.9 and 0.95 (Neitsch et al., 2011). Herbicides were used on crops but were not included in management practices, because pest or pesticide impacts were not modeled. Time-based management operations were used instead of the default method, which used the fraction of PHU.

Table 4.1 Plant and harvest dates and N and P fertilizer application amounts (kg ha-1) and tillage practices for corn and soybean

Management practices	Corn	Soybean
Planting Date	April 30	May 15
Harvesting Date	October 10	October 10
Fertilizer (Date/Amount)		
Nitrogen	[1]May 1; 170 kg ha^{-1}	None
Phosphorus	[2]May 1; 45 kg ha^{-1}	[3]May 18; 23 kg ha^{-1}
Tillage	Conventional fall tillage, disc + 3-4 field cultivators	Disc + 4 field cultivators

[1] 1.25 lb-N bu^{-1} corn × (county average corn yield [bu ha^{-1}] + 10% for yield goal)

[2] 0.33 lb-P_2O_5 bu^{-1} corn × (county average corn yield [bu ha^{-1}] + 10% for yield goal)

[3] 0.5 lb-P_2O_5 bu^{-1} soybean × (county average soybean yield [bu ha^{-1}] + 10% for yield goal)

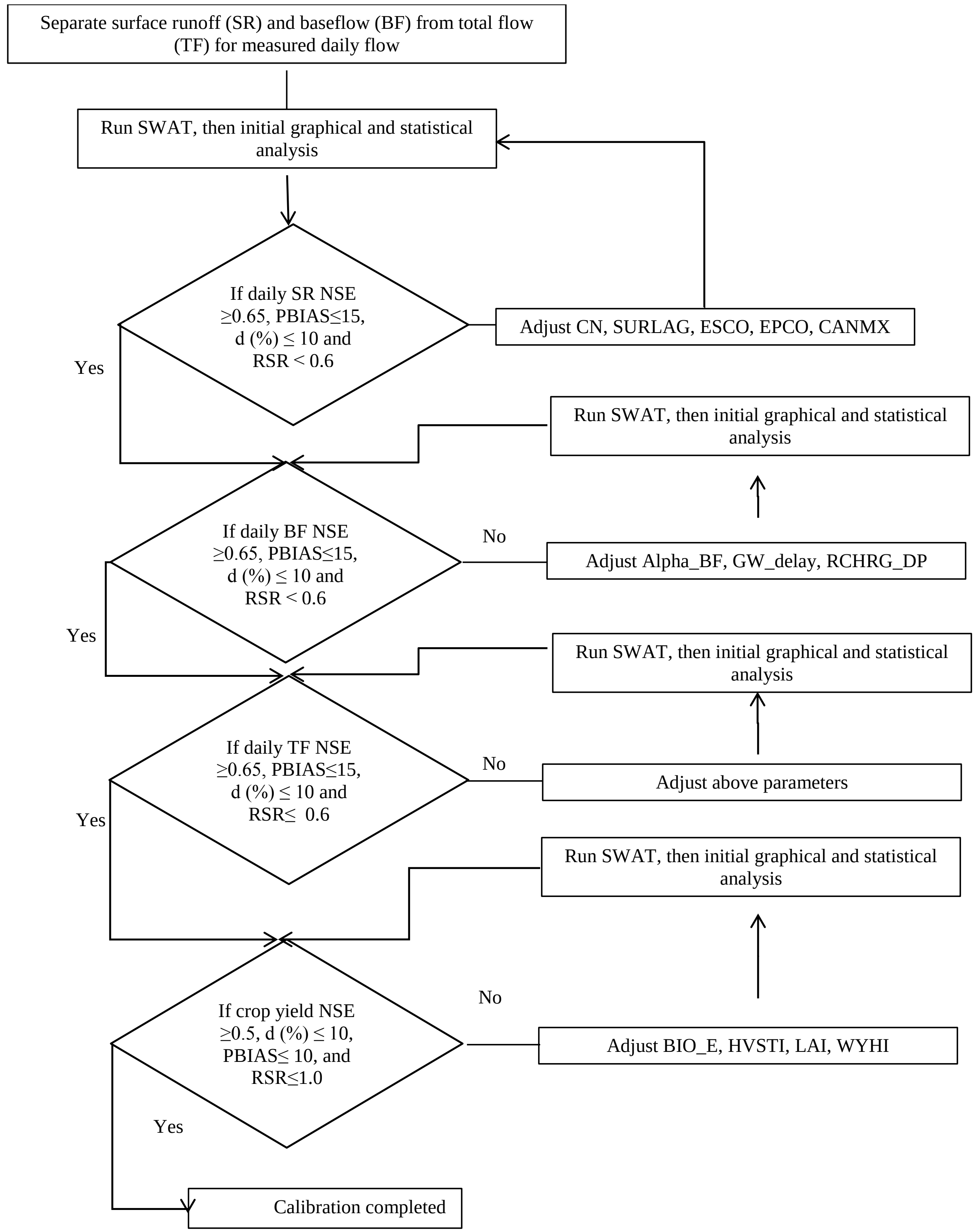
4.2.2.2 Model calibration

A multi-objective function using the three quantitative statistics: Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR) was used in this study. These are the standard statistics recommended in model evaluation by Moriasi et al. (2007) and commonly used in SWAT applications (Douglas-Mankin et al., 2010).

A multistep manual calibration procedure for flow components (baseflow, streamflow and total flow) and crop is shown in Figure 4.2. Initially, baseflow was separated from surface flow for both observed and simulated streamflow using an automated digital filter technique (Nathan and McMahon, 1990; Arnold and Allen, 1999). Second iteration in baseflow filter program, which comprises approximately 25-34% baseflow of streamflow was used in this study. This value closely resembles the baseflow/ total streamflow fraction presented by Wolock (2003). The model parameters were adjusted over the recommended ranges until the daily model output fall within 10% of average measured values and then acceptable statistics were reached. If all model parameters were adjusted to the limit and the calibration criteria were still not met, then calibration was stopped for that output and then the best set of parameters until then was selected in the final model.

Streamflow was first calibrated at Delaware R NR Muscota (USGS 06890100) and at the watershed outlet from Delaware R BL Perry Dam (USGS 06890900) (USGS, 2013). Surface runoff and baseflow were continued at daily time step until average measured and simulated surface runoff were within 10% , daily NSE reached a threshold of ≥ 0.65 (good level), PBIAS ≤ 15% (good level) and RSR ≤ 0.60 (good level). If all the conditions met at one station and the calibration procedure was continued until other station meet the criteria. Finally a local optimum parameter set which yielded the higher NSE, lower RSR and PBIAS statistics at both stations was used in the model. If all model parameters were adjusted to the limit and the calibration criteria were still not met, then calibration was stopped for that output and best set better statistical performance with higher NSE, lower RSR and PBIAS of parameters until then were used in the model. While calibrating baseflow, surface flow was continually rechecked as the baseflow calibration variables also affect surface runoff. At the end of baseflow and surface runoff calibration, the total streamflow statistics were checked with same criteria. Finally, crop was calibrated and continued until NSE ≥ 0.50, RSR ≤ 1.0 and PBIAS ≤ 10%. The final parameter values after each calibration and tested ranges are presented in Table 4.1.

Figure 4.2 Calibration procedure for flow and crop yield (based on calibration chart for SWAT from Santhi et al., 2001).



NSE=Nash-Suttcliffe efficiency
RSR=RME/OBSTDEV ratio
d=percent difference between measured and simulated values
pBias=Percent bias

Table 4.2 Calibration procedure for flow and crop yield (based on calibration chart for SWAT from Santhi et al., 2001).

Parameters	Definition	Default value	Tested range		Magnitude Of tested value	Final value
Flow						
ICN	Daily curve number calculation method	antecedent soil moisture condition			0 or 1	plant evapotranspiration
CNCOEF	Plant ET CN Coefficient	1.0	0.5	-1.5	±0.1	1.3
CN2.mgt	SCS runoff curve number for moisture condition 2	35-98	-15% ×CN2[1]	15% ×CN2[1]	±1%	-5% ×CN2 for all sub-watershed above Perry at Delaware +12% ×CN2 for all sub-watershed below Perry at Delaware
ESCO.hru	Plant evaporation compensation factor	0.95	0	1	±0.05	0.6 all HRU
SURLAG.bsn	Surface runoff lag coefficient	4	0	10	±1	1
ALPHA_BF.gw	Baseflow alpha factor (days)	0.048	0	1	±0.001	0.10 all HRU
GW_DELAY.gw	Groundwater delay (days)	31	0	500	±5	0 all HRU
RCHRG_DP	Aquifer fraction coefficient	0.05	0	0.5	±0.01	0
CANMX	Maximum canopy	0				Agricultural and

	storage					pasture areas 3 Forests 8 Urban 1.5
Crop						
BIO_E	Biomass-energy ratio					
	Corn	39	40	25	±1	35
	Soybean	25	28	20	±1	20
HVSTI	Harvest index					
	Corn	0.50	0.60	0.20	±0.01	0.46
	Soybean	0.31	0.30	0.20	±0.01	0.31
WYHI	Lower limit of harvest index					
	Corn	0.30	0.35	0.40	±0.01	0.35
	Soybean	0.01	0.30	0.01	±0.01	0.20
LAI	Leaf area index					
	Corn	5	4	6	±0.5	5
	Soybean	3	2	5	±0.5	2

4.2.2.2.1 Flow

As SWAT is a deterministic hydrologic model that simulates many interactive processes, many parameters are involved in simulating multiple processes. When surface runoff related parameters are adjusted, they directly change surface runoff and indirectly affect other hydrological and related process. Therefore, streamflow was calibrated first (Figure 4.2). Two USGS gage stations within the Perry Lake watershed, Delaware R NR Muscota and Delaware R at Perry Lake, were used for streamflow calibration. Data from 1978-1996 were selected for calibration period. Data from 1997-2011 were used as validation period. During calibration and validation period, data from 1975-77 and 1994-1996 were used as spin-up period. Both calibration and validation periods include wet, moderate and dry periods (Arnold et al., 2012). The runoff curve number (CN2) was first reduced within 5% from the default values to reflect conservation tillage practices and soil residue cover conditions in the sub-basins above Delaware River NR Muscota (Arabi et al., 2007; Table 4.2). The CN2 value was increased in downstream watersheds to reflect improved landuse through CRP. Second, the surface runoff lag coefficient (SURLAG) was adjusted to allow the surface runoff to reach the river in a day. Third, the baseflow recession factor (ALPHA_BF) and the groundwater delay (GW_DELAY) were adjusted so that there is no delay for recharging aquifer and increases groundwater flow to the reach. Finally, other flow related parameters such as maximum canopy storage (CANMX), soil evaporation compensation factor (ESCO), daily curve number calculation method (ICN) and plant ET CN Coefficient (CNCOEF) were adjusted to match the simulated and observed flows (Table 4.2). Guse et al. (2014) reported values were used for CANMX to represent the water capacity of the canopy storage. Reducing ESCO allows reducing water yield by increasing evapotranspiration from the deeper soil layers. Changing ICN method to plant evapotranspiration rather than available moisture capacity to adjust antecedent soil moisture condition and increased CNCOEF reduced evapotranspiration and decreased runoff at acceptable range. Default Potential evapotranspiration (PET) method, the Penman/Monteith Method, was used to model ET as it provided better results in this study.

4.2.2.2.2 Crop Yield

During crop yield calibration, crop yield parameters were adjusted within acceptable range to achieve highest NSE, lower bias (at least NSE ≥ 0.50 and PBIAS ≤ 10%) and RSR is ≤ 1.0. Following crop calibration, crop specific ET and annual basin ET values were verified as plant growth and biomass production can have an effect on water balance (Nair et al., 2011). The primary agricultural crops of Perry Lake watershed, non-irrigated corn and soybean, were selected for county level calibration.

Jackson and Brown Counties corn and soybean crop yields from 1996 to 2009 were used for calibrating the crop sub-model (Figure 4.1). Initially, simulated corn and soybean crop yields were much higher than USDA-NASS published Jackson and Brown County values. Corn crop yields were calibrated by adjusting each crop's biomass energy factor (Bio_E), harvest index for optimal growing condition (HVSTI), maximum leaf area index (BLAI) and the lower limit of harvest index (WYHI) in the SWAT crop database file. These are the four commonly used crop calibration parameters (Nair et al., 2011; Sinnathamby et al., 2014). Bio_E for corn was reduced from 39 to 35 to correspond more closely with published crop yields for Jackson and Brown County. In case of soybean Bio_E also was reduced from the default value. This adjustment was mainly made to accommodate potential impacts of climate and management stress factors on yields (Baumgart, 2005). In addition, corn HVSTI was reduced from 0.50 to 0.46 to account for generally less production from dry land (non-irrigated) corn production systems. Finally, WYHI was adjusted to improve the yield results based on SWAT water stress and nutrient stress calculations (Table 4.2).

4.2.2.3 Model validation

During all validation process, the model parameters were set to final calibrated value without any change and the results compared to the remaining observational data to evaluate model prediction. The streamflow measurements from 1996 to 2011 were selected for validation for Delaware R NR Muscota and Delaware R at Perry Lake. Nemaha, Atchison and Jefferson Counties yields were used for crop yield validation. The same statistical measures were used to evaluate the model simulations in both conditions.

4.2.3 Model evaluation for hydrological application

Typically larger SWAT models are calibrated at watershed-outlet stream gage locations for streamflow ("blue water flow"; Schuol et al., 2008) to demonstrate their hydrological performance. The additional step of calibrating for crop yield is uncommon or has rarely been reported in SWAT studies (Baumgart, 2005; Gassman et al., 2007). This is particularly true at the large/medium river-basin scale. When stream gages are available, model calibration and validation for streamflow is relatively straightforward, due to the accuracy and availability of these data (Srinivasan et al., 2010). But assessing model performance by streamflow alone may not appropriately represent all aspects of watershed hydrology. Lu et al. (2008), for example, reported that crop biomass production and yield were more relevant to the water balance than rainfall-runoff processes. Additional model performance assessment of plant processes would help reduce overall model uncertainty and provide greater confidence in watershed-scale hydrologic results.

Srinivasan et al. (2010) used four-digit HUC basin level crop yield to represent evapotranspiration ("green water flow"; Schuol et al., 2008) and soil moisture ("green water storage"; Schuol et al., 2008) required for vegetative growth in addition to streamflow for evaluating large ungaged watersheds. Better modeling of crop growth and development characteristics not only improves simulation of hydrological, but also soil erosion and nutrient transport processes. This may be particularly true in agricultural watersheds. For example, Anand et al. (2007) demonstrated that calibration of runoff curve number (CN) at the field scale in both SWAT (Arnold et al., 2012) and ADAPT (Agricultural Drainage and Pesticide Transport;

Gowda et al., 2012: an extension of GLEAMS, Knisel and Douglas-Mankin, 2012) was closely related to plant ET through its influence on soil water. Even though calibration of the crop simulation components of watershed models demands intensive input and output comparison data and additional modeling effort, the resulting improvement in simulation of the crop elements and interactions may be critical to describing the hydrological system.

Similar to Srinivasan et al. (2010), the crop yield and streamflow were evaluated in this study. To further ensure crop water usage over the growing season (Nair et al., 2011) was modeled appropriately, seasonal distributions of ET and LAI for non irrigated corn, and soybean, "slope of yield vs. ET" and "Threshold ET" for a randomly selected corn and soybean HRUs were analysed. The "slope of yield vs. ET" is important identity that assess crop responses to water use. The "Threshold ET" is the ET value when crop yield is zero. Since there are no references available on ET for dry land crops for these region, Stone and Schlegel (2006), which reported results from a study in western Kansas under limitted irrigation, was used.

4.2.3 Model evaluation for ecohydrologic application

SWAT model outputs were used to estimate six WRIs and 32 IHAs (Table 4.3) and model performance was assessed in comparison to the use of observed streamflow to estimate these same WRIs and IHAs. Six WRIs were first calculated for the analysis. The spring month mean was calculated by averaging the standardized runoff from March to May. Also summer, autumn and winter values were calculated by averaging June to August, September to November and December to February, respectively. The center of timing (CT) of annual flow (day of occurrence of 50% annual flow between October and September) was calculated from

$$CT = \sum(t_i\, q_i) / \sum q_i, \quad (4.1)$$

where t_i is time in days from October 1 (water year) and q_i is the corresponding standardized runoff for water year day i.

In addition, a set of 32 IHA (Table 4.3) variables were calculated using Nature Conservancy's IHA software v. 7.1 (The Nature Conservancy, 2009) for hydrological years (1st October to 30th September). The IHA software was developed in early 1990s and has been used throughout United States (U.S.) and worldwide for hydrologic evaluation (The Nature Conservancy, 2005 and 2007). The Nature Conservancy (2006) recommended 20 years of data as a baseline requirement for hydrologic index analysis. In this study, 33 years of discharge records (1978-2011) were used for analysis. Because of the skewed nature of hydrological datasets non-parameteric statistics was used. This results median values for all IHA parameters except 1-day to 90- day minimums and maximums. The 1-day to 90- day minimums and maximums were calculated from moving averages of every possible period. If there is multiple periods have same value, the earliest will be reported. The 25th and 75th percentile flow was used as threshold for low-flow and high-flow pulse calculations. The flow reversals are calculated by dividing the hydrological record into 'rising' and 'falling' periods, which correspond to periods in which daily changes in flows were either positive or negative, respectively. The number of zero-flow days was excluded as both stations did not experience zero flow days over the analysis period. IHAs characterize statistical magnitude and timing of events (e.g., annual maximum/ minimum 3-, 7-, 30-, and 90-day mean flows), intra-annual and inter-annual variability in flow conditions (e.g., rise/fall rate and number of reversals in the hydrograph). A detailed description on the IHAs and their ecological significance can be readily found in original IHA articles (Richter et al., 1996; Poff et al., 1997; The Nature Conservancy, 2009).

Table 4.3 Water resources indicators (WRIs) and indicators of hydrologic alterations (IHAs) evaluated in this study *

Hydrologic Indicators	Examples of hydrologic influence	Examples of ecological influence
Water resource Indicators		
Annual volume ($m^3\ s^{-1}$), median seasonal flow Winter (December–January–February) Spring (March–April–May) Summer (June–July–August) Autumn (September–October–November) ($m^3\ s^{-1}$) and center of timing of annual flow (day of occurrence of 50% annual flow between October and September) (day)	Annual water balance, magnitude and timing of seasonal conditions	Availability and suitability of habitat for aquatic organisms
Indicators of hydrologic alterations (IHAs)		
Group 1: Monthly flow ($m^3\ s^{-1}$) (Water year October to September)	Magnitude of monthly water availability	Suitable habitat availability; influence on secondary variables, e.g., water temperature, oxygen
Group 2: Annual mean 1-day, 3-day, 7-day, 30-day, 90-day minimum and maximum ($m^3\ s^{-1}$), and baseflow (7-day minimum/mean annual	Magnitude of annual flood and drought conditions	Duration of stressful conditions (high and low flows)

flow)		
Group 3: Day of each annual 1-day minimum and maximum(water year) (day)	Timing of annual flood and drought conditions	Spawning cues for fish; compatibility with life cycles of organisms
Group 4: Number of low (annual median 25th percentile) and high (annual median + 25th percentile) pulses in a year, median duration of low and high pulses within each year (day)	Frequency and duration of high and low-flow conditions	Availability of floodplain habitat; influences channel morphology, e.g., bed load transport
Group 5: Rise/fall rate (median of all positive/negative changes in flow between consecutive days), number of reversals (no. of switches between rising and falling period)	Rate and frequency of hydrograph changes	Drought (falling levels), flooding (rising levels) or desiccation stress for low mobility organisms

*adopted from Shrestha et al., 2013

Four statistical tests: (i) Nash-Sutcliffe efficiency (NSE), (ii) Pearson correlation test, (iii) Kolmogorov-Smirnov (K-S) test, and (iv) hydrologic alteration factor (HAF) were employed for the comparisons.

Since NSE is very commonly used statistics in SWAT application, it was considered in eco-hydrological indicator evaluation. The NSE values ≥ 0.5 considered as an acceptable range similar to other applications (Moriasi et al., 2007).

The Pearson correlation coefficient measures the strength of the linear relationship between two variables. If they don't have linear relationship, then the correlation coefficient does not adequately represent the strength of the relationship between the variables. The correlation values ≥ 0.5 considered as the criteria.

The K-S test is a nonparametric test that evaluates the probability distributions. Two sample K-S test, the test applied in this study, tests the cumulative distribution of two data sets. The null hypothesis of this test states that the observed and simulated samples have identical distribution and the alternate hypothesis is they are different. The K-S test's statistical significance was measured at a 95% significance level. During this test, it was assumed that samples are independent and the effect of serial correlation on the K-S test is noncritical (Shrestha et al., 2013).

The HAF have been used for hydrologic evaluation in many studies (Mathews and Richter, 2007; Yang et al., 2008; Zolezzi et al., 2009; Suen, 2010; Shrestha et al., 2013). HAF test the replicability of the observed and simulated distribution as below:

HAF= (Simulated frequency – Observed frequency) / Observed frequency

The 25th and 75th percentiles (inter-quartile range) of the observed dataset were set as the target range following Mathews and Richter (2007), Suen (2010) and Shrestha et al. (2013). The HAF ranges between -1 and 1. HAF equal to zero imply a perfect agreement between observed and simulated frequencies and HAF greater than zero and lower than zero imply higher and lower frequency of simulated values than of observed values. The simulated frequencies within ±33% of the observed frequencies acceptable were considered as the model range (Suen, 2010).

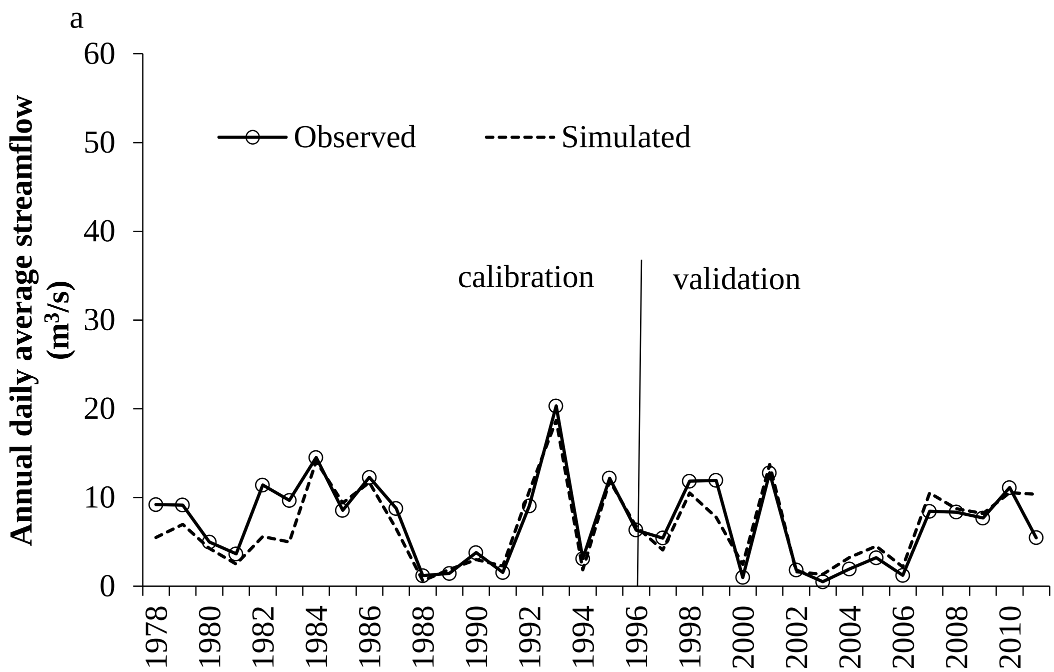
4.3 Results and Discussion

4.3.1 Manual calibration and validation

4.3.1.1 Flow

Visual observation indicated reasonable correspondence in trends, timing of peaks, and magnitudes of SWAT-predicted vs. observed annual, monthly, and daily average flows at Delaware R NR Muscota and Delaware River at Perry Lake gaging stations during calibration (1978-1996) and validation (1997-2011) periods (Figures 4.3 to 4.5). However, discrepancies in peak flow predictions were noted, especially at Delaware R NR Muscota. Calibrated model performance met all evaluation criteria for NSE, PBIAS, and RSR (Moriasi et al., 2007) and regression (Santhi et al., 2001). For both subwatersheds (Table 4.5), NSE was < 0.65 (except daily surface flow [NSE=0.57]), PBIAS was < ±16% (except daily baseflow PBIAS = 29%]), RSR was < 0.65 (except daily baseflow [RSR = 0.85]) during calibration period (1975-1996), monthly daily average flow intercepts of regression (Figure 4.4) were not significantly different from zero, and R^2 was > 0.5. Daily percent exceedance probability curves for both stations showed good matches for high and average magnitude flows (Figure 4.5). During calibration period, the observed proportions of baseflows relative to observed flows were 25% at Delaware R NR Muscota and 34% at Delaware River at Perry Lake from the automated baseflow filter technique, compared to 21% and 33%, respectively, for the same locations for SWAT simulated flows. During visual analysis mismatch in baseflows were observed both in calibration and validation period at both locations (Figure 4.6). Uncertainty in low streamflow observed data (streamflow gauging and stage discharge uncertainties; Nair et al., 2013), use of auto-irrigation instead of actual irrigation and exclusion of diversions and small impoundments in current model may explain these conditions.

Figure 4.3 Observed and simulated annual average of daily streamflows at a) Delaware R NR Muscota and b) Delaware River at Perry Lake over calibration (1978-1996) and validation (1997-2011) periods.



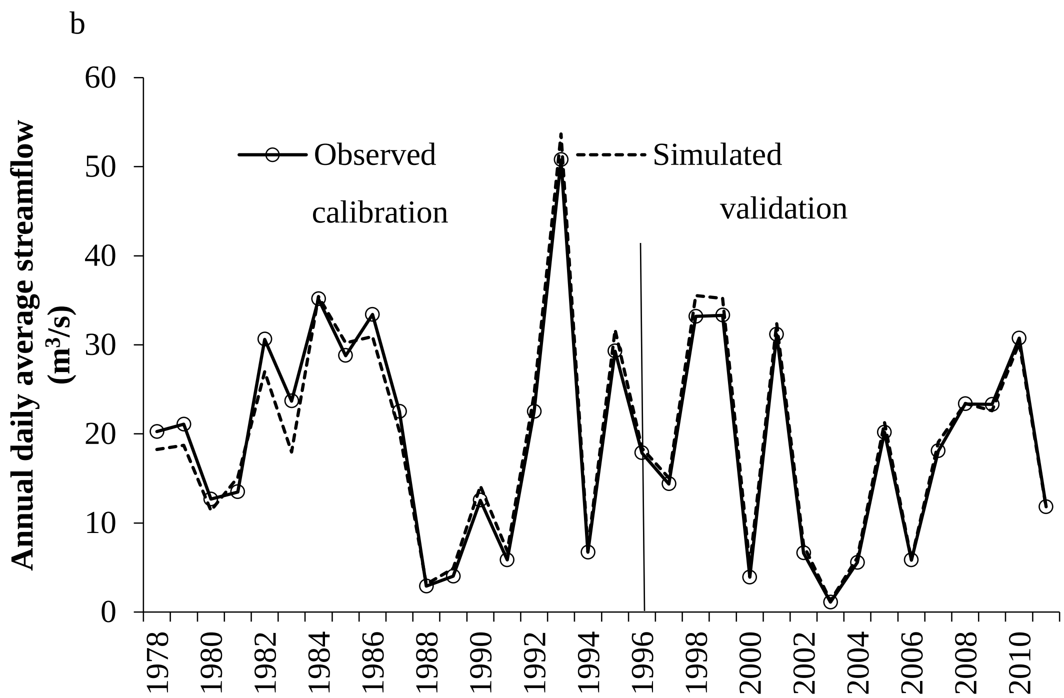


Figure 4.4 Observed and simulated monthly average of daily stream flows at a) Delaware R NR Muscota and b) Delaware River at Perry Lake over calibration (1978-1996) and validation (1997-2011) periods.

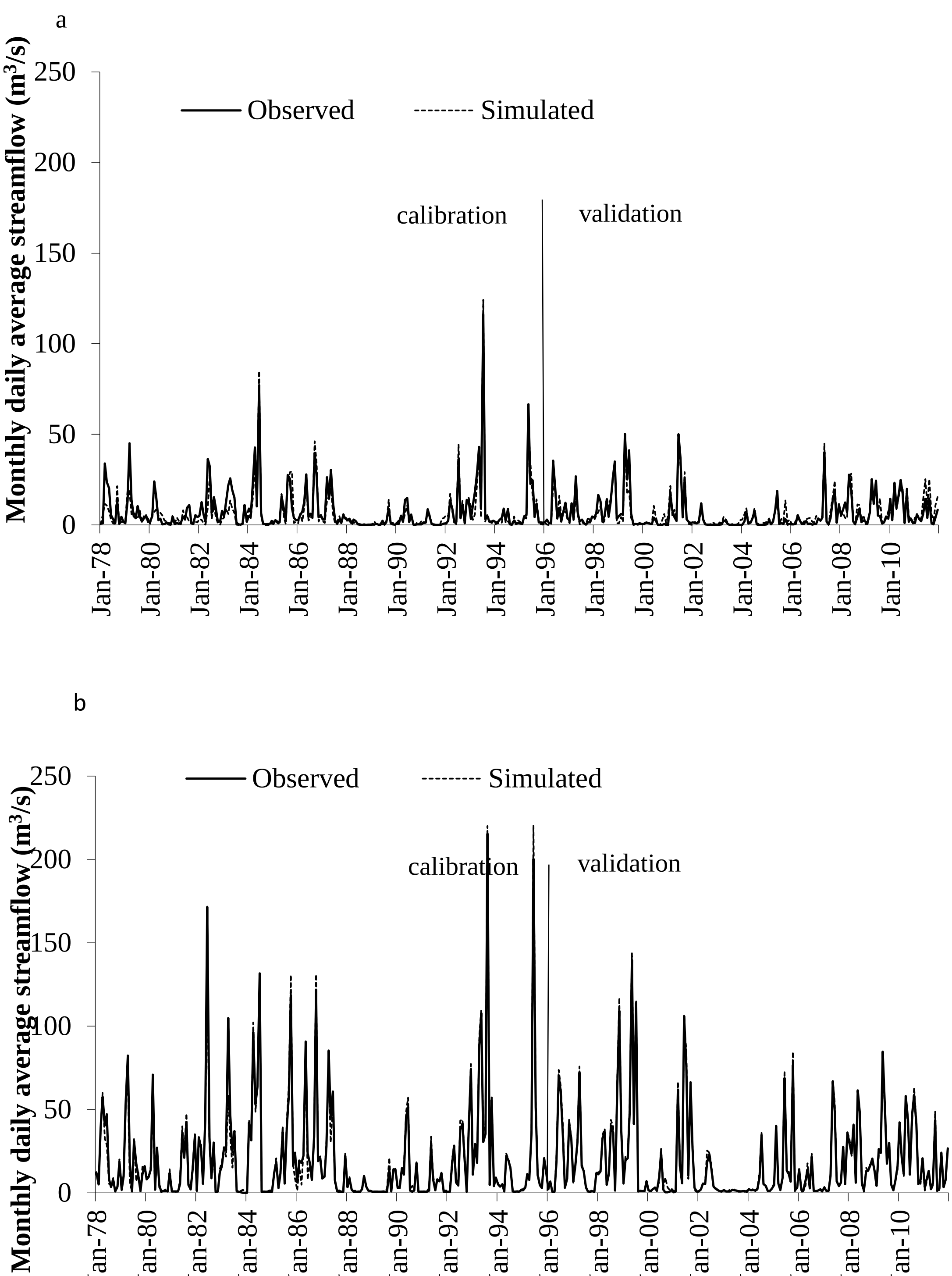


Figure 4.5 Observed and simulated daily average (monthly) flows at Delaware R NR Muscota (upper panel) and Delaware River at Perry Lake (down) for calibration period (1978-1996; right side) and validation period (1997-2011; left side)

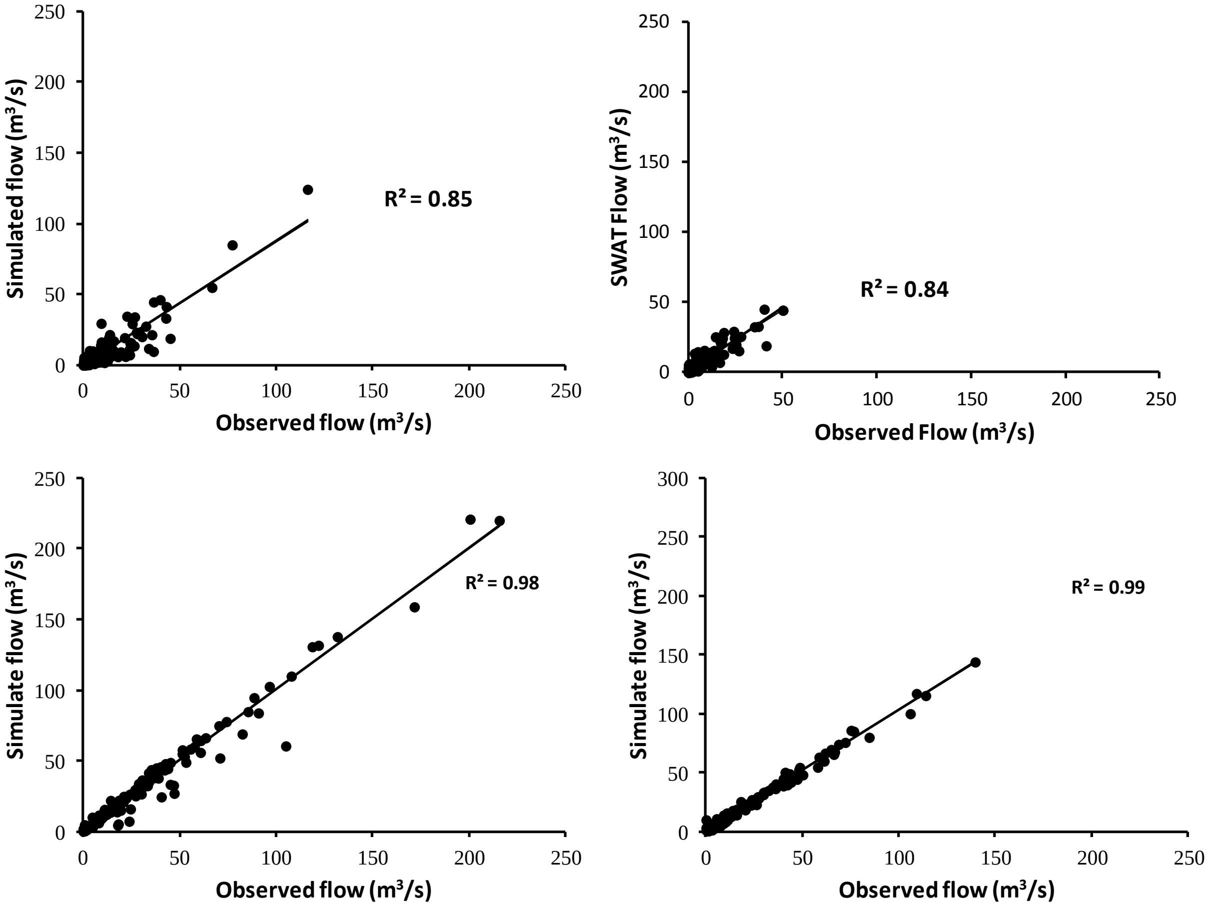


Figure 4.6 Percent exceedance probability curves for daily flow at Delaware R NR Muscota (upper panel) and Delaware River at Perry Lake (down) for calibration period (1978-1996; right side) and validation period (1997-2011; left side)

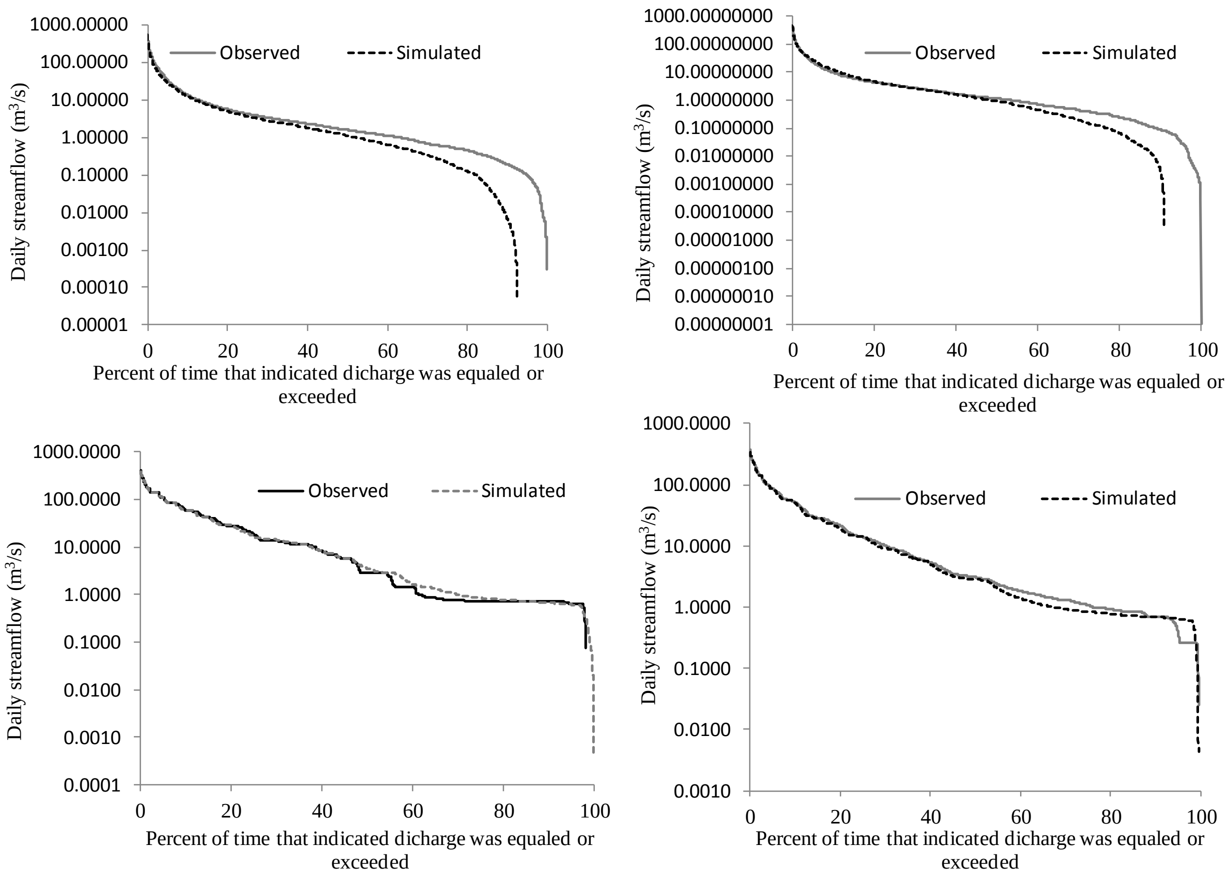


Figure 4.7 Baseflow at Delaware R NR Muscota (upper panel) and Delaware River at Perry Lake (down) for calibration period (1978-1996; right side) and validation period (1997-2011; left side)

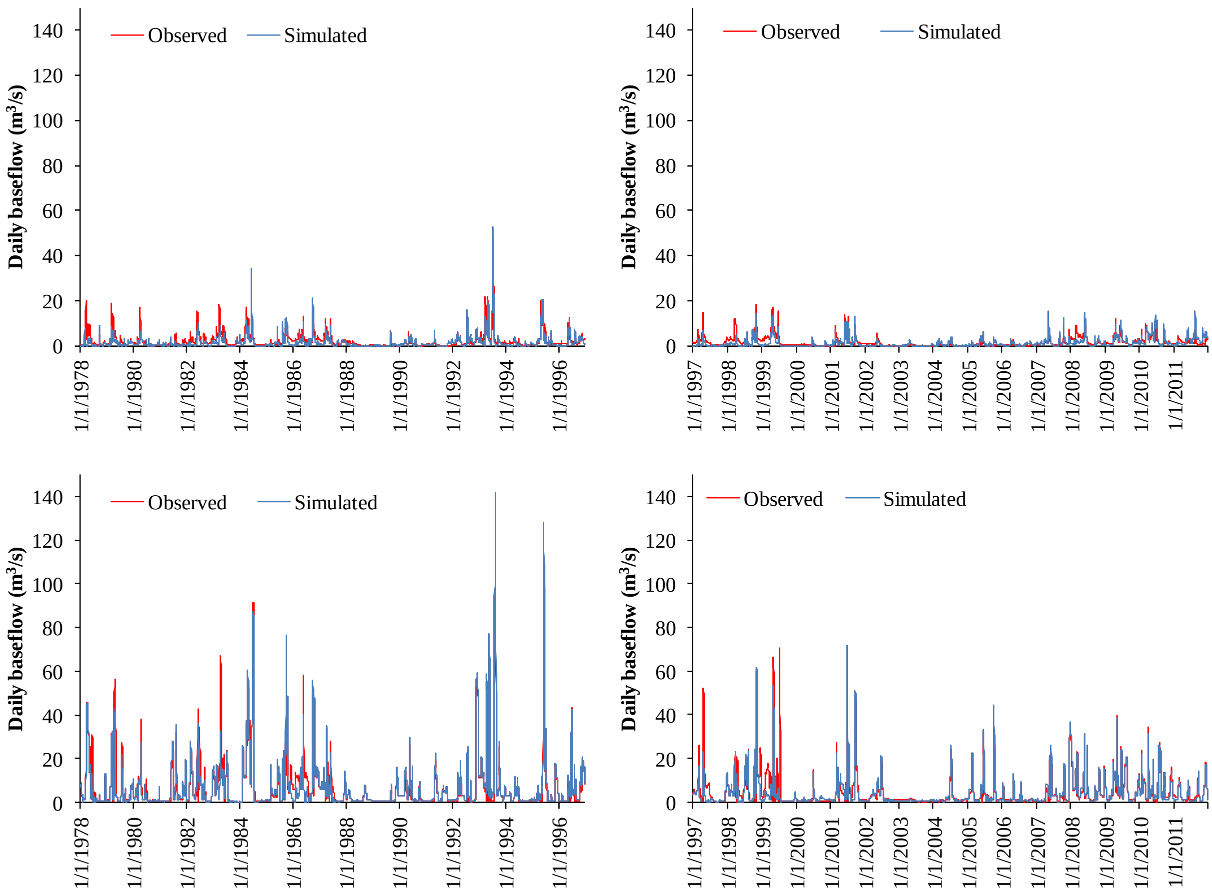


Table 4.4 Stream flow results at Delaware River near Muscota and Delaware River at Perry Lake

	NSE		PBIAS (%)		RSR	
	After parameterization	Final	After parameterization	Final	After parameterization	Final
Delaware River near Muscota						
Annual Calibration (1978-1996)	0.82	0.80	14.41	-3.75	0.43	0.19
Monthly Calibration	0.80	0.84	12.97	-15.66	0.44	0.26
Daily Calibration	0.37	0.65	-12.85	5.68	0.79	0.59

Surface flow	0.25	0.57	-4.67	-15.03	0.86	0.65
Baseflow Calibration	0.22	0.69	5.54	28.99	0.88	0.85
Annual Validation (1997-2011)	0.51	0.79	40.05	7.46	0.70	0.46
Monthly Validation	0.73	0.84	40.05	7.46	0.51	0.40
Daily Validation	0.15	0.74	25.84	0.13	0.92	0.51
Surface flow	0.21	0.76	45.99	3.00	0.74	0.49
Baseflow Validation	0.15	0.47	-17.36	-20.55	0.91	0.72
Delaware River at Perry Lake						
Annual Calibration (1978-1996)	0.99	0.99	2.45	1.13	0.11	0.08
Monthly Calibration	0.98	0.98	5.27	4.70	0.13	0.09
Daily Calibration	0.91	0.90	5.04	1.44	0.31	0.32
Surface flow	0.86	0.84	5.51	1.15	0.37	0.40
Baseflow Calibration	0.72	0.93	-22.98	-1.44	0.52	0.25
Annual Validation (1997-2011)	0.99	0.99	7.22	1.14	0.10	0.10
Monthly Validation	0.99	0.99	4.73	3.96	0.10	0.10
Daily Validation	0.87	0.87	0.75	-1.75	0.36	0.36
Surface flow	0.83	0.86	0.37	-0.1	0.41	0.38
BaseflowValidation	0.83	0.84	-1.56	-6.39	0.40	0.40

4.3.1.2 Crop

After calibration, the simulated area-weighted average yield from 1999 to 2009 closely matched the measured yield of the crops (Figure 4.8). Some variations in annual crop yields were not captured by the calibrated model. This is likely due to many factors that determine annual crop yield that are not simulated in SWAT, such as crop stress or damage from pests or meteorological events (hail, wind). However, temporal variability in yield was captured in most cases. Average annual yield for corn and soybean and statistics for both calibration and validation datasets (Figures 4.8 and 4.9,Table 4.5) indicate model performance for corn in all periods and locations had NSE > 0.5, PBIAS < 5% (except Atchison, 9.9%), and RSR < 0.7, which are consistent with other reported values (Nair et al., 2011). Results for soybean calibration and validation indicate the need to improve soybean yield simulation, with NSE > 0.5, PBIAS < 5%, and RSR < 0.7 in only one case (Jackson Co, calibration). However, because of shortage of NASS reported soybean yield, soybean calibration was stopped to the limit and the calibration criteria were still not met, then calibration was stopped and optimum parameter set was selected.

Figure 4.8 Simulated and observed (USDA-NASS) reported crop yield for dry land corn (left) and soybean (right) for a) Jackson County and b) Brown Counties

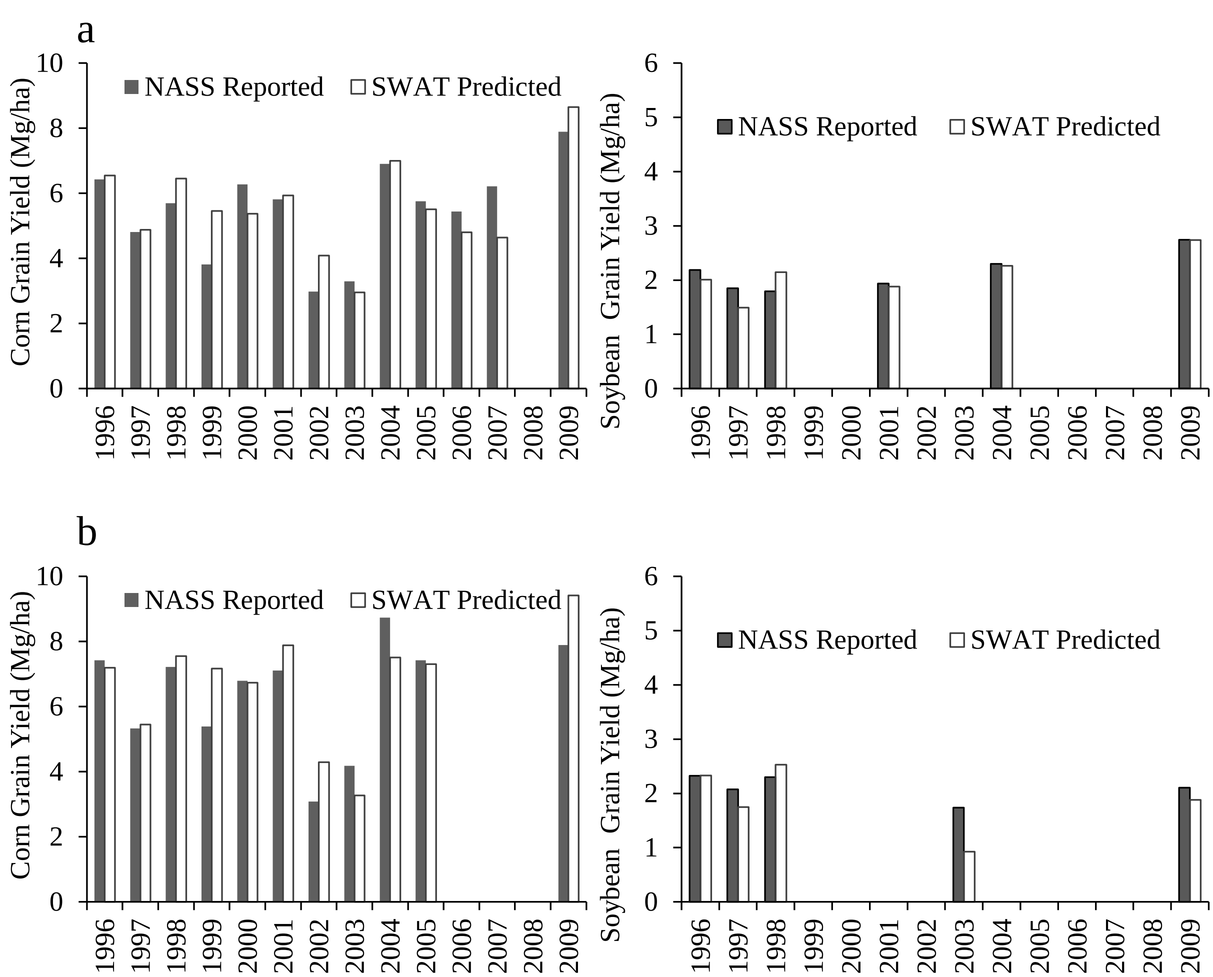


Figure 4.9 SWAT predicted and observed (USDA-NASS) reported crop yield for dry land corn (left) and soybean (Jackson) for a) Jefferson, b) Atchison and c) Nemaha Counties

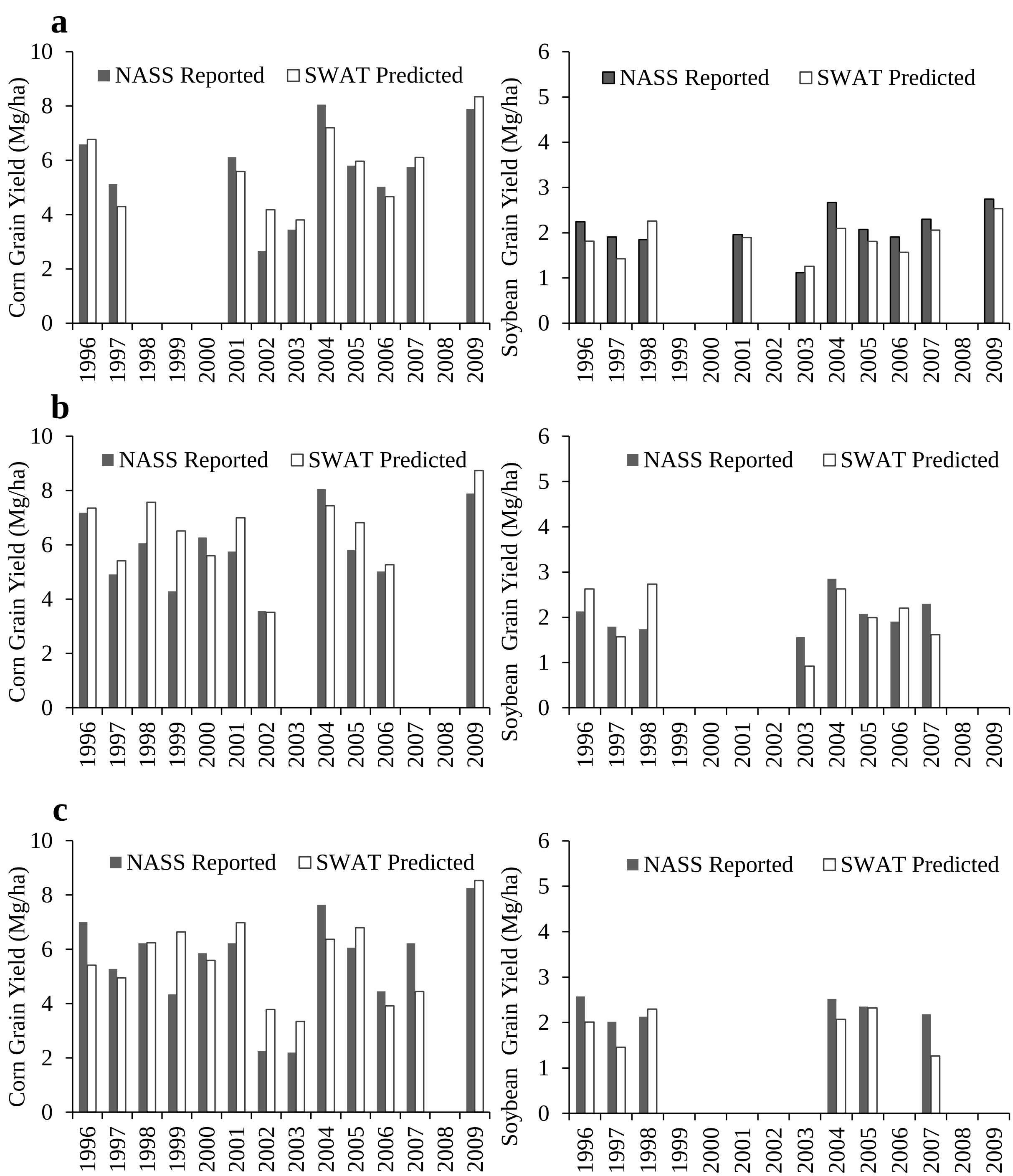


Table 4.5 Average reported and SWAT predicted crop yields and calibration statistics

Counties	Number of Observation	Crop yield (Mg ha^{-1})							
		Reported	Modeled	NSE		PBIAS (%)		RSR	
				Default	Final	Default	Final	Default	Final
Dry land corn									
Jackson	13	5.49	5.56	-13.42	0.55	78.72	1.83	3.80	0.67
Brown	11	6.42	6.70	-3.64	0.65	50.80	4.48	2.15	0.59
Jefferson	10	5.65	5.69	-8.29	0.83	89.36	0.83	3.05	0.42
Atchison	11	5.89	6.47	-4.41	0.79	87.12	9.92	2.32	0.46
Nemaha	13	5.54	5.61	-2.48	0.64	62.41	1.35	1.87	0.60
Soybean									
Jackson	6	2.13	2.90	-3.46	0.55	30.94	-2.09	2.11	0.67
Brown	4	2.10	1.88	3.50	-1.29	7.83	-8.56	0.67	1.51
Jefferson	10	2.07	1.87	-1.11	0.37	27.68	-9.85	1.45	0.80
Atchison	8	2.04	2.03	-3.64	-1.05	20.00	-0.39	1.73	0.95
Nemaha	6	2.29	1.90	-3.00	-0.57	8.50	-11.24	0.76	0.99

4.3.2 Model evaluation for hydrological application

Annual ET values for each watershed were investigated following crop calibration. Thirty-seven year average annual ET was 695.5 mm for Perry Lake watershed, ranging from 45 mm to 1232 mm (Figure 4.10). Highest ET values were observed in water bodies. Wetter (1987) reported normal ET values ranged from 711 mm (28 in.) to 762 mm (30 in.) for the same area, which within 10% of annual average simulated ET. To ensure crop water usage over the growing season was modeled appropriately, growing season distributions of ET and LAI for corn and soybean for a randomly selected HRU were visually analysed (Figure 4.11). SWAT-predicted ET using the Penman-Monteith method was 697 mm for corn and 661 mm for soybean, which were within 10% of the corresponding ET values of 635 mm for corn and 610 mm for soybeans reported by Stone and Schlegel (2006) in western Kansas. Stone and Schlegel (2006) values represented irrigated fields whereas this study represent dryland crop yields. Corn ET values also closely resemble the values presented by Gordon et al. (1995). Gordon et al. (1995) ET values were collected during 1981-1991 near Scandia, Kansas (around 220 km from study area).

To further ensure that simulation of crop water usage was reasonable, the simulated yield vs. ET relationship was analysed. Based on SWAT results, slope of the yield vs. ET relationship was 0.04 Mg ha^{-1} mm^{-1} (15.0 bu ac^{-1} in^{-1}) for corn and 0.007 Mg ha^{-1} mm^{-1} (3.0 bu ac^{-1} in^{-1}) for soybean (Figure 4.12) compared to 0.042 Mg ha^{-1} mm^{-1} (16.9 bu ac^{-1} in^{-1}) for corn and 0.014 Mg ha^{-1} mm^{-1} (5.5 bu ac^{-1} in^{-1}) for soybean reported by Stone and Schlegel (2006) for western Kansas. Similarly SWAT predicted threshold ET was 390 mm (15.35 in.) for corn and 165 mm (6.49 mm) for sybean compared to 277 mm (10.9 in.) for corn and 229 mm (9.0 in.) for soybean reported by Stone and Schlegel (2006).

Figure 4.10 Thirty-seven year average annual modeled ET for Perry Lake watershed

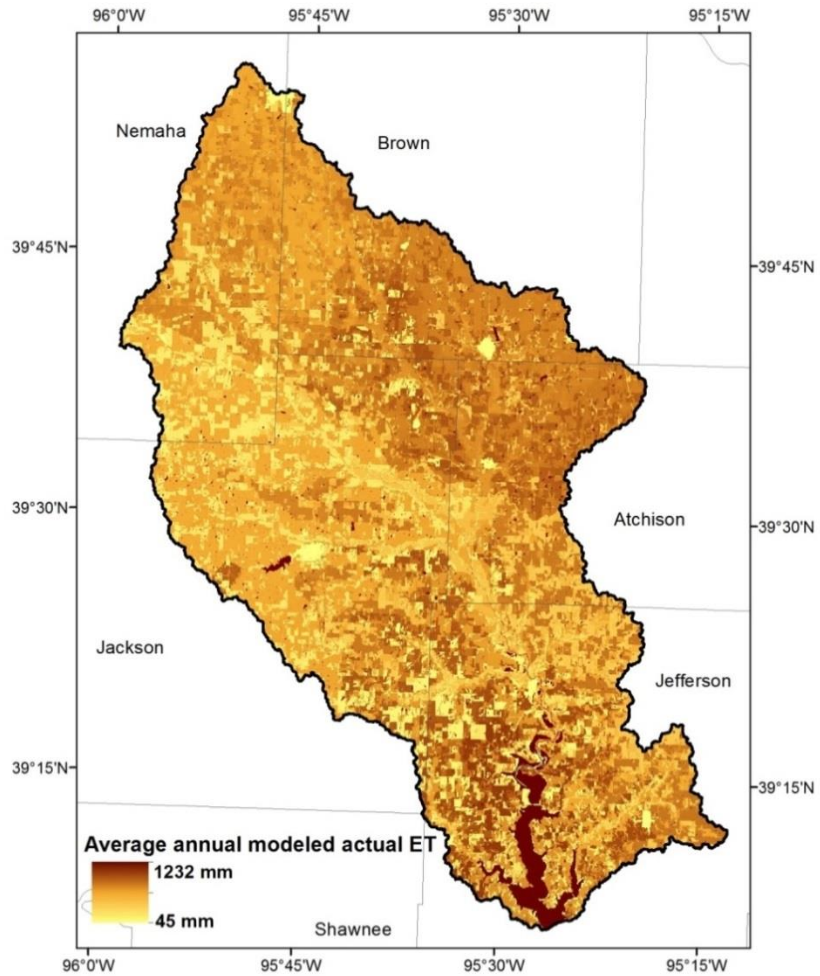
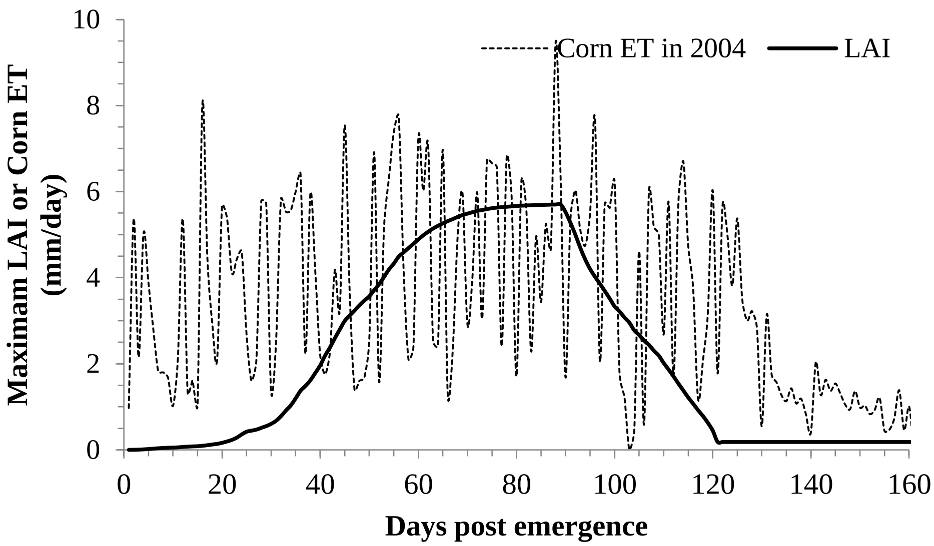


Figure 4.11 Daily SWAT simulated ET (mm) and LAI (m^2 m^{-2}) for a) corn and b) soybean



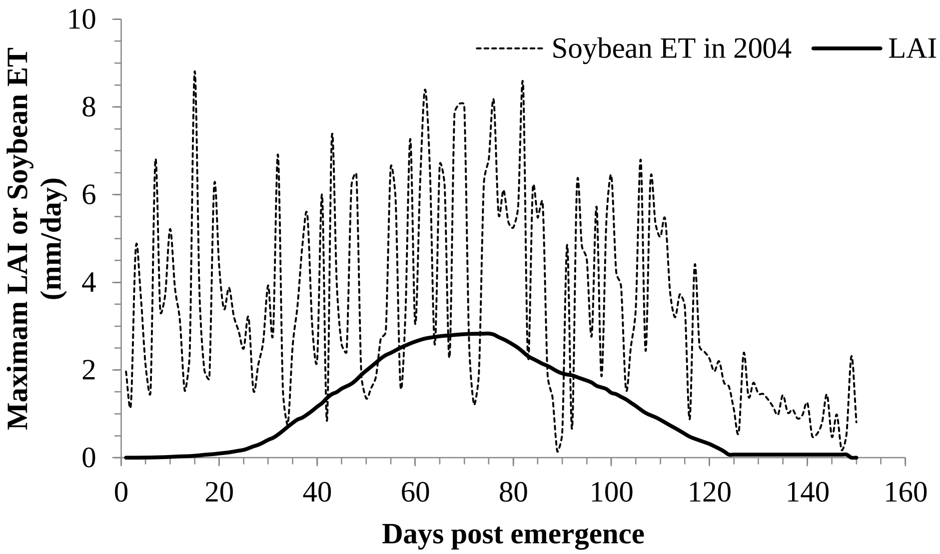
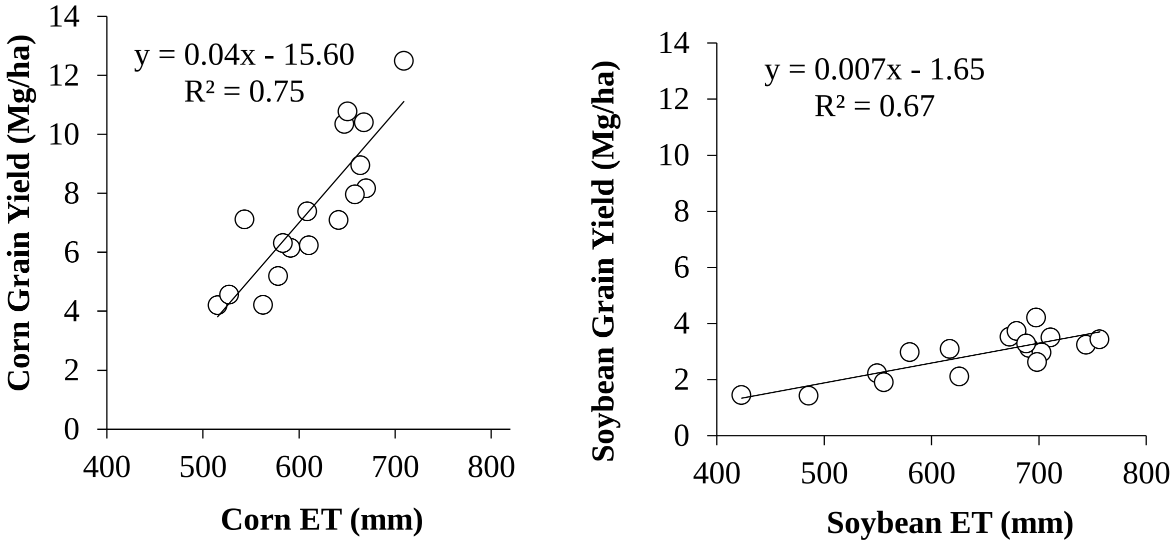


Figure 4.12 Relationship show modeled yield vs crop ET

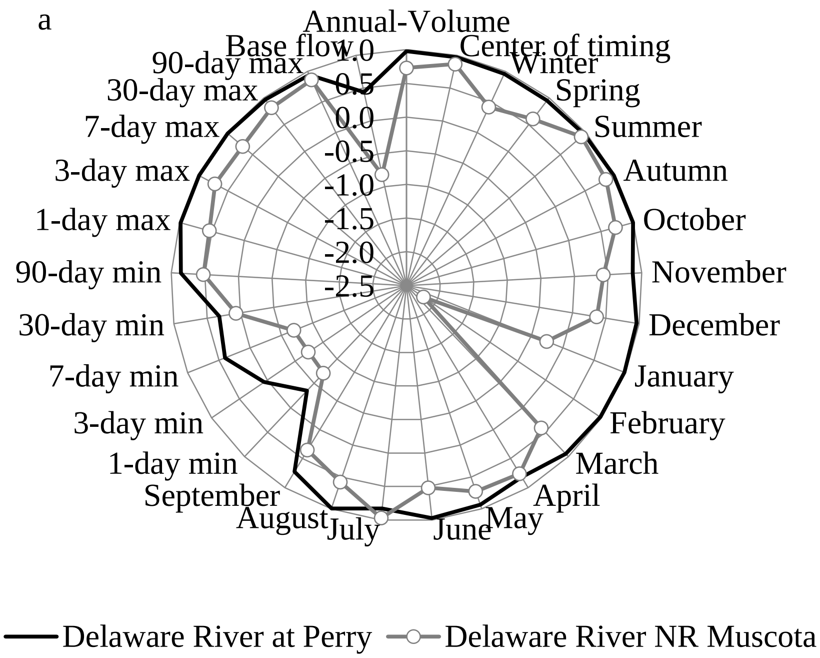


4.3.3 Model evaluation for ecohydrologic application

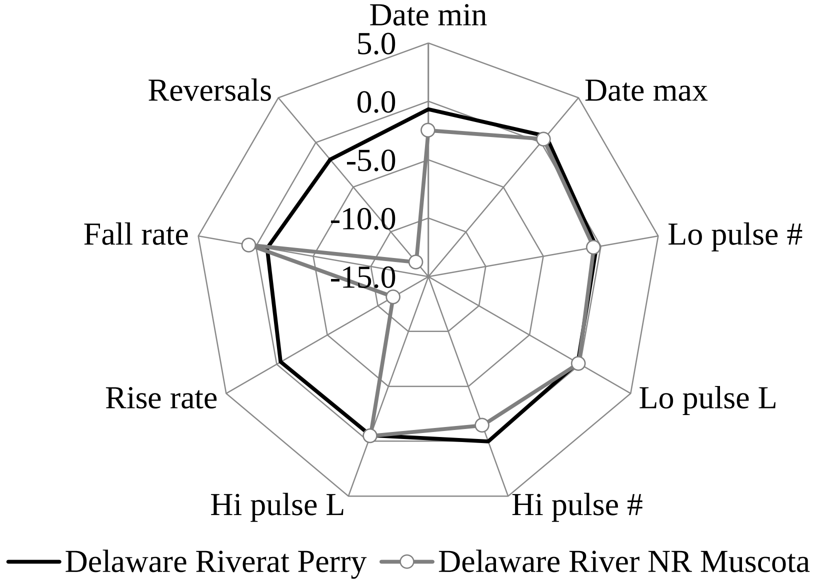
The NSE for WRIs and IHAs calculated for Delaware River at Perry Lake and Delaware River NR Muscota are presented in Figure 4.13. Most WRIs and monthly magnitudes, 90-day minimum, all maximums, and date of maximum flow had NSE > 0.5 (satisfactory performance; Moriasi et al., 2007). Out of five minimum flow periods, four (1-day, 3-day, 7- day and 30-day minimum flows) along with date of minimum flow did not meet the criteria (i.e., NSE < 0.5) for both sites (Figure 4.13, Table 4.7). Also all frequencies and durations of high- and low-flow condition indicators and all rate and frequency of hydrograph changes, except fall rate at Delaware River NR Muscota, did not meet the NSE criteria.

Figure 4.13 Glyph display for NSE of a) 38 WRIs and Group I-III IHAs b) Group IV-V IHAs

a

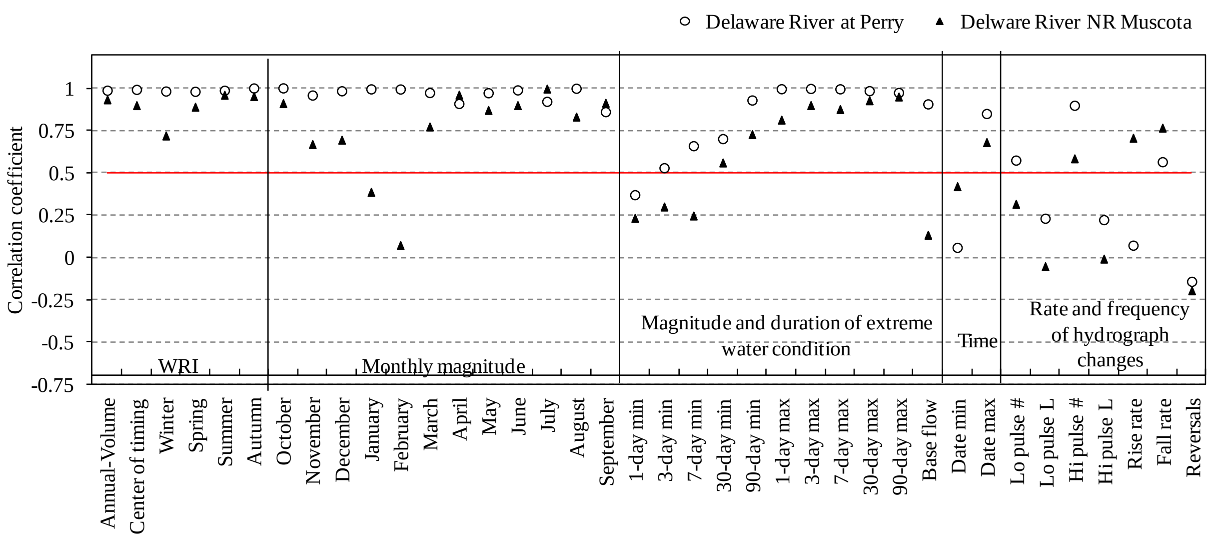


b



The Pearson correlation coefficients between the observed and simulated results are presented in Figure 4.14. All WRIs and monthly, maximum and most minimum flows show relatively high correlations, with a value ≥ 0.5 at least for one station, whereas date minimum, 1-day minimum flow date, low-flow and high-flow pulse duration, and reversals show low correlation coefficient values (≤ 0.5) for both stations.

Figure 4.14 Pearson correlation coefficients between observed and SWAT simulated water resource indicators (WRI) and IHAs for the Perry Lake watershed (Water Years 1979-2010). Open circles (○) represent Delaware River at Perry and filled triangles (▲) represent Delaware River NR Muscota. Symbols above red line met the criteria.



The K-S results are shown in Table 4.6. The null hypothesis h=0 when the observed and simulated samples have identical distribution or not significant differences. When they are different h=1. In other words, lesser p concludes that the two groups were sampled from populations with different distributions. At Delaware River at Perry Lake, only 7 (18%) of the ecohydrological parameters show significant differences; whereas in Delaware River at NR Muscota it was 10 (26%). All WRIs and monthly magnitudes, except January median flow at Delaware River NR Muscota, show accepted null hypothesis, which states that the observed and simulated data have identical distribution. These results show generally showed good model performance of SWAT model in replicating WRIs and most IHAs.

Table 4.6 K-S test results for Delaware River at Perry and Delaware River NR Muscota. Bold values were statistically significant at p=0.05. (The null hypothesis of this test states that the

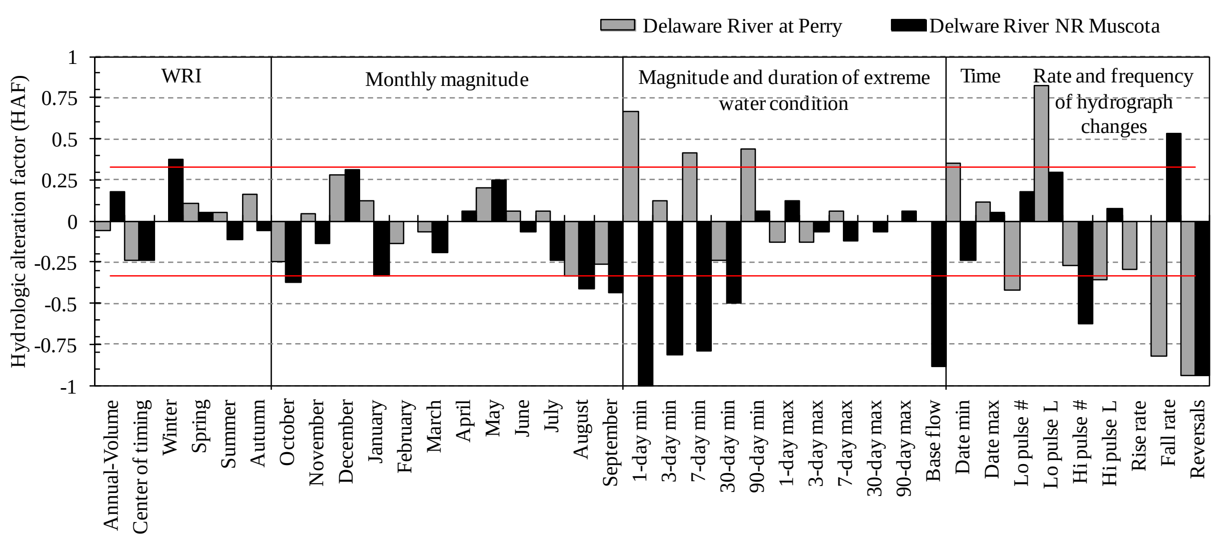
observed and simulated samples have identical distribution ; h=1 indicates the rejection of the null hypothesis at the alpha significance level and h=0 indicates a failure to reject the null hypothesis at the Alpha significance level.

Hydrological Indicators	Delaware R at Perry		Delaware R NR Muscota	
	h	p	h	p
Annual-Volume	0	1.00	0	0.96
Center of timing	0	1.00	0	1.00
Winter	0	1.00	0	0.83
Spring	0	1.00	0	0.09
Summer	0	1.00	0	0.96
Autumn	0	0.62	0	0.96
October	0	0.95	0	0.38
November	0	0.23	0	0.95
December	0	0.58	0	0.58
January	0	0.80	**1**	**0.03**
February	0	0.80	0	0.58
March	0	1.00	0	0.23
April	0	0.80	0	0.23
May	0	0.80	0	0.95
June	0	1.00	0	0.23
July	0	0.95	0	0.38
August	0	0.23	0	0.07
September	0	0.95	0	0.03
1-day min	0	0.13	**1**	**0.00**
3-day min	**1**	**0.01**	**1**	**0.00**
7-day min	**1**	**0.00**	**1**	**0.00**
30-day min	0	0.80	**1**	**0.02**
90-day min	0	0.38	0	0.80
1-day max	0	0.95	0	0.58
3-day max	0	0.95	0	0.23
7-day max	0	1.00	0	0.23
30-day max	0	0.95	0	0.38
90-day max	0	0.95	0	0.58
Base flow	0	0.38	**1**	**0.00**
Date min	0	0.38	**1**	**0.03**
Date max	0	1.00	0	0.95
Lo pulse #	**1**	**0.00**	0	0.70
Lo pulse L	**1**	**0.00**	**1**	**0.00**
Hi pulse #	0	0.13	**1**	**0.00**

Hi pulse L	**1**	**0.00**	**1**	**0.03**
Rise rate	**1**	**0.01**	0	0.23
Fall rate	**1**	**0.00**	0	0.38
Reversals	**1**	**0.00**	**1**	**0.00**

Most HAF values for WRIs and IHAs (28 for Delaware River at Perry and 25 for Delaware River NR Muscota, out of 38 total indicators) fell within the range of acceptable model-performance criteria (±0.33), indicating good performance of the SWAT model. All WRIs had HAFs that were within acceptable criteria, except winter seasonal flows in Delaware River NR Muscota (HAF=0.375). All monthly IHA for Delaware River at Perry Lake met the criteria. October, August and September monthly IHAs showed negative HAF values slightly outside the criteria for acceptable performance. The HAF values of most minimum flows (3 for Delaware River at Perry Lake and 4 for Delaware River NR Muscota, out of 5) showed larger deviations, whereas all 1- to 90-day maximum flows met performance criteria. Flow pulses, and rise and fall rates show mixed performance. The number of reversals show more-negative HAF (HAF = -0.94) indicating under-predicted model performance.

Figure 4.15 Hydrologic alteration factor (HAF) values for observed and SWAT simulated water resource indicators (WRI) and IHAs for the Perry Lake watershed (Water year 1979-2010). Filled bars represent Delaware River at Perry and open bars represent Delaware River NR Muscota. Bars with magnitudes between the red lines met the performance criteria.



In summary (Table 4.7) 30 of 38 ecohydrological indicators at Delaware River at Perry Lake and 27 of 38 ecohydrological indicators at Delaware River NR Muscota met acceptable performance criteria for K-S test (h=0, no significant difference). For NSE, 25 of 38 indicators met the criteria (NSE ≥ 0.5) at Delaware River at Perry Lake and 18 of 38 indicators at Delaware River NR Muscota. Pearson correlation coefficient (R) was ≥ 0.5 for 31 ecohydrological indicators and at Delaware River at Perry Lake and 27 Delaware River NR Muscota. Similarly HAF was within ±0.33 for Delaware River at Perry Lake and 25 for Delaware River NR Muscota. A set of 29 parameters met all 4 criteria at least one site.

The WRIs results show satisfactory model performance SWAT model performance in replicating annual flow volumes, center of timing and seasonal flows. This performance illustrates that the SWAT model can replicate seasonal flows and annual cycle. Well replicated most monthly IHAs illustrate SWAT's good level of performance in replicating intra-annual variability. However, the results also show the difficulties in replicating lower monthly flows. This can be due to the data and model uncertainties. Uncertainty in observed data (streamflow gauging and stage discharge uncertainties; Nair et al., 2013) can cause mismatch between observed and simulated data. Especially, reliable low discharge measurements are difficult to record and have considerable uncertainties due to hyporheic flow exchange (in channel water exchange with groundwater) and the presence of ice and vegetation (Hamilton, 2008 and Shrestha et al., 2013). Discrepancies in winter months, only in Delaware NR Muscota denote the need of the model calibration for lower flow months at this site. Also considerable deviation in 1- to 90-day-minimum flows, flow pulses, rise and fall rates and reversals further emphasize the limitation modeling low flows. Better model performance in reproducing 1-day maximum flows and high pulses suggest good performance in reproducing high flows. Failure to reproduce rise rate, fall rate and reversals may attribute to hydrologic model structure and parameter uncertainties.

Table 4.7 Summary results of eco-hydrological evaluation (1=met criteria, 0=did not meet criteria).

	Delaware River at Perry					Delaware River NR Muscota					
Parameter	KS h=0	NSE≥ 0.5	R ≥0 .5	HAF± 0.33	Rati ng	KS h=0	NSE≥ 0.5	R ≥0 .5	HAF± 0.33	Rati ng	Overall Rating
Annual-Volume	1	1	1	1	●	1	1	1	1	●	●
Center of timing	1	1	1	1	●	1	1	1	1	●	●
Winter	1	1	1	1	●	1	0	1	0	○	◐

Spring	1	1	1	1	●	1	1	1	1	●	●
Summer	1	1	1	1	●	1	1	1	1	●	●
Autumn	1	1	1	1	●	1	1	1	1	●	●
October	1	1	1	1	●	1	1	1	0	●	●
November	1	1	1	1	●	1	0	1	1	●	●
December	1	1	1	1	●	1	0	1	1	●	●
January	1	1	1	1	●	0	0	0	0	○	◐
February	1	1	1	1	●	1	0	0	1	○	◐
March	1	1	1	1	●	1	0	1	1	●	●
April	1	1	1	1	●	1	1	1	1	●	●
May	1	1	1	1	●	1	1	1	1	●	●
June	1	1	1	1	●	1	1	1	1	●	●
July	1	1	1	1	●	1	1	1	1	●	●
August	1	1	1	0	●	1	1	1	0	●	●
September	1	1	1	1	●	1	0	1	0	○	◐
1-day min	1	0	0	0	○	0	0	0	0	○	○
3-day min	0	0	1	1	○	0	0	0	0	○	○
7-day min	0	0	1	0	○	0	0	0	0	○	○
30-day min	1	0	1	1	●	0	0	1	0	○	◐
90-day min	1	1	1	0	●	1	1	1	1	●	●
1-day max	1	1	1	1	●	1	1	1	1	●	●
3-day max	1	1	1	1	●	1	1	1	1	●	●
7-day max	1	1	1	1	●	1	1	1	1	●	●
30-day max	1	1	1	1	●	1	1	1	1	●	●
90-day max	1	1	1	1	●	1	1	1	1	●	●
Baseflow	1	0	1	1	●	0	0	0	0	○	◐
Date min	1	0	0	0	○	0	0	0	1	○	○
Date max	1	1	1	1	●	1	0	1	1	●	●
Lo pulse #	0	0	1	0	○	1	0	0	1	○	○
Lo pulse L	0	0	0	0	○	0	0	0	1	○	○
Hi pulse #	1	0	1	1	●	0	0	1	0	○	
Hi pulse L	0	0	0	0	○	0	0	0	1	○	○
Rise rate	0	0	0	1	○	1	0	1	1	○	○
Fall rate	0	0	1	0	○	1	1	1	0	●	◐
Reversals	0	0	0	0	○	0	0	0	0	○	○
Total # of parameters met criteria	30	25	31	28	28	27	18	27	25	22	29

Key:
● = met at least 3 criteria
○ =didn't meet the criteria
◐ = at least one site met the criteria

4.4 Conclusions

SWAT replicates all WRIs and most IHAs, including monthly flows, seasonal flows, 30- and 90-day minimum flow, 1- to 90-day maximum flows, baseflow, date of maximum annual flow, high-flow pulse count, and fall rate. This shows SWAT results can simulate these aspects of hydrologic inter- and intra-annual variability with acceptable performance. However, replicating winter month flows, 30-day minimum flow, baseflow and fall rate require a higher level of model calibration. Both data and model uncertainties may contribute to these limitations. Failure to reproduce 1- to 7-day minimum flows, date of minimum annual flow, low-flow pulse count and duration, high-flow pulse duration, rise rate and reversals indicates limitation in SWAT hydrologic model structure and parameterization uncertainties. It can be concluded that SWAT model provided robust performance in simulating high-flow-rate ecohydrological indicators, but that simulation of low-flow-rate ecohydrological indicators requires extensive calibration or a different model.

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Chapter 5 - Conclusion and Recommendations

5.1 Conclusion

The overall goal of this study was to improve the development and analysis of watershed-level ecohydrological characteristics. Detection of past trends, changes, and variability of flow regime by assessing hydrologic indices may help to understand potential future changes in hydrological regime and associated ecological impacts. Ecohydrological modeling will help to identify future changes, test restoration and protection efforts and guide conservation strategies. However, analysis and modeling of watershed level ecohydrological characteristics requires a clear understanding of the dynamic relationship between hydrology and ecology.

The first study characterized the unregulated streams of KRB. The change in ecohydrological indicators were substantiated by computing Mann-Kendall, Seasonal Kendall and Sen's slope. Overall, all hydrological indicators showed decreasing trend in all ecoregions. The decreasing trend was relatively higher in the High Plains ecoregion. Alarmingly, the minimum flows, the days with no (zero) flow and baseflow were also increasing in many of High Plan streams. The distribution of tested species in this study (Plains Minnow *[Hybognathus placitus]*, Common Shiner [*Luxilus cornutus]*) were correlated with selected ecohydrological indicators trends (mean summer daily discharge, mean spring daily discharge, number of zero-flow days, high-flow pulse count and high-flow pulse duration). Streams with higher magnitude trends, both negative and positive, and higher variations have already lost those species. Therefore, it can be concluded that most of KRB streams are changing and the changes have altered the selected fish species' habits. Even though change in precipitation and streamflow were correlated with the changes in flow there were not statistically significant.

The second study assessed multiple parameterization, calibration and validation strategies that highlight SWAT model performance for different spatial scales and hydrologic conditions. SWAT models were built for two different watersheds with different hydrologic conditions and scales within KRB. Parameterization increased model performance significantly. Greatest model overall flow performance for flow, crop and ecohydrological indicators were observed after flow and crop calibration. Highest improvement in PBIAS for flow was observed at daily and annual scale for flow after crop calibration. Overall both models were able to predict streamflow and crop yields for corn, soybean, winter wheat and grain sorghum reasonably accurately and over a range of climatic conditions after flow and crop calibration. SWAT was suitable for simulating high-flow-rate ecohydrologic indicators. SWAT simulated high-flow-ratel ecohydrological indicators without even calibration in one watershed. This shows that SWAT is robust enough that it doesn't need calibration to be a useful tool for high-flow-rate ecohydrological indicators based analysis.

The final study provided insights on the suitability of SWAT to reproduce ecohydrological indicators. The results show SWAT was able to reproduce water resource indicators (WRIs), such as monthly, seasonal, and annual flows; center of timing of annual flows and the Indicators of Hydrologic Alteration (IHA), including monthly flows, 90-day minimum flow, 1- to 90-day maximum flows, baseflow, date max, high-flow pulse count and fall rate. However, replicating winter month flows, 30-day minimum flow, baseflow and fall rate needed a high level model calibration. The SWAT was not able to replicate any of 1- to 7- day minimum flows, low-flow flow pulse count and duration, high-flow pulse duration, rise rate and reversals in this study. It can be concluded that a detailed evaluation of modeled hydrologic indicators beyond calibration and validation is crucial before SWAT's ecohydrological application.

5.2 Recommendation

1. Linking hydrology and ecology is a challenging task. Despite need of a rigorous hydrological modeling approach, ecosystem interactions, complexity and diversity poses even greater uncertainties. Also ecosystem resilience to the changes and time-lag in the responses of fauna to flow-indicator change make the task yet more complicated. . Ecological response for the hydrological indicator changes of this study may have limitations because of these reasons. This study used available fish survey data (presence/absence) gathered from Kansas Aquatic Gap Database, which includes collections from the Kansas Department of Wildlife, Parks and Tourism, museum records, university research collections and various other sources. However, sampling density and/ or abundance in same location at greater resolution of sampling dates and location with similar sampling strategy is recommended for this type of study and would have strengthened these results. In addition, measurement of habitat characteristic (depth, velocity, turbidity, etc.) would have been beneficial to help better understand the various factors that interact with

hydrological indicators and create the observed changes in species presence and changes in density.

2. Understanding hydrodynamic and biogeochemical processes in hyporheic zone and the coupling of those processes with geomorphology, microbiology and ecology is important. More research related on dynamics of the hyporheic zone, particularly as related to ecologically relevant characteristics, is recommended.
3. It is clear that there is more aquatic habitat destruction (Figure A-1) within Kansas River Basin. Those destructions are associated with changes in streamflow volumes and patterns and water quality, especially sedimentation. This study attempt to address the hydrology part. However, the impact of dams, diversions, other impoundments like ponds, and long term historical study on water quality are lacking for this region. Also future changes in streamflow volume and pattern and potential ecological changes are unexplored. These types of studies are highly needed and recommended along with potential restoration methods. This information can be used in evaluation and regulation of water supplies, recreation, aquatic-life habitat, and pollution control (Perry et al., 2002) and is important for managing agricultural, ecological and other socio-economic sectors in the region.
4. Watershed models built in this study do not include impoundments. The study areas were selected to avoid inclusion of large reservoirs, but each study area still included many smaller impoundments, including farm ponds, conservation terraces, water detention structures, poorly graded road ditches, impoundments and wells built for irrigation, municipal and industrial purposes (especially in northwestern and central Kansas), etc., that could influence the hydrological response to rainfall. Including impoundments in models may help to represent watershed hydrology more accurately. Also uncertainties due to above mentioned factors need to be studied.
5. Current study used available ET results and/or ET-yield relationship. However, more research on dry and irrigated ET and their yield relationship is needed for various land cover throughout the State of Kansas. In addition, measurement of soil moisture at surface and various depth will be helpful for accurate hydrologic modeling.
6. This study also used static land use data (2005 Kansas Level IV map land cover, Kansas Applied Remote Sensing [KARS] Program) and most recent rotation information. Including dynamic landcover along with rotations may help to model plant water relations more

preciously. Also using region-specific tillage practices is highly recommended, especially before any water quality (sedimentation) applications. This study also used a single management practice on crop lands and no management on range land, which, in reality, spatially varies across the watershed. The uncertainties in model performance due to variability in landuse, tillage practices and management practices may be investigated.

7. This study used STATSGO soil data (1:250,000 scale). Soil characteristics influences moisture distribution and runoff general potential. Detailed SSURGO database (at 1:24,000 scale) may impact model simulated runoff/ streamflow. The uncertainties due to soil variability could be investigated.

5.3 References

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Appendix A - Fish habitat degradation risk (source: Kansas Biological Survey, University of Kansas)