January 2017

Modification Methods For Soil And Water Assessment Tool (SWAT) Performance In Simulating Runoff And Sediment Of Watersheds In Cold Regions

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MODIFICATION METHODS FOR SOIL AND WATER ASSESSMENT TOOL (SWAT) PERFORMANCE IN SIMULATING RUNOFF AND SEDIMENT OF WATERSHEDS IN COLD REGIONS

By

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A Dissertation
Submitted to the Graduate Faculty

Of the

University of North Dakota

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Grand Forks, North Dakota

December
2017

This dissertation, submitted by Bahareh Shoghli in partial fulfillment of the requirements for the Degree of Doctor of Philosophy from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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Date

PERMISSION

Title Modification methods for Soil and Water Assessment Tools (SWAT) performance in simulating runoff and sediment of watersheds in cold regions

Department Civil Engineering

Degree Doctor of Philosophy

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Bahareh Shoghli

11/26/2017

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ACKNOWLEDGMENT

I would like sincerely thank Dr. Yeo Howe Lim, the chairman of my doctoral committee, for his support, guidance, understanding and patience during my graduate studies at University of North Dakota. I would like to thank members of my PhD committee for their valuable discussion and guidance that made this document mush stronger. In particular, I would like to thank Dr. Iraj Mamaghani, Dr. Taufique Mahmood, Dr. Feng Xiao and Dr. Matthew Gilmore.

Many friends and colleagues sincerely supported my Ph.D. studies. I would like to gratefully thank and appreciate all their contributions. I would like to make a special mention to Dr. Sara Pourjafar, for her friendship and moral support throughout all the years in graduate school. This dissertation would not have been possible without their kind helps and supports.

I am grateful to the Department of Civil Engineering at University of North Dakota for the opportunity of pursing graduate studies, and would like to express my appreciation to Dr. Sukhvarsh Jerath the Chair of Civil Engineering Department for his support.

Finally, I would like to thank my parents, sisters (Neda and Mahsa), and brother for their encouragement in all my pursuits and their continued love and support that helped me go through the stressful times. I would like to express my special thanks to my brother Dr. Omidreza Shoghli for his support, guidance and unconditional helps. Although words cannot express my gratitude and appreciation, I absolutely owe my highest appreciation and thanks to you.

I would like to gratefully thank Amir Ghorbanpour for his guidance and patience during this stressful time of my study.

I appreciate the financial support from College of Engineering and Mines (CEM) and School of Graduate Study at University of North Dakota and North Dakota Water Resource Research Institute (NDWRRI) for their two-year fellowship award.

To the Memory of my father, **Mansour Shoghli,**

for inspiring my fascination in science and learning.

To my mother, **Nasrin Maboodi**,

for her unconditional love and support

ABSTRACT

Streamflow predication is an important task in water management studies. It is needed in the operation and optimization of water resources and flood control projects. The accuracy of these predictions has a great influence on the water resources management and decision making processes. Various models and tool packages have been developed for simulation and prediction of streamflow. Among them, the Soil and Water Assessment Tool (SWAT) is one of the most widely used models, which was originally developed to predict the impacts of land management on water, sediment and agricultural chemical yield in large watershed simulations. Results of the SWAT streamflow simulations have indicated that this tool has deficiencies in simulating the peaks in streamflow generated by snow melting processes in the cold regions. Since global temperature is projected to be increased and the phenomena will change the snow melting characteristics in the snow dominant areas, such as the time of first melt and rate of melting. This trend along with more precipitation will cause more flooding problems in these regions. To improve daily streamflow prediction in these regions, two methods were developed. Firstly, a method was performed by separation of winter and summer seasons simulated streamflow with subsequent validation conducted in two different seasons using Calibration Uncertainty Procedure (SWAT_CUP). It should be noted that sensitivity analysis was performed on each of the seasons separately. The second method was conducted based on coupling Artificial Neural Networks (ANNs) with calibrated and validated results of SWAT_CUP without any separation of the seasons. The calibrated streamflow, precipitation, maximum temperature, minimum

temperature, snow depth, wind speed, and relative humidity were used as inputs to the ANNs model. The results of both methods have indicated significant improvements in the simulated series. In comparison between these two methods, the operation of the second method is considered better than the first method. Although, the first method has shown improvement in the simulated results but there is still a difference between the peak streamflow and the measured streamflow by USGS (United State Geological Survey) stations. However, this difference was found diminished in the simulations using the second method. ANNs method have increased peak streamflow predication in about 70%. With this improvement, the weakness of the SWAT model in simulating sediment accumulation due to improper peak run off simulation was eliminated.

CHAPTER I

INTRODUCTION

Background

The world's reservoirs are currently filled up with sediment at a rate of about 1% per year (World Commission on Dams, 2000). This implies that within about 50 years, the world's water storage in reservoirs will be half of the current storage. This trend will have large economic and environmental consequence, especially in the semi-arid environment where many reservoirs have been built for irrigation, water supply, flood control, and electricity generation. Besides, this sediment storage can have large implications for the ecosystem and coastal development downstream of large river systems. Therefore, it is utmost importance to predict sediment yield at the basin scale and understand which factors determine the sedimentation rates of reservoirs. This knowledge will allow estimating the probable lifespan of a reservoir and moreover, to take proper measures against reservoir sedimentation, water storage loss, river bank and coastal erosion. At the moment, the prediction of sediment yield in the basins larger than 50 km^2 is still one of the largest challenges in soil erosion research.

Reservoir and Sediment Deposition

Dams are the structures that are built for many different reasons: water supply, flood control, electricity generation, etc. These hydraulic structures disturbed the natural equilibrium of a stream. The velocity of water flow is reduced, and the large volume of sediment is usually deposited in the reservoir's basin.These sediment deposition have many effects on the reservoir, as well as on the downstream and upstream parts of the reservoir. These effects are of great concerns to water resources engineers. In planning and designing a reservoir, it is very important to have a good knowledge of the sediment deposit distribution and incorporation of its effect on design measures or reservoir management.

Statement of Problem

Deposition of the sediment in the reservoir has a different influence on the surrounding environment. Sediment deposition in the reservoir not only affect the reservoir operation, it also affect the physical characteristics of both upstream and downstream parts of the reservoir.

The first significant problem is the influence of sediment deposition in decreasing a storage capacity of the reservoir,and that affect the function of the reservoirs. The important functions of the reservoirs that affected by sedimentation are: loss of flood control, blockage of the gates, water yield, and water quality.

The effect of sedimentation on the upstream part of the reservoir is another problem in reservoir sedimentation study. Sediment deposition in the deltaic region increases flooding in the upstream region.

The other significant problem occurs in the downstream part of the reservoir. The lack of sediment in the water that exit from the reservoir causes scouring as the water entrains bed materials downstream of the dam wall. Some other environmental effects are summarized as follow:

a) Accumulated sediment behind the dams can affect the flood attenuation function of the reservoir. As a result, the ecosystem of the river will change. Recently in the United States, removal of the unsafe and unusable dams has been implemented to restore fish passage and rivers ecosystem, but it has its own disadvantages. Dam removal can increase the sediment entrance to the downstream. As a result, the quality of water in downstream area will decrease, and more sediments deposited in the channel. Therefore, before any dam removal, the effects on sediment accumulation should be studied.

b) sediment trapping by dams creates methane emission hot spots. The existence and emission of CH4 from the surface of the reservoir comes from the combination of two important factors: continuous trapping of allochthonous and autochthonous organic material in the reservoir and increased CH4 production via anaerobic degradation of organic carbon in the reservoir sediments. In the small reservoirs, the sediment accumulation area covers a large fraction of the surface area. Hence, the sediment accumulation rate is higher as compared with the larger reservoirs.

c) An accurate streamflow prediction is required before making an accurate sediment accumulation forecast. However, accurate predictions of rainfall-runoff and consequent stream flows from a regional scale watershed are extremely difficult because of the tremendous spatial and temporal variability of watershed characteristics and weather patterns.

d) Predicting summer streamflow is typically more accurate than the winter streamflow. Because of the complexity of snowmelt hydrology, predicting runoff generated by the melting of snow is challenging. Since most of the northern and western parts of the U.S. are snow dominated regions, the impact of global warmings in these regions is more likely than any other regions. With global rise in temperature, the spring snow melting process tends to start earlier and spring flooding events tend to be more frequent.

In future, we will encounter with more frequent early snow melting in this region. It will have effects on the amount of sediment accumulation and reduce the life span of the reservoirs. Hence, an accurate simulation and prediction models in these regions is of the utmost importance.

Effective Factors on Sedimentation of Reservoirs

The important steps in understanding, controlling, and modeling the sediment deposition are recognizing and finding the effective factors on deposition of sediment in the reservoir formed by dams. There are many interrelated factors and some of them are summarized as follows:

Sediment Discharge

The amount of sediment discharge is one of the most important factors in reservoir sedimentation. Sediment discharge is related to some parameters such as runoff yield of the basin, vegetation covers in the basin, geometry, and dimensions of the basin. Since sediment discharge is related to the streamflow, it is very important to have an accurate tool for the simulation of streamflow.

Trap Efficiency

The ratio of the sediment retained in the reservoir to the total inflow of river sediment is called trap efficiency. The capacity of the reservoir, water, and sediment inflow, sediment specification, the shape of the reservoir, operation duration curve, and density current are factors that affect the trap efficiency of the reservoir.

Density of Deposited Sediment

Knowing the density of the sediment that deposited in the reservoir may help in finding the weight of the deposited sediment. The important parameters affecting the density of sediments are the depth of sediment deposition, sediment compositions, chemical characteristics of sediment, and the age of deposited sediment.

Turbidity Current

When water with high-suspended sediment flows into the clear ambient water of a reservoir, the difference between two densities will create two different layers in the reservoir. This phenomenon has a significant effect on the pattern of sediment deposition in some large reservoirs. There are some other factors that can affect the reservoir sedimentation, but their effect are negligible.

Objective of Research

The major objectives of the research are twofold: (1) to investigate sediment accumulation in the reservoir of dams and (2) to improve the simulation and prediction methods for accurate prediction of sediment in reservoirs in cold regions. The specific objectives of this project are:

a) Evaluating performance of SWAT in the simulation of streamflow in a watershed in the region with cold climatic weather

b) Evaluating SWAT model in the simulation of sediment yield in the reservoir formed by an embankment dams

c) Finding the trap efficiency of the reservoir according to the SWAT simulation results

d) Improving SWAT performance in simulating of peak streamflow in the cold region

Research Questions

The following important concerns related to sediment accumulation in the reservoir are being answered in this research:

a) Are SWAT and SWAT-CUP able to simulate peak flood effectively and accurately in the area that spring floods are generated by melting of snow?

b) How to know the trend of sediment accumulation in the reservoir? (Base on this trend, the reservoir could keep its sustainability)

c) Which parameters are more sensitive in these model simulations?

d) What is the effect of snow in this simulation of streamflow?

e) What is the best method for simulation of peak streamflow in the cold regions?

Research Methods

SWAT (Arnold et al., 1998) is employed to model reservoir of Lake Ashtabula and to estimate the sediment accumulation in the reservoir under the impact of climate and land use changes. The model is calibrated and validated against daily United States Geological Surveys (USGS) stream gauge records using the SWAT-CUP tool (Abbaspour, 2011). Entrance sediments in the reservoir are divided into bed load and suspended load sediments. Bed load sediments are considered minor (less than 5% of the total sediment), and therefore are not evaluated in this study. Subsequently, both the calibration and validation processes were performed solely with the suspended sediment load.

Simulation of sediment accumulation in the reservoir was started by simulating Total Suspended Sediment (TSS) entrance to the reservoir with the help of SWAT. TSS data were downloaded from the North Dakota Department of Health (NDDoH).

Daily sediment loads for the three sediment stations were estimated using the program LOADEST simulation model which is developed and made available by the USGS. This program estimated the sediment loads using rating curves developed from the best-fitted polynomial model and the coefficients were derived based on an Adjusted Maximum Likelihood Estimation Method (AMLE).

Since North Dakota is located in a cold region with extreme spring floods, which are triggered by synchronous occurrences of snow melting and precipitation, it is necessary to use a suitable streamflow simulation method or making modifications to the existing methods for predicting streamflow in these conditions.

Artificial Neural Network (ANN) is a flexible mathematical structure that could find the complex nonlinear relationships between the input and output data sets. In this study, the multilayer feedforward network (MFN) with back propagation (BP) training algorithm was selected for improving the deficiency of SWAT in simulation of floods that arise from melting of snow.

The research objectives are accomplished through the following research tasks:

a) Model development: Using SWAT, the watershed of Lake Ashtabula is delineated into six subbasins and further divided into several hydrologic response units based on unique combination of land use, soil type, and slope. The base of the SWAT model is consisted of a USGS 10m Digital Elevation Model, soil data and land use data provided by crop layer compiled by US Department of Agriculture (USDA) National Agricultural Statistics Service, USDA STATSGO/SSURGO soil map, and daily weather data for four stations extracted from NCDC. The sensitivity analysis method used is Latin-hypercube regression (McKay et al.,1979) which is available in SWAT-CUP, simulated model is calibrated and validated in this step with the help of sensitive parameters. SWAT performances in simulating streamflow were verified by two statistical analysis: I) Coefficient of Determination (R) and (II) Nash-Sutcliffe Efficiency (ENS).

b) Sediment simulation: After the simulation of the watershed of the Lake Ashtabula, the next step is to calculate sediment accumulation due to the entrance of sediment into the reservoir. Daily sediment loads for the three sediment stations were estimated using the program LOADEST simulation model. This program estimated the sediment loads using rating curves developed from the best-fitted polynomial model and the coefficients were derived based on an Adjusted Maximum Likelihood Estimation Method (AMLE). Calibration and validation were performed based on the calculate Total Suspended Sediment (TSS) and what are observed in the specified stations.

c) The trap efficiency of the reservoir was calculated based on the entrance sediment to the reservoir and what exits from the reservoir.

d) In the cold region, parameters related to the snow melting process are more sensitive than the other regions, so the results show a discrepancy in simulating peak streamflow. Two different methods were investigated in this research for improving the SWAT results:

   1) The results of SWAT simulated streamflow series was separated into summer and winter periods. By separating these two seasons, the sensitive parameters were

identified and recalibrated. For example, the snow melting parameters are just used for the wintertime.

2) Feedforward Artificial Neural Networks (ANNs) that is trained with the back propagation algorithm was used for improving the disability of SWAT in simulating peak streamflow of the cold region. Input data are the calibrated and validated stream flow, maximum temperature, minimum temperature, relative humidity, snow depth, wind speed and the output data is streamflow series that has been measured at the USGS stations. Evaluation of ANNs model was performed by the Correlation Coefficient (R) and Mean Square Error (MSE).

Scope of the Research

In accordance with the objective outline, this dissertation is designed in two-paper format. It consists of four chapters, which accomplish the research objectives and answer the research questions. Chapter II provides answers to this question whether SWAT model is adequate enough for simulating streamflow and sediment entrance series in the watershed of Lake Ashtabula and for estimating the sustainability of the reservoir of Baldhill Dam. By considering the sediment accumulation and water elevation in the reservoir. Chapter III describes the details of Artificial Neural Network that was used for improving deficiency in SWAT for simulating streamflow series and predicting peak streamflow events cauesed by extreme floods. Chapter IV was allocated for summary and conclusion sections, which summarized the findings of this research in modification methods for soil and water assessment tool (SWAT) performance in simulating runoff and sedimnet of watershed in cold regions

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CHAPTER II

MODIFICATION METHODS FOR SWAT IN SIMULATING RUNOFF AND SEDIMENT OF WATERSHEDS IN A COLD REGION

Introduction

The process of sediment inflow from a watershed and subsequent deposition and accumulation within a dam's reservoir, also, known as reservoir sedimentation, can threaten the proper functioning of the reservoir itself as well as the safety of the dam. Understanding the reservoir sedimentation process is of fundamental significance in hydro systems engineering. The reservoirs formed by dams are vital to the world's economy in the perspective of electricity generation, flood control, water supply, and recreation. In most stable reaches of natural rivers, sediment movements are approximately balanced by the amount of sediment inflow and outflow. However, a dam can dramatically alter this balance because of an expected increase in the flow depth and the corresponding decrease in the flow velocity within the reservoir. These changes would reduce the sediment transport capacity and result in the settling of sediments. Overall, reservoir sedimentation is a complicated process that depends on the watershed sediment production, flood frequencies, reservoir geometry and operation flocculation potential, sediment consolidation, density currents, and land-use changes over the life expectancy of the reservoir. Accumulated sediment behind dams can affect the flood attenuation function of the reservoir. As a result, the ecosystem of the river will change. Recently in the United States, removal of unsafe and unusable dams has been implemented benefiting fish passage and ecosystems.

However, dam removal also has its own disadvantages. Dam removal can increase the sediment entrance to the downstream channels. As a result, the quality of water in downstream areas will decrease as more sediments are deposited in the channels (Warrick et al., 2015).

In another perspective, sediment trapping by dams creates methane (CH_4) emission hot spots. It is known that emission of CH_4 from the surface of the reservoir is caused by a combination of two important factors: continuous trapping of allochthonous and autochthonous organic materials in the reservoir, and increased CH_4 production via anaerobic degradation of organic carbon in the reservoir sediments. In the small reservoirs, the sediment accumulation area covers a larger fraction of the surface area and sediment accumulation rate is relatively higher when compared with the larger reservoirs (Maeck et al., 2013).

The environmental impacts of reservoir sedimentation are not limited to those described above. In the long term, sedimentation has serious impacts on the local and regional economic situation related to drinking water supply, irrigation, and power generation. Reduction of water availability is a major impact of reservoir siltation in semi-arid regions (De Araujo, Guntner, & Bronstert, 2006). Understanding the sediment dynamics and identifying the main effective parameters on erosion of soil will help to optimize the strategies for minimizing sediment entrance to the reservoirs. Prediction of sediment deposition is always necessary for the planning, design and operation stages of reservoirs. The method of trap efficiency (TE) is one of the methods used for predicting reservoir sedimentation. Trap efficiency is defined as the ratio of the total weight of annual sediment accumulation behind a dam to the total weight of annual sediment inflow to the reservoir. TE is dependent on several parameters. One of these parameters is particle size distribution of the incoming sediment to the reservoir, which controls the TE in terms of retention time (the average time the incoming runoff remains in the reservoir). Coarser materials have higher settling velocities than the finer material thus less time is required for its deposition. The particle size distribution of incoming sediment is related to the soils in the catchment that are being eroded in the sedimentation process. The retention time in the reservoir is related to the characteristic of inflow hydrograph and geometric characteristics of the reservoir or ponds including storage capacity, shape, and outlet typology. Likewise, the location of the outlet structure is important. If it is located at the top of a dam in the form of a spillway, the runoff has an extended time for mixing with the water already detained in the reservoir. Inversely, if it is located near the bottom of the dam, the runoff has much less mixing time.

Investigations on 17 small flood mitigation reservoirs in the southern and northern United States have shown that their trapping efficiency varies from 81 to 98 percent for periods of 4 to 16 years, although these reservoirs have different size, shape, sediment load, flow, and velocity (Dendy, 1974). Some geographic factors such as land use, land cover, slope (topography of the land), vegetation, and soil structure, are important parameters in soil erosion. (Yigzaw & Hossain, 2016) studied the impacts of land use and land cover on probable maximum flood and sedimentation for man-made reservoirs in Owyhee River Watershed. Results of this study have indicated that by changing the land cover from grassland to shrub land, the sediment yield has decreased over the watershed. Geographic factors are not the only effective parameters influencing soil erosion; climatic factors are also having impacts on sedimentation. Wind and precipitation intensities are examples of climatic factors. (Yigzaw & Hossain, 2016) also pointed out the effect of precipitation intensity on reservoir sedimentation and showed a significant 0.1% storage loss over just a 21-day storm period.

Among all the factors described above, land use and climate are the two main factors that would affect watershed hydrologic process the most (Brath, Montanari, & Moretti, 2006; Shoghli, Lim, & Alikhani, 2016; Shoghli & Lim, 2017; Wu, Liu, & Gallant, 2012). Although several studies have highlighted the concerns of effective parameters on sedimentation, there is still a clear lack of efforts in assessing the impacts of climate and land use change on the storage capacity of the small reservoirs.

The main objective of this study is to assess the effective parameters affecting the rate of sediment accumulation in a relatively small reservoir formed by an embankment dam. The second objective is to evaluate the impacts of snowmelt in a small watershed with mild-slope in a cold region. To achieve the objectives, Soil and Water Assessment Tool (SWAT) was selected. SWAT is a semi-empirical, semi-physical and watershed-based hydrological model developed to assess the impact of alternative management parameters and nonpoint-source pollution in large river basins (J. Arnold & Allen, 1996). It is used widely for the prediction of long-term water and sediment yield from the basin areas. This tool has been used to simulate the effects of climate change, land use change, reservoir management, and ground water withdrawal (J. G. Arnold et al., 2012)

Methods

Study Area

Baldhill Dam, which creates the reservoir of Lake Ashtabula (see the location in Figure 1), is located on the Sheyenne River approximately 271 river miles upstream from its confluence with the Red River of the North. Lake Ashtabula is a multipurpose reservoir used for rural and municipal water supply, flood control, municipal pollution abatement, fish and wildlife habitat, and recreation. The dam is a compacted, earth-filled dam with a length of 1650 feet (502.92m), and a crest elevation of 1278.5 feet (389.69 m) above mean sea level. The freeboard above the pool level is 12.5 feet (3.81m) and the reservoir has a storage capacity of 68,600 acre-feet (84.61×10^6 m^3) with a surface area of 5430 acres(2.19×10^7 m^2), length and width of 27 miles (43.45 km) and 0.6 miles (0.96 km) respectively. The ogee spillway of this dam is gated with the crest elevation of 1252 feet (381.6) and length of 140 feet (42.67m). The top of the gates when sealed is at an elevation of 1267 feet (386.2m). The construction of the dam began in July 1947 and formally dedicated in September 1952.

Baldhill Dam has been classified as a high-hazard dam according to National Inventory of Dams (NID). Since the dam is located in a long, narrow valley above Valley City, North Dakota, a dam failure would extensively damage downstream properties and create the potential for loss of life. Both Baldhill Dam and Lake Ashtabula are in Barnes County. Barnes County is usually warm in the summer and very cold in the winter. Total annual precipitation is about 18 inches (457.2 mm), of which more than 75% are usually fallen in April through September. The average seasonal snowfall for the county is about 21 inches (533.4 mm).

Sheyenne River and Baldhill Creek are the two main rivers that flow into the reservoir of Lake Ashtabula (Figure 1). The average topographic slope of the watershed of Lake Ashtabula of is about 3%. The Sheyenne River upstream of the Baldhill Dam has a total drainage area of 3812 mi^2 (9873.03 km^2), of which 462 mi^2 (1196.6 km^2) are contributing. The mean annual streamflow, measured near Cooperstown at station 05057000 showed the main inflow to Lake Ashtabula was about 144 ft^3/s (4.07 m^3/s) for the period of 1945-2009. Generally, the highest streamflow happens in the spring (March through May) and lowest occurs in the winter (November through February).

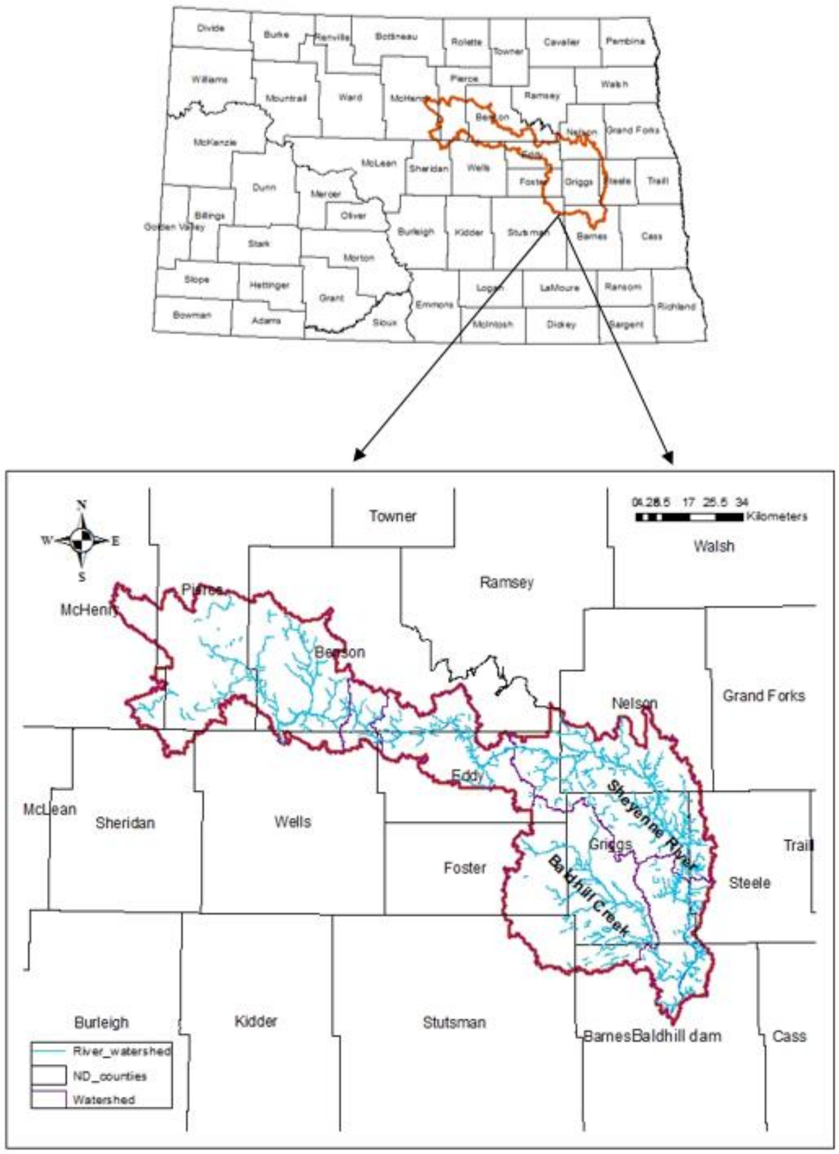

Figure 1. Location of Lake Ashtabula and Baldhill Dam.

One of the significant concerns of natural resources management effort for a watershed is controlling the amount of erosion, primarily the wind and water erosion on cropland, and animal unit densities. Of the 956,800 acres within Barnes County, 82% is cropland, 13% grass, and the remaining 5% is urban/water. Corn and soybeans are the principal crops grown, with some wheat and sunflower.

According to 2011 land use developed by National Agricultural Statistics Service (NASS), pasture (26%), soybeans (20%), spring wheat (17%), wetland (11%), and corn (4%) combined to form the land use distribution of the watershed of Lake Ashtabula.

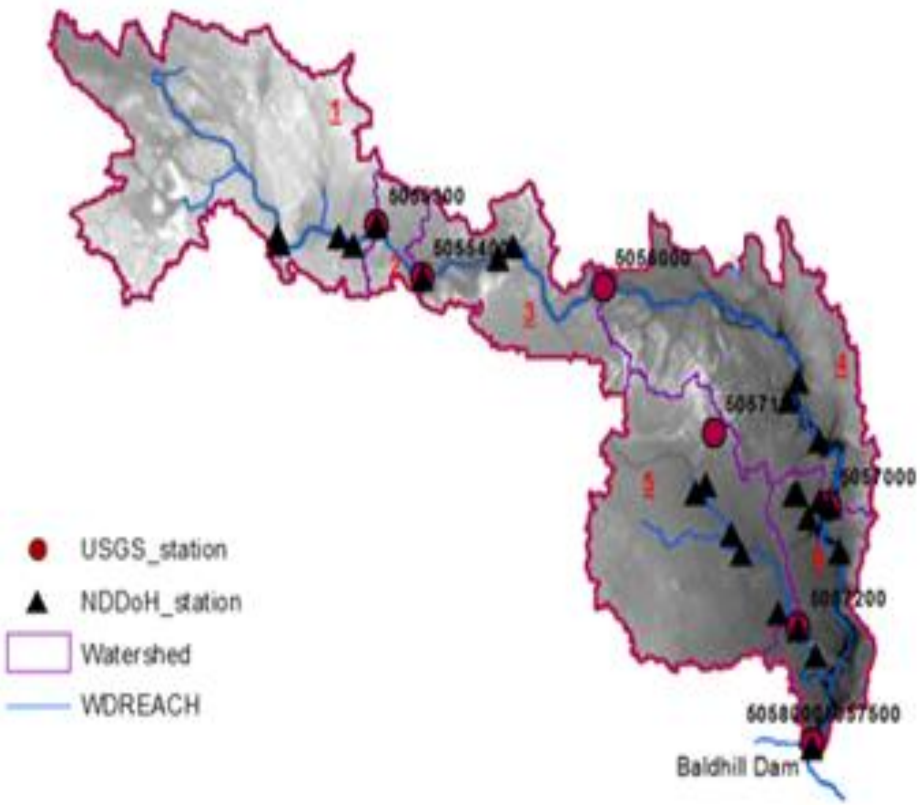

Figure 2. Location of USGS and NDDoH stations and determined subbasin in watershed of Lake Ashtabula

Model and Input Data

SWAT Model Setup

The first step in setting up the model is to perform the physiographic analysis based on catchment topography at the Baldhill Dam's watershed. SWAT automatically subdivides and delineates the watershed areas into sub-watershed areas, with the same homogeneous characteristics. In this study, 10-meter USGS Digital Elevation Model (DEM) was provided for topographic analysis, delineation of sub-watershed, and stream network generation. Soil map was extracted from STATESGO dataset, and land use was prepared from the USDA National Agriculture Statistic Service (NASS). SWAT accounts for snow accumulation and melting; it classifies precipitation as rain or freezing rain/snow by the mean daily air temperature. The user defines a boundary temperature. If the mean daily air temperature is less than the boundary temperature, then the precipitation within each Hydrologic Response Unit (HRU) is classified as snow. Subsequently, the water equivalent of the snow precipitation is added to the snow pack. Since our selected study area has been located in the semi-arid area with cold and long winter duration time, this option of SWAT could be vital in the modeling process. SWAT presented two methods for calculating surface runoff: Soil Conservation Service (SCS) curve number procedure (SCS, 1972) and Green & Ampt infiltration method (1911). And for calculating potential evapotranspiration, SWAT presented three methods: Penman-Monteith Method, Priestiely-Taylor Method, and Hargreaves Method. In this study, the SCS Curve number method and the Hargreaves method were chosen for surface runoff and for potential evapotranspiration, respectively. The basis of SWAT Model for erosion calculation, especially for erosion caused by rainfall and runoff, is the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975). Each subbasin has the main routing reach where sediment from upland subbasin is routed and then added to downstream reaches. In SWAT model, a simplified version of Bagnold (1977) streams power equation was used to calculate the maximum amount of sediment that can be transported in stream segment. Lateral surface flow in the soil profile (0-2m) is calculated simultaneously with percolation through soil columns. A kinematic storage routing method, which is based on slope, slope length, and saturated hydraulic conductivity, is used to predict lateral flow in each soil layer. Lateral flow occurs when the storage in any layer exceeds field capacity after percolation.

Groundwater flow contribution to total streamflow comes from shallow aquifer storage (Arnold and Allen, 1996). Percolation from the bottom of the root zone is considered as recharge into the shallow aquifer. Water is routed through the channel network using the variable storage routing method. The required input data for the SWAT simulations are DEM, land use map, soil map, daily precipitation, maximum and minimum temperature, and solar radiation.

Data of daily precipitation, minimum and maximum temperature, wind speed, and solar radiation data were downloaded from the United State Department of Agriculture (USDA) and they are derived from the National Oceanic and Atmospheric Administration (NOAA) dataset. The data from this website are available up to 2010. For the following years (2011 to 2013), the data were downloaded from PRISM Climate Data prepared by the PRISM Climate Group.

As shown in (Figure 2), there are six USGS streamflow gaging stations in the watershed area. The characteristic of the stations are described in (Table 1) Of the six available stations in the watershed area, just four of them are usable because the observations at the other two stations give very short records (started in 2005) and are not sufficient for our calibration purposes. For evaluating and calibrating the watershed according to the active USGS stations, the following classification was adopted: subbasins 1, 2, and 3 correspond to USGS station 05056000 as Outlet 3, subbasin 5 corresponds to USGS station 05057200 as Outlet 5, subbasin 4 corresponds to station 05057000 as Outlet 4, and finally subbasin 6 corresponds to USGS station 05057500 as Outlet 6.

Table 1. Characteristics of USGS and NDDoH observation stations in the watershed of Lake Ashtabula

	Station Name	ID	Period of Record	Hydrology Calibration	Sediment Calibration
USGS	Sheyenne River Near Warwick, ND	05056000	1949-10 2016-12	√	
NDDoH		385345	2005-2012		x
USGS	Baldhill Creek Near Dazey, ND	05057200	1956-04 2016-12	√	
NDDoH		384126	1998-2015		√
USGS	Sheyenne River Near Cooperstown, ND	05057000	1944-10 2016-12	√	
NDDoH		380009	1996-2015		√
USGS	Sheyenne River Below Baldhill Dam, ND	05058000	1949-10 2016-12	√	
NDDoH		380153	1995-2015		√
USGS	Sheyenne River AB Above Devils Lake State Outlet Near Flora, ND	05055300	2004-10 2016-12	x	
NDDoH		385505	2010		x
USGS	Sheyenne River Below Devils Lake State Outlet Near Bremen, ND	05055400	2005-04 2016-12	x	
NDDoH		385502	2010		x

The Baldhill Dam watershed runoff simulation was performed for the period from 1985 to 2014. Three years were allocated for the warm up period 1985-1988, while the calibration period is 1988-2005 and the validation period is 2006-2014.

Simulation of sediment accumulation in the reservoir was started by simulating Total Suspended Sediment (TSS) entrance to the reservoir with the help of SWAT. TSS data were downloaded from the North Dakota Department of Health (NDDoH). TSS data in the USGS stations were not published for the study time period; therefore, we used the NDDoH stations which are in proximity of the USGS station. (Table 1) shows the status of the usage of streamflow data from the USGS stations and the corresponding NDDoH stations.

Daily sediment loads for the three sediment stations were estimated using the program LOADEST simulation model. This program estimated the sediment loads using rating curves developed from the best-fitted polynomial model and the coefficients were derived based on an Adjusted Maximum Likelihood Estimation Method (AMLE).

Model Calibration and Validation

Calibration of the SWAT model was performed and optimized by SWAT Calibration and Uncertainty Programs (SWAT-CUP). SWAT-CUP is a computer program for sensitivity analysis, calibration, validation, and uncertainty analysis of the SWAT models. Abbaspour (2011) developed this program which links Sequential Uncertainty Fitting (SUFI2), Particle Swarm Optimization (PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (Parasol), and Markov Chain Monte Carlo (MCMC) procedures in the SWAT models.

The SWAT-CUP with SUFI2 algorithm was used in this research. In the simulated watershed, a few parameters related to the discharge and sediment have uncertainty issues. In SUFI-2, the uncertainties in parameters are depicted as uniform distribution ranges and all sources of uncertainties are explained. The uncertainties in model parameters lead to uncertainties in the model output variables, which are presented as the 95% probability distributions. These ranges, calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable, are produced by the propagations of the parameter uncertainties using Latin Hypercube sampling. This was named as 95PPU or 95 PPUs (Abbaspour 2011).

(Moriasi et al., 2007) recommended three other statistical factors for the evaluation of the model calibration: Nash-Sutcliffe efficiency (NSE), Percent Bias (PBIAS) and RMSE-observation standard deviation ratio (PSR). NSE measures the fitness of observed and simulated data, and it varies from $-\infty$ to 1. The closer to 1, the better in performance the model is. PBIAS indicates the average tendency under and above prediction; positive values explain an underestimate prediction, and negative values show the overestimation prediction by the model.

Table 2. General performance ratings for recommended statistics (Moriasi et al 2007)

Performance Rating	PSR	NSE	PBIAS Streamflow	PBIAS Sediment
Very Good	0.00≤PSR≤0.50	0.75<NSE≤1.00	PBIAS<±10	PBIAS<+15
Good	0.50<PSR≤0.60	0.65<NSE≤0.75	±10≤PBIAS<±15	15<PBIAS<+30
Satisfactory	0.60<PSR≤0.70	0.50<NSE≤0.65	±15≤PBIAS<±25	30<PBIAS<+55
Unsatisfactory	PSR>0.70	NSE≤0.50	PBIAS≥±25	PBIAS>+55

(Moriasi et al., 2007) classified the model performance (for model using monthly data) into four ratings according to these three statistical indicators. As shown in (Table2), these ratings are very good, good, satisfactory, and unsatisfactory range. Although, this classification was conducted with the monthly simulation, it could give us a general view for evaluating the daily data calibration results. (Moriasi et al., 2015) in their recent publication indicated that the model performance can be judged satisfactory for streamflow simulations if the daily, monthly, or annually simulated result show R^2>0.60, NSE>0.5, and PBIAS±0.15%.

Results and Discussions

Model Calibration and Validation

Calculation of sediment accumulation in the reservoir of Baldhill Dam was performed with the help of the developed SWAT model. As described above, the calibration and validation procedures were conducted by SWAT CUP. Calibration was implemented in a two-step procedure consisting of first, conducting a sensitivity analysis to identify the parameters that are sensitive for simulation and then adjusting the values for the identified sensitive parameters. The identified sensitive parameters and the calibrated values for streamflow and sediment load simulation are presented in (Table 3).

Table 3. SWAT's sensitive parameters and fitted values

Variable	Parameter name	Description	Sub 1, 2, 3	Sub 4	Sub 6	Sub 5
Flow	1:R*__CN2.mgt	SCS runoff curve number	0.0124	0.018	-0.101	-0.105
	2:R__SOL_K(..).sol	Saturated hydraulic conductivity	-0.0934	-0.094	-0.053	0.125
	3:V*__CH_N2.rte	Manning's "n" value for the main channel	0.1274	0.127	0.125	0.126
	4:V__EPCO.hru	Plant uptake compensation factor	0.8625	0.151	0.616	0.975
	5:V__ESCO.hru	Soil evaporation compensation factor.	0.8715	0.076	0.459	0.925
	6:V__ALPHA_BF.gw	Base flow alpha factor (days)	0.2248	0.225	0.160	0.280
	7:V__GW_REVAP.gw	Groundwater "revap" coefficient	0.1488	0.149	0.146	0.145
	8:V__REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	1.6228	1.627	1.923	1.856
	9:V__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	5.6678	5.666	5.670	7.750
	10:V__GW_DELAY.gw	Groundwater delay (days)	349.742	333.24	279.78	334.9
	11:R__SLSUBBSN.hru	Average slope length	0.5175	0.227	0.646	0.115
	12:V__OV_N.hru	Manning's "n" value for overland flow.	0.164	0.126	0.195	0.135
	13:R__SOL_AWC(..).sol	Available water capacity of the soil layer	0.2234	0.223	0.731	0.378
	14:V__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium.	0.2221	0.227	0.223	2.674
	15:V__SMTMP.bsn	Snow melt base temperature.	4.0625	4.062	4.062	5.436
	16:V__SFTMP.bsn	Snowfall temperature.	-3.1489	-3.149	-3.149	-0.120
	17:V__SURLAG.bsn	Surface runoff lag time.	24.1933	24.193	24.193	25.2
	18:V__SMFMX.bsn	Maximum melt rate for snow during year	18.2700	18.270	18.270	17.329
	19:V__SMFMN.bsn	Minimum melt rate for snow during the year (occurs on winter solstice).	1.3078	1.308	1.308	3.145
	20:V__TIMP.bsn	Snow pack temperature lag factor	0.9671	0.967	0.967	0.951
Sediment	21:V__SPCON.bsn	Linear parameter for calculating the maximum amount of sediment that can be re entrained during channel sediment routing	0.00775	0.00775		0.00093
	22:V__SPEXP.bsn	Exponent parameter for calculating sediment re entrained in channel sediment routing	1.1	1.1		1.13
	23:V__CH_COV1.rte	Channel erodibility factor	0.0045	0.0045		0.8063
	25:V__CH_ERODMO.rte	Jan. channel erodability factor	0.4485	0.4485		0.96
	26:V__USLE_K.sol	USLE equation soil erodibility (K) factor	0.284	0.284		0.01

* The qualifier "R" refers to relative change in parameter where 1 plus a factor in given range multiplies the value from SWAT database

* The qualifier "V" refers to the substitution of a parameter by a value in given range

Calibration and validation of streamflow

Based on the discharge data measured at the USGS stations, the calibration and validation of simulated watersheds were performed. The watershed of Lake Ashtabula was divided into four subbasins and the calibration was performed for mean daily streamflow with gages 05056000, 05057000, 05058000 and 05057200 as shown in (Figure 2 and Table 1). (Table 4) displays a comparison between the simulated and observed discharge in the watershed of Lake Ashtabula.

Table 4. Statistical evaluation of simulated watershed base on the daily discharge data and sediment entrance (ton/day)

Calibration (1985-1999)						
Variable	R^2	NSE	PBIAS	KGE	RSR	MNS
FLOW_OUT_3	0.75	0.74	7.3	0.83	0.51	0.59
FLOW_OUT_4	0.78	0.75	7.3	0.85	0.5	0.54
FLOW_OUT_6	0.78	0.76	16.4	0.8	0.49	0.48
FLOW_OUT_5	0.76	0.76	7.9	0.8	0.49	0.64
Validation (2000-2013)						
Variable	R^2	NSE	PBIAS	KGE	RSR	MNS
FLOW_OUT_3	0.67	0.65	28.4	0.6	0.59	0.4
FLOW_OUT_4	0.69	0.64	43	0.48	0.6	0.38
FLOW_OUT_6	0.72	0.66	43.1	0.49	0.59	0.35
FLOW_OUT_5	0.62	0.61	16	0.7	0.62	0.52

Calibration (1995-2008)				
Variable	R2	NSE	PBIAS	RSR
SED_OUT_4	0.53	0.43	62.7	0.75
SED_OUT_5	0.74	0.66	-19.3	0.59
Validation (2008-2013)				
Variable	R2	NSE	PBIAS	RSR
SED_OUT_4	0.52	0.31	74.5	0.84
SED_OUT_5	0.59	0.33	-33.1	0.84

The calibration and validation results show that NSE, PBIAS and PSR parameters, based on the (Table 2) classification, are in the "good" condition category. (Figure 3) depicted the simulated discharge plotted against the measurement discharge during calibration and validation time period. Based on the NSE, PBIAS, and PSR parameters, we can consider this model in the "good" category. Nevertheless, it is obvious that under some specific conditions as shown in the highlighted (using circles) cases in (Figure 3), there are big differences between the simulated and the observed streamflow.

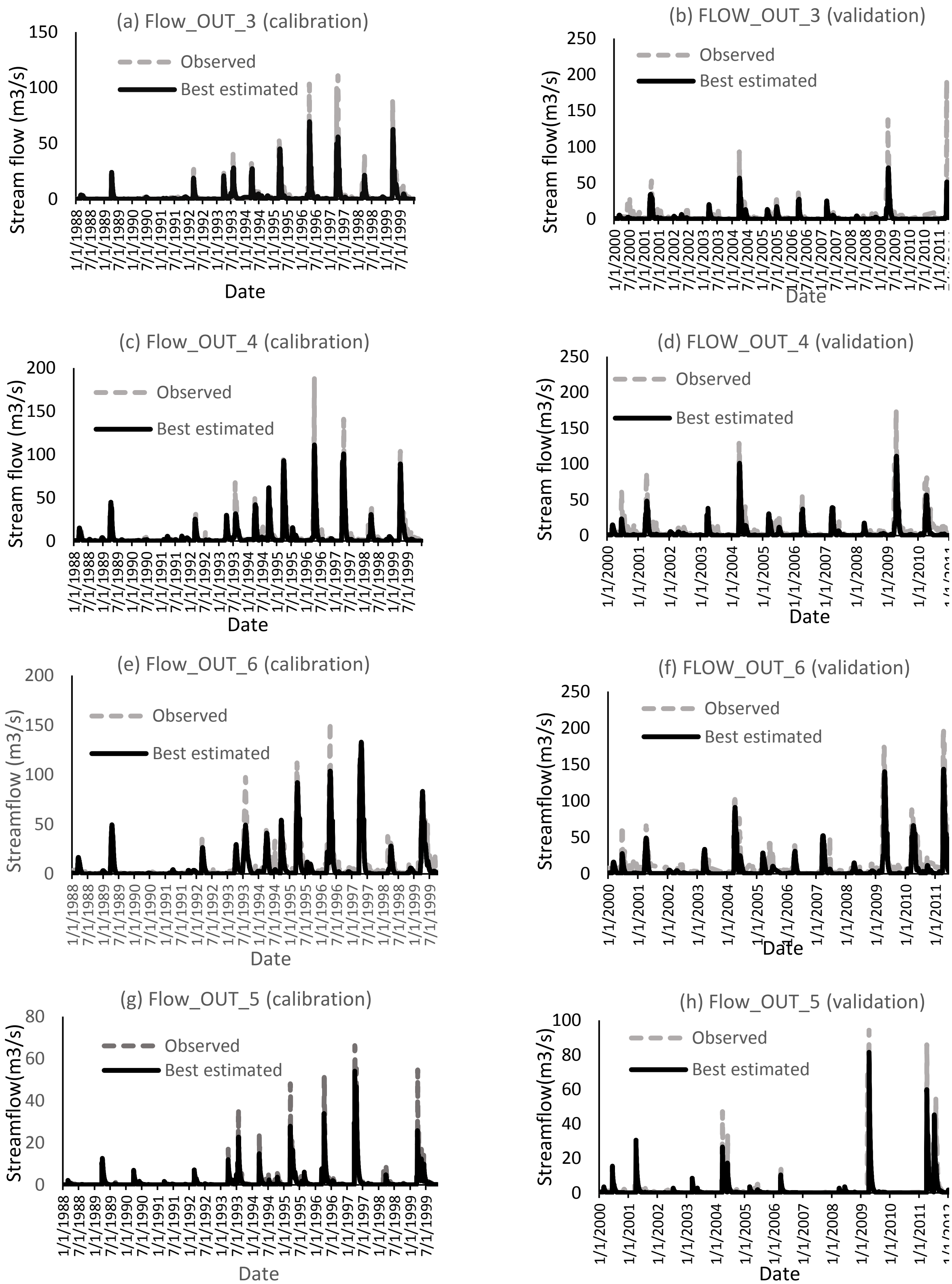

Figure 3. Observed and best estimated streamflow in four different Outlets during calibration and validation periods ((a, c, d, and g calibrated data) and (b, e, f, and h validation data).

Calibration and validation of suspended sediment load

After the simulation of watershed of the Lake Ashtabula, the next step is to calculate sediment accumulation due to the entrance of sediment into the reservoir. Entrance sediments in the reservoir are divided into bed load and suspended load sediments. Bed load sediments are considered minor (less than 5% of the total sediment), and therefore are not evaluated in this study. Subsequently, both the calibration and validation processes were performed solely with the suspended sediment load.

It was postulated that the sediment entrance gateways to the reservoir of Baldhill Dams are Baldhill Creek near Dazey (Outlet 5) and Sheyenne River station near Cooperstown (Outlet 4). Suspended sediment was conducted with the gage station 384126, 380009, and 380153. (Table 4) displays a comparison between the simulated and observed suspended sediment load entering to Lake Ashtabula. (Table 4 and Figure 4) show the results of simulated and measured sediment quantities in the entrance gateway of the reservoir.

Results in Figure 4 show that simulation of the sediment load is not as accurate as the streamflow simulation. There are many reasons for these variabilities. They could arise from the uncertainties of the measured sediment data and the input parameters at the basin scale. For computing the trap efficiency in the SWAT model, the sediments that enter the reservoir (Outlet 4 and Outlet 5) and the sediments that exit from the reservoir (Outlet 6) are simulated.

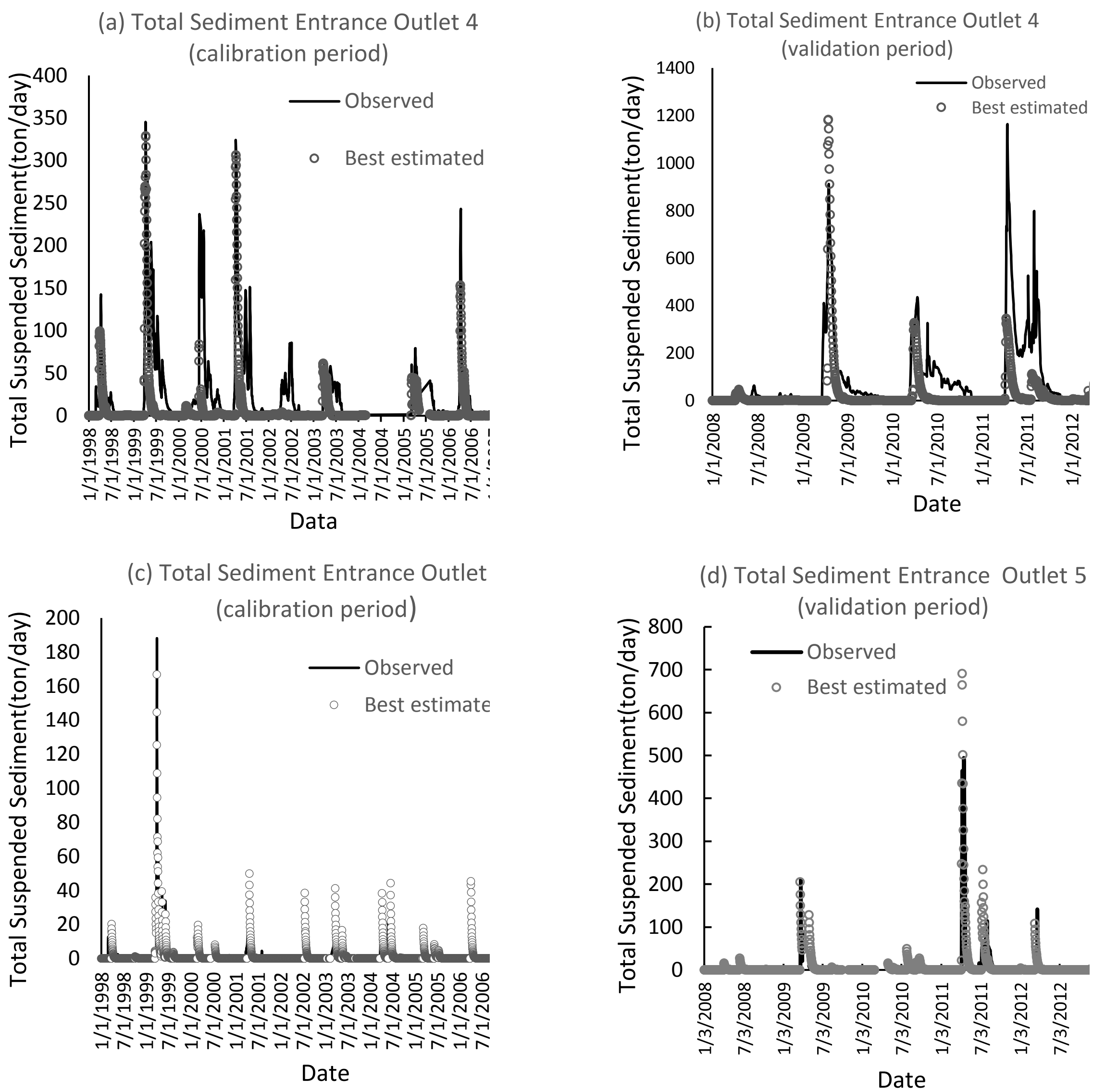

Figure 4. Simulated and observed TSS at the entrance gateways of the reservoir

Reservoir sediment accumulation

Reservoir sediment accumulation was calculated based on the simulated model with entrance of sediment to the reservoir and exit from the reservoir. (Figure 5) shows annual sediment accumulation in the reservoir, and it can be seen that the maximum sedimentation occurred in the years 2011 and 1997.

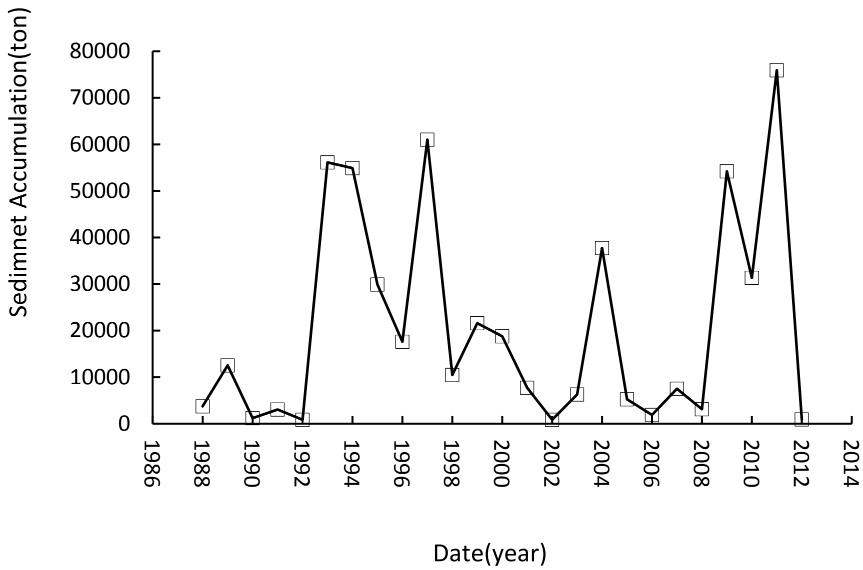

Figure 5. Annual sediment accumulation in the Ashtabula reservoir

Extreme snowmelt events

Although the statistical results of the simulation of streamflow in the watershed of Lake Ashtabula has been considered as generally satisfactory by comparing the simulated and observation data in (Figure 4). It is obvious that there are large differences between the observed discharges and simulated discharges in extreme flood events in April 1997, April 1996 and April 2011. It should be notified that winter 1996 and 1997 were the worst winter in history North Dakota in over 100 years with over 100 inches of snow in Red River Valley.

These discrepancies among the simulated and observed data have inspired us to search for possible improvements in the accuracy of measured data and qualification of simulated data. In order to ascertain the accuracy of the observed data, we investigate the history of the floods in the Sheyenne River. According to flood records, there was the great flood in April of 1997 when frigid water inundated Grand Forks, the second largest city downstream of Baldhill Dam. The main negative features of this flood were early snow melting, cold weather in the winter, and harsh blizzard in the first few days of the month of April. In 2011, there was also a flood which was triggered by another massive snow melting event. The next phase of the modeling procedure is to evaluate the qualification of simulated streamflow of the watershed. A lot of uncertainties exist in the watershed modeling. Those uncertainties are attributed to the simplification process which is not accounted for by the model and some processes that are not well known by the modeler in the watershed simulation. For example, the effects of wetland and reservoirs on the hydrology of the watershed, interactions between surface and groundwater, and occurrences of large constructions on sediment entrance. The watershed of Lake Ashtabula is not exempted from these changes and some of them are known such as the pumping of water from Devils Lake to Sheyenne River. A report published by USGS (Galloway, 2011) indicated that in an effort to reduce the rate of the rising water level in Devils Lake, the state of North Dakota began construction of an outlet near Minnewaukan, North Dakota, that diverts water into the Peterson Coulee and subsequently into Sheyenne River. The Devils Lake's state outlet pumped 100 ft^3/s from late 2009 through early 2010 because of the increasing water elevation of Devils Lake. The water was pumped at a rate of 250 ft^3/s near the end of June 2010. All these are considered as human activities in our model simulations and there are model uncertainties related to the process of simplification. The other major source of uncertainties as described above are related to the input data such as rainfall and temperature. In SWAT, the climate data for every subbasin is mainly delivered from the observation station that is in close proximity to the center of the subbasin, but the spatial distribution within each subbasin may not be uniform as assumed. The uncertainties in the rainfall data and temperature have far greater influence on the overall performance of the model.

In this section, the precipitation, and maximum and minimum temperature of two different years in the Outlet 4 are compared. The winter months (November-May) were chosen for the study. The results of the simulation show that the most of the discrepancies are found during the month of April. The flood of this month is substantially related to the snowmelting and snow precipitation of winter. The first chosen year is 1992 (November 1991-May 1992) which has no discrepancy between the data and the simulation. The second year is 1997 (November 1996-May 1997). The maximum and minimum temperature and precipitation of winter 1996 and spring1997 at Oulet4 are plotted in (Figure 6).

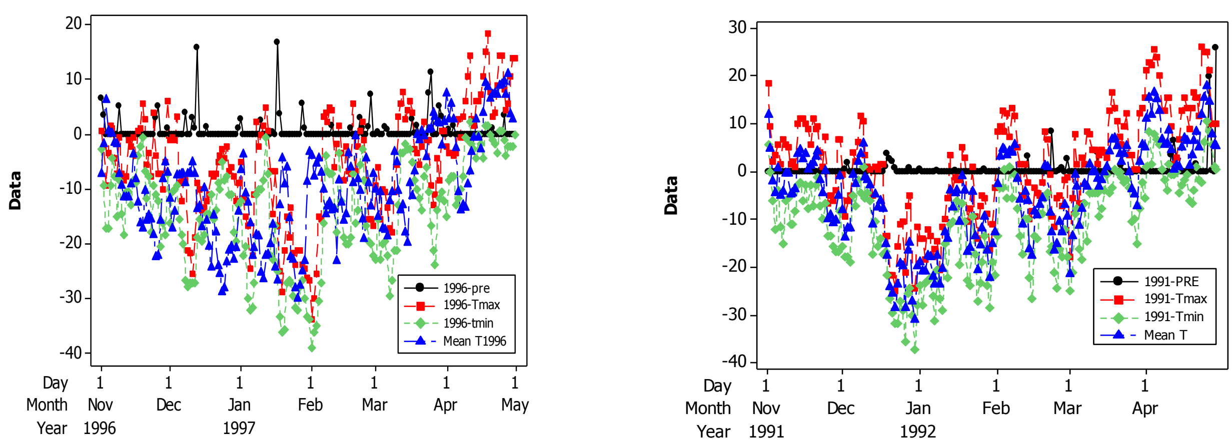

Figure 6. a) Maximum and minimum temperature, and precipitation at Outlet 4 (November 1996-April 1997), b) Maximum and minimum temperature, and precipitation at Outlet 4 (November 1991-April 1992),

Comparison between the maximum and minimum temperature has indicated that during the November through April period in 1997, the minimum temperature and maximum temperature have very little differences; most of the time the maximum temperature is below zero or at about 0 C°. It is obvious that streamflow in the spring is predominantly generated from the melting of snow, but the plot of 1992 data highlights the fact that alternating temperatures between freeze and thaw during the November to April period give rise to some snow melting events during the winter time period.

(Chu & Shirmohammadi, 2004b; Peterson & Hamlett, 1998; Qi & Grunwald, 2005; Srinivasan, Hamlett, Day, Sams, & Petersen, 1998) have emphasized in their research that snowmelt hydrologic process is one of the most important components in simulating watersheds. Evaluations of SWAT's performance in modeling the watershed where the streamflow is largely generated by melting of snow have shown that it is not performing well in simulating this category of watershed.

Many researches have studied methods for minimizing this deficiency of SWAT. (Fontaine, Cruickshank, Arnold, & Hotchkiss, 2002) used elevation bands which distribute temperature and precipitation in different elevation, and to a certain extent, the errors in the SWAT simulation results was successfully reduced. The method of Fontaine couldn't be used for the watershed of Lake Ashtabula because it has completely different conditions from the watershed of the Fontaine's study. The watershed of Lake Ashtabula has a much lower topographic relief which means neither temperature nor precipitation has a measurable variation with topographic elevation. Hence, this method was not applicable for our model simulation.

For improving the results of simulation especially in the peak flood time each year is conveniently divided into two seasons, winter season (WS) and summer season (SS). WS starts from November to April and SS from May to Oct. Parameters that are sensitive to snow melts (SMFMX, SMFMN, SFTMP, SMTMP, and TIMP) were set up just according to the WS data. The other assumption is about SURLAG (surface runoff lag time) for WS. Snowmelt hydrology is confounded by many different parameters including soil moisture, soil temperature and the rate and quantity of the meltwater released from the snow cover. We assumed in the winter time runoff has more lagged time.

Results of calibration showed that there is a change in the peak runoff in the WS in comparison with previous calibration. Base on the results the peak streamflow in month of April 1996 in outlet 3 and outlet 4 and outlet 6 before separating of seasons were 68.6, 108.4, and 102.5 (m^3/s), respectively. After separation of seasons, the corresponding discharges changed to 104, 166.3, and 139.9 (m^3/s) showing that there are enhancements. In Figure 7 the modification of the winter, results are obvious as the simulated peak discharges (calculated with improvement series) are much closer to the observation data.

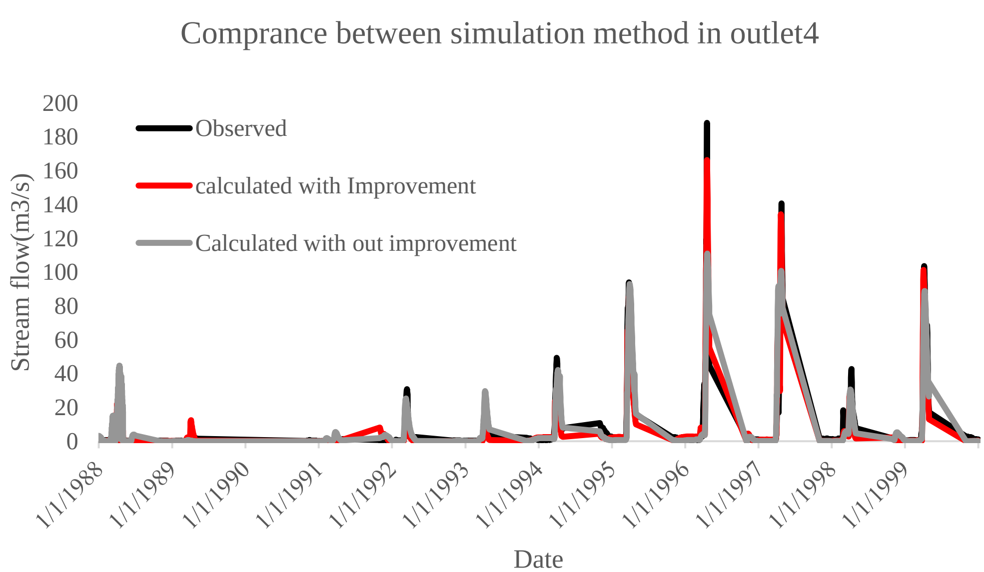

Figure 7. Comparance of winter simulation results after modification

Conclusions

This study evaluated the performance of SWAT model on simulating the streamflow and sediment transportation in the watershed of Lake Ashtabula, located in North Dakota. In addition, a method was developed for overcoming SWAT's inability to simulate peak streamflow in the periods of winter in a similar watershed with gentle topography in cold region.

Sensitivity analysis indicated that among the parameters affecting snow melting processes, six parameters were sensitive, namely the snowmelt temperature, snowfall temperature, snow pack temperature factor, maximum snowmelt factor, and minimum snowmelt factor.

Overall, performances analysis of the simulated watershed models indicates that utilizing SWAT in this study achieved a "good" performance rating in simulation of the daily streamflow and "satisfactory" for daily TSS. However, by having a closer inspection of the results of simulation in extreme flood peaks in a few spring melt periods, disability of SWAT on simulating peak streamflow in the snow dominate area will appear.

Since simulation and predicting streamflow is one of the important task for design of hydraulic structures, flood control and water resource management, it is imperative to find the methods for improving the streamflow simulation. Since North Dakota is in a cold region with extreme spring floods, which are triggered by synchronous occurrences of snow melting and precipitation, it is necessary to use a better simulation method or by making modifications to the existing methods for predicting streamflow in these conditions.

There are many solutions to improve the simulation accuracy of the SWAT, but because of specific geometrical and environmental characteristics of watershed area on Lake Ashtabula, none of those classic solutions would be appropriate. For catchments similar to the study area which has significant flat area, the following strategies would increase the simulation accuracies for both streamflow and sediment simulations. Some of those strategies have been examined in similar cases and proved their advantages in improving the prediction accuracy performances. In this case study, we testified some of those strategies in similar cases and developed several adjusted strategies to improve the simulation accuracy. The strategies are:

- Calibration and validation of data performed with separated winter and summer seasons
- Snow parameters determined by the calibration of winter seasons data but not used in the calibration of summer season data
- Increasing the surlag time (surface runoff lag time) for the winter time to provide more time for the streamflow for considering the impact of snow melting

Numerical results have consistently shown that the applying those strategies improved the prediction accuracy significantly. The comparison of the observed and simulated sediment entering to the reservoir of Lake Ashtabula at two entrance locations at Outlet 4 and Outlet 5 proved the reliability of validated hypotheses. The simulated sedimentation values showed that sediment accumulation has been increased over the time, and with the existing sedimentation rate, significant volume of the reservoir in Lake Ashtabula will be lost. Of course, by losing the storage capacity of the reservoir, the required volume of the reservoir for flood controlling purposes cannot be relied upon any more.

Acknowledgment

This study was supported by 2015 and 2016 Fellowship Awards under the North Dakota Water Resource Research Institute (NDWRRI), NSF EPSCoR RII SEED grant UND0021102, and College of Engineering and Mines (CEM), University of North Dakota.

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CHAPTER III

ENHANCING SWAT STREAMFLOW SIMULATION IN COLD REGION WITH ARTIFICIAL NEURAL NETWORKS

Introduction

Streamflow predication is one of the most important tasks in watershed management. It is needed in the optimization of water resources, flood control, dam safety, and design of the hydraulic structure (bridge, dam, and culvert). Accuracy of these predictions have great influence on the decision-making processes in water resource management. Various models and tools have been developed for simulating and predicting streamflow. The Soil and Water Assessment Tool (SWAT) is one of the most applicable tools for simulating and predicting streamflow. This tool is a conceptual, semi-distributed model (Arnold et al., 1998), and it has the ability to simulate streamflow under the different land use and soil type with the different climatic condition. Similar to all tools and software that their performance and quality of simulation are related to the quality of input data and methods of simulation, this tool is not an exception. So accurate simulation need accurate data and methods of simulation. In this regards, the operation of the tools should be evaluated for having the best simulation free of errors. Many studies have been performed on the performance of SWAT on simulation of streamflow series. (Spruill, Workman, & Taraba, 2000) indicate in their studies that SWAT model is effective in simulating monthly streamflow data rather than daily data in the small watershed of Kentucky. In their evaluation of

SWAT performance found that SWAT was unable to account for subsurface flows that contributing from outsides of the watershed. Also, a lot of researchers (Chu & Shirmohammadi, 2004a; Peterson & Hamlett, 1998; Qi & Grunwald, 2005; Shoghli & Lim, 2017) have pointed out that SWAT performance on simulating streamflow is poor in the region where extreme streamflow events are generated from snow melting in the springs.

By considering the fact that global temperature is going on an upward trend, we will encounter with more snow melting phenomena. Hence, finding the best method for modeling the streamflow generation in the cold region is imperative.

Processes of snow melting cannot be observed directly and hydrological models must rely on a complex snowmelt routine to account for such events (Turpin, Ferguson, & Johansson, 1999). Knowledge of snow water equivalent and energy budget are thus crucial to hydrological modeling in snow dominant area.

On another perspective, spring flood have been reported transporting a large part of sediment and nutrient annual loads (Jamiesson et al., 2003; Gollamudi, 2006;Quilne et al., 2006; Michaud et al., 2007) stressing the need for a functional snow hydrology component (Zhang et al.,2008).

(Peterson & Hamlett, 1998) efforts on evaluating the hydrological routines of SWAT tool at the daily time indicates some difficulties in base flow and snowmelt predictions. At that time the base of SWAT on calculating snowmelt was on temperature index and a constant snowmelt rate factor.

Since then, (Fontaine et al., 2002) have improved snowmelt routines. They work on compromising temperature and spatial coverage evaluation of snowpack, and the inclusion of seasonal variation of snowmelt rate. These modification improved streamflow simulation and prediction performance for basin and watershed that are located in the mountainous area.

(Wang & Melesse, 2005) evaluated the actual SWAT snowmelt algorithm on the watershed that is located in Minnesota. The study area of Wang has differences with the study area of the Fontaine. This place was flat and gently sloping uplands. Hence, the method of Fountain could not applicable on the snowmelt uncertainties. However, they report satisfactory monthly and acceptable daily performances.

Results of studies by (Zhang, Pulliainen, Koponen, & Hallikainen, 2002) on SWAT performance in simulating streamflow showed that SWAT model performed well in calibration and after that subsequently the combination of the temperature index and elevation band model provides equally good performance as the energy budget -based SNOW17 model.

(Ahl, Woods, & Zuuring, 2008) indicate that SWAT performed well during the spring and early summer snowmelt runoff period, but its performance for predicting late summer and winter base flow was poor.

(Stehr, Debels, ARUMI, Romero, & Alcayaga, 2009) attempted to overcome SWAT deficiency in simulating streamflow in snow dominate area used Moderate Resolution Imaging Spectro-radiometer (MODIS) image as a source of snow distribution for validating SWAT snow validation.

The method of Fontaine could not be used for the all the watersheds, some watersheds in cold regions have a much lower topographic relief which means neither temperature nor precipitation has a measurable variation with topographic elevation. Hence, this method was not applicable for this kind of simulation.

(Shoghli, Lim, & Zamani sabzi, 2017) on their study on the flat watershed in North Dakota suggested to separate the winter and summer time in the step of calibration and their results show improvement in simulating but still, there are differences among data.

(Noori & Kalin, 2016) used Artificial Neural Network (ANN) for enhancing the SWAT streamflow prediction. They used SWAT simulation results as the input of their network and their results show more accuracy in simulation of daily streamflow.

Artificial Neural Networks (ANNs) is a flexible mathematical structure, which is inspired by human nerves system. This system is capable of identifying the complex nonlinear relationship between input and output data sets.

In recent years, artificial neural networks (ANNs) have been used widely in hydrology and water resource area, particularly in streamflow forecasting (Adamowski, 2008; Coulibaly, Anctil, & Bobee, 2000; Hsu, Gupta, & Sorooshian, 1995; Maier & Dandy, 2000; Rezaeianzadeh, Tabari, Yazdi, Isik, & Kalin, 2014; Sabzi, King, & Abudu, 2017). However, these investigations were performed with ANNs was different in terms of flow patterns of the streamflow, the type and number of variable as input and output data sets, the type of neural network and the systems they choose for the training of their networks. But all studies gave the acceptable simulation and predicted results.

Snow dominant areas will be affected more as compare with the other regions under global warming phenomena. Change in the amount of the precipitation and temperatures tend to affect the volume of melted snow, and the capacity of the most hydraulics structure is not adequate for this volume of water. In the future, more places will experience the flood if the management and prediction were not performed in these areas. All these concerns will increase the need for having accurate simulation and prediction in the snow dominant area.

The objective of this study is to enhance the performance of SWAT in simulating the streamflow in snow dominate and flat area with the help of ANN.

Most common types of ANNs structure in hydrologic problems is Multilayer feedforward network (MFN) (Hsu et al., 1995). A comprehensive study of the application of ANNs in Hydrology can be found in ASCE Task committee (2000).

Many studies have compared the performance of SWAT and ANNs in simulation of streamflow (Demirel, Venancio, & Kahya, 2009; Srivastava, McNair, & Johnson, 2006) but there are a few study about the improvement of SWAT performance by the ANN. (Noori & Kalin, 2016) used the ability of ANN for enhancing the daily streamflow simulation with SWAT. In our study, we will use ANN for improving calibrated and validated results of SWAT-CUP in simulating streamflow series.

Materials and Methods

Study area

Baldhill Dam, which creates the reservoir of Lake Ashtabula (see the location in Figure 8), is located on the Sheyenne River at approximately 271 river miles upstream from the confluence with the Red River of the North. Lake Ashtabula is a multipurpose reservoir used for rural and municipal water supply, flood control, municipal pollution abatement, fish and wildlife habitat, and recreation.The storage capacity of the reservoir is 68,600 acre-feet (84.61 m^3) with a surface area of 5430 acres(2.19 m^2), length and width of 27 miles (43.45 km) and 0.6 miles (0.96 km) respectively.The construction of the dam began in July 1947 and formally dedicated in September 1952.

Both Baldhill Dam and Lake Ashtabula are in Barnes County. Barnes County is usually warm in the summer and very cold in the winter. Total annual precipitation is about 18 inches (457.2 mm), of which more than 75% are usually fallen in April through September. The average seasonal snowfall for the county is about 21 inches (533.4 mm).

Sheyenne River and Baldhill Creek are the two main rivers that flow into the reservoir of Lake Ashtabula (Figure 8). The average topographic slope of the watershed of Lake Ashtabula of is about 3%. The Sheyenne River upstream of the Baldhill Dam has a total drainage area of 3812 mi^2 (9873.03 km^2), of which 462 mi^2 (1196.6 km^2) are contributing. The mean annual streamflow, measured near Cooperstown at station 05057000 showed the main inflow to Lake Ashtabula was about 144 ft^3/s (4.07 m^3/s) for the period of 1945-2009.

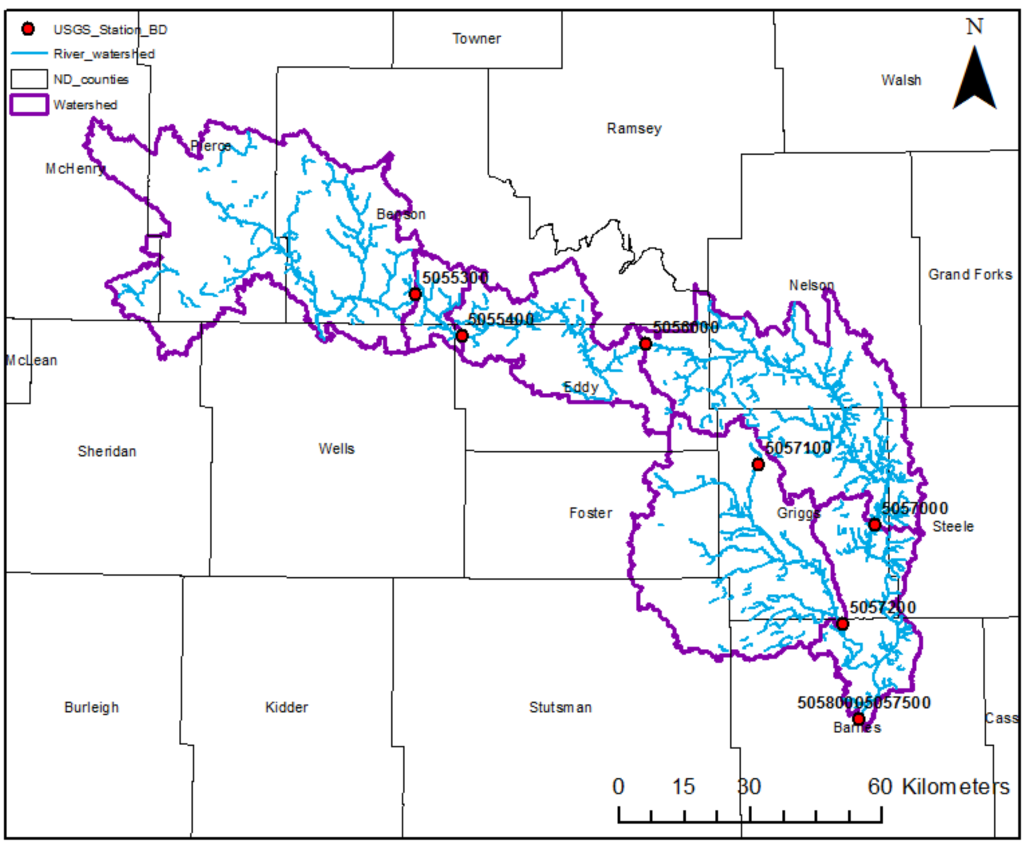


Figure 8. Location of watershed Lake Ashtabula

One of the significant concerns of natural resources management effort for a watershed is controlling the amount of erosion, primarily the wind and water erosion on cropland, and animal unit densities. According to 2011 land use developed by National Agricultural Statistics Service (NASS), pasture (26%), soybeans (20%), spring wheat (17%), wetland (11%), and corn (4%) combined to form the land use distribution of the watershed of Lake Ashtabula.

Soil Water Assessment Tool (SWAT)

SWAT is a semi-empirical, semi-physical, and watershed-based hydrological model that was developed to simulate the impact of different alternative management parameter and non-point-source pollution in large river basins (J. Arnold & Allen, 1996).

In order to delineate the watershed and find the flow directions of the streams, a digital elevation model (DEM) with a 10m resolution from USGS was employed. Soil maps were extracted from STATESGO dataset, and the land use information was prepared from the USDA National Agriculture Statistic Service (NASS). Climate data, which include precipitation, maximum temperature, minimum temperature, wind speed, and relative humidity, were downloaded from the National Oceanic and Atmospheric Administration (NOAA) dataset and snow depth data were available in dataset of NOAA in the gateway of Global Climatology Network (GHCN). Streamflow data were extracted from observed series at USGS stations that have been installed in the Lake Ashtabula. Figure 8 shows the active USGS station in the Lake Ashtabula. Of the six available stations in the watershed area, just four of them are usable because the observations at the other two stations give very short records (started in 2005) and are not sufficient for our calibration purposes. For evaluating and calibrating the watershed streamflow series observed at the active USGS stations, the following classification was adopted:

Subbasins 1, 2, and 3 correspond to USGS Station 05056000 as Outlet 3, Subbasin 5 corresponds to USGS Station 05057200 as Outlet 5, Subbasin 4 corresponds to Station 05057000 as Outlet 4, and finally Subbasin 6 corresponds to USGS Station 05057500 as Outlet 6.

SWAT snow melting

The base of SWAT for calculating the amount of water stored in the snowpack is snow water equivalent. The mass balance for calculating the snowpack is:

$$SNO_{i+1}=SNO_i+R_{day}-E_{sub}-SNO_{mlr}$$

where SNO_i and SNO_{i+1} is the water content of the snowpack on day *i* and *i+1 (mm* H_2O*),* R_{day} is the amount of precipitation on a day *i,* E_{sub} is the amount of sublimation on day *i (mm* H_2O*).* SNO_{mlr} is the amount of snowmelt on the day i (mm H_2O).

SNO_{mlr} is the amount of snowmelt on the day i (mm H_2O).

Mean daily air temperature is an important parameter on analysis of snowmelt hydrology. The base of classification among snow and rain will proceed by mean daily air temperature. The user sets the boundary temperature if the mean daily temperature is less than the boundary temperature which the SWAT asset precipitation as snow and it is added to snowpack. Definitely, temperature of the previous day have an influence on the temperature of current day's snowpack. This influence is described as a lag factor, it is specified by the variable *TIMP* in the SWAT. The snow pack temperature is calculated as

$$T_{snow(i)}=T_{snow(i-1)} \times (1-TIMP)+ \bar{T}_{ai} \times TIMP$$

where $T_{snow(i)}$ and $T_{snow(i-1)}$ are the temperatures of snow pack on the day*(i)* and day*(i-1),* respectively, and $\bar{T}_{ai}$ is the mean air temperature on day *i*.

If the TIMP is equal to 1.0 then mean air temperature has more influence on the temperature of snowpack, and if TIMP is equal to zero, the temperature of pervious day snow pack has more influence on the temperature of the snowpack.

The amount of snowmelt on day(i), $SNO_{melt(i)}$ expressed as an equivalent amount of water in mm, or malting rate which is calculated in SWAT as:

$$SNO_{melt(i)} = b_{melt(i)} \times sno_{cov} \times \left[\frac{T_{snow} + T_{mx}}{2} - SMTMP\right]$$

where $b_{melt(i)}$ is the melt factor (mm H_2O day^{-1} $^{o}C^{-1}$), SMTMP threshold temperature for snowmelt (ºC) and T_{mx} maximum air temperature for a given day.

$$b_{melt(i)} = \frac{SMFMX + SMFMN}{2} + \frac{SMFMX - SMFMN}{2} . sin\left[\frac{2\pi}{365}(di - 81)\right]$$

Snow is rarely distributed uniformly over the area; in SWAT, the areal coverage of snow over the total HRU area is defined using the areal depletion curve.In addition to the snowpack temperature that controls the amount of snow melting, areal coverage of snow is an important factor in snow melting rate.

$$sno_{cov(i)} = \frac{SNO_i}{SNOCOVMX}\left[\frac{SNO_i}{SNCOVMX} + exp(cov_1 - cov_2 . \frac{SNO_i}{SNOCOVMX})\right]^{-1}$$

SMFMX is melt factor on June 21 (mm H_2O day^{-1} $^{o}C^{-1}$), SMFMN is melt factor on Decembre 21(mm H_2O day^{-1} $^{o}C^{-1}$), SMTMP is threshold temperature for snowmelt and SFTMP is mean air temperature at which precipitation is equally likely to be rain on snow (ºC) and d_i is the number of the day in th year.

$SNOCOVMX$ is the minimum snow water content that corresponds to 100% snow cover (mm H_2O), $cov_1$and cov_2 are the coefficients that define the shape of the curve.

There are seven parameters that play important roles in determining the snowpack accumulation and melt: *TIMP, SMTMP, SMFMX, SMFMN, SFTMP, SNCOVMX* and *SNO50COV.*

SNO50COV is the fraction of $SNOCOVMX$ that provides 50 percent coverage of snow.

Results of the previous study (Shoghli et al., 2017) watershed of Lake Ashtabula showed some big discrepancies on the flood events of 1996, 1997, and 2011. Research about the discrepancies indicated that SWAT has a problem on simulating watershed that there are located in the snow dominated region where the main cause of spring flood is the melting of snow.

In recent years, there appears tendecies of huge flood, occuring in early snow melting period, where there are synchronizing of snow melting with spring precipitation.

because of the change in climate condition, nature encounter with early snow melting, synchronizing of snow melting and spring precipitation caused the huge flood.

In this study, two methods were developed for improving the discrepancies of simulated streamflow during the winter-spring periods.

Streamflow prediction and calibration

The Baldhill Dam watershed streamflow simulation was performed for the period from 1985 to 2014. Three years were allocated for the warm up period in 1985-1988, while the calibration period is in 1988-2005 and the validation period is in 2006-2014.

Calibration of SWAT model was performed with SWAT Calibration and Uncertainty Program (SWAT-CUP). SWAT-CUP is a computer program for sensitivity analysis, calibration, validation, and uncertainty analysis of the SWAT model. This program was developed by Abbaspour, and links Sequential Uncertainty Fitting (SUFI2), Particle Swarm Optimization

(PSO), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (Parasol), and Markov Chain Monte Carlo (MCMC) procedures in the SWAT models.

In this research, SWAT-CUP with SUFI algorithm was used to calibrate the simulated result of SWAT, more detail is available on previous work of the author (Shoghli et al., 2017)

Using ANN in modification of SWAT CUP

Artificial Neural Networks (ANNs)

An artificial neural network (ANN) is a flexible mathematical structure which could be used to find the complex nonlinear relationships between the input and output datasets. In this study, the multilayer feedforward network (MFN) with back propagation (BP) training algorithm was selected. The architecture of the networks includes nodes and neurons, which are organized by layers. All the ANNs structures begin with an input layer and end with an output layer. A typical MFN has one or more hidden layers between the input and output layer. Each hidden layer has more than one node that passed the information from the input layer to output layer. In BP training algorithm, the information network in the hidden layer can pass the information from the output layer to the input layer. Each node from one layer is connected to the nodes of another layer and the strength of these connections will be provided by the connection weights.Thus, each layer received the weighted input from the previous layer. The sum of the received weighted input will be converted to the single output using activation function.

Meanwhile, the role of training algorithm is to optimize the connection weight to produce the output that is very close to the value that were set as the output datasets. Figure 9 shows the basic view of the ANNs structures; the BP algorithm is a gradient descent technique that minimizes the network error function. In the training process, the effect of the input was passed forward through the network. The error between the measured value and the predicted value by the network was estimated at output layer. Next, the error is back propagated toward the input layer to adjust the connection weight. This process would be repeated until the error between the measured and predicted value reaches to the set goal error limits.

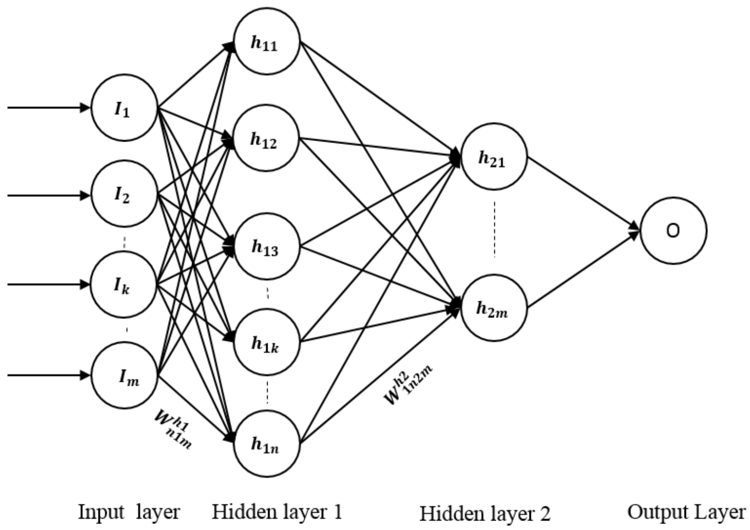


Figure 9. A four-layer feedforward neural network

Among different types of BP training algorithm that are available in the Toolbox of MATLAB, the Levenberg-Marquart (LM) training algorithm was selected because it was the most efficient method. The transfer functions that we used in this study to translate the input signals into the output signals was tangent sigmoid.

Evaluation of ANN prediction

The performance of ANN is evaluated with four statistical efficiency terms: correlation coefficient (R), mean square error (MSE), root mean square error (RMSE), and mean error (ME).

The correlation coefficient (R-value) is used to evaluate the goodness of fit of hydrologic and hydrodynamic models (Lagets and McCabe Jr., 1999). *R* is calculated by performing the linear regression between the ANN-predicted value and the targets.

$$R = \frac{\sum_{i=1}^{N}(q_{obsi} \times q_{pi})}{\sqrt{\sum_{i=1}^{n} q_{obsi}^{2}} \times \sqrt{\sum_{i=1}^{n} q_{pi}^{2}}}$$

$q_{obsi} = Q_{obs}i - Q_{obsmean}$

$q_{pi} = Q_{p}i - Q_{pmean}$

where N is the Number of samples;

Q_{obs}i and Q_{p}i are the target and predicted value, and

Q_{obs}mean and Q_{p} mean are the mean of target and predicted data.

It should be noted that when *R* is equal or close to one, it means that there is good correlation between the predicted and the target value. In the worst case, R is equal to zero.

Mean Square error (MSE) is used to evaluate the performance of the training process in ANN structure. It is defined as the average sum of squares of difference between the measured target and the ANN predicted values:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{Qobsi} - \mathrm{Qpi})^2$$

Root mean square error (RMSE) is used to evaluate the ability of ANN-predicted values to match measured data, as defined below:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{Qobsi} - \mathrm{Qpi})^2}$$

Mean error (ME) is the bias in predicted values and it is calculated as:

$$ME = \frac{1}{N}\sum_{i=1}^{N}(\text{Qobsi} - \text{Qpi})$$

In the case when the value of ME is equal or close to zero, the predicted values are matching with the target values.

Overall, the best goal in prediction using ANN will be achieved when *R, ME, MSE* and *RMSE* are found close to 1, 0, 0 and 0, respectively. Evaluation of the training process will be performed based on *MSE,* and the validation phase were assessed with *R, RMSE* and *ME*.

In this study, data sets on the input layer were precipitation, maximum temperature, minimum temperature, relative humidity, wind speed, snow depth, and simulated streamflow by SWAT. The measured streamflow in the station is defined as an output layer. The object of this training exercise is to overcome deficiency of SWAT in the simulation of peak discharge in the cold region.

Results and Discussions

As noted in the Introduction section, the purpose of this study was to enhance the capability of SWAT in the simulation of streamflow in the cold regions. Data from 1985 through 2012 were selected for SWAT and ANN simulations. Since the first 3 years of data were selected for warm up periods in SWAT, data within this period was not used for calibration. The calibration and validation periods are (1988-2000) and (2000-2013) respectively. The next step in the simulation would be to calibration and validation of the model with sensitive parameters, which were determined by sensitivity analysis of SWAT_CUP. Figure 10 shows time series of measured streamflow (USGS station), calibrated and validate simulated streamflow in Outlet 4 and Outlet 5. These figures indicate that except for the winter-spring period (which is defined as starting in November and ending in April), SWAT simulation falls within the acceptable level.

However, in the winter-spring periods in 1993, 1996, 1997, 2006, 2009, and 2011. SWAT doesn't exhibit streamflow simulations well in both outlets. The worst is found in simulating the peaks of streamflow in 1997.

For example, the observed streamflow of Outlet 4 which were registered by the instrument at the USGS station on 18th of April in 1997 is 188.3067 (m^3/s) and the simulated value by SWAT is 108.4 (m^3/s), approximately 70 % is the difference between the calculation and measurement streamflow. This magnitude of a difference is not acceptable.

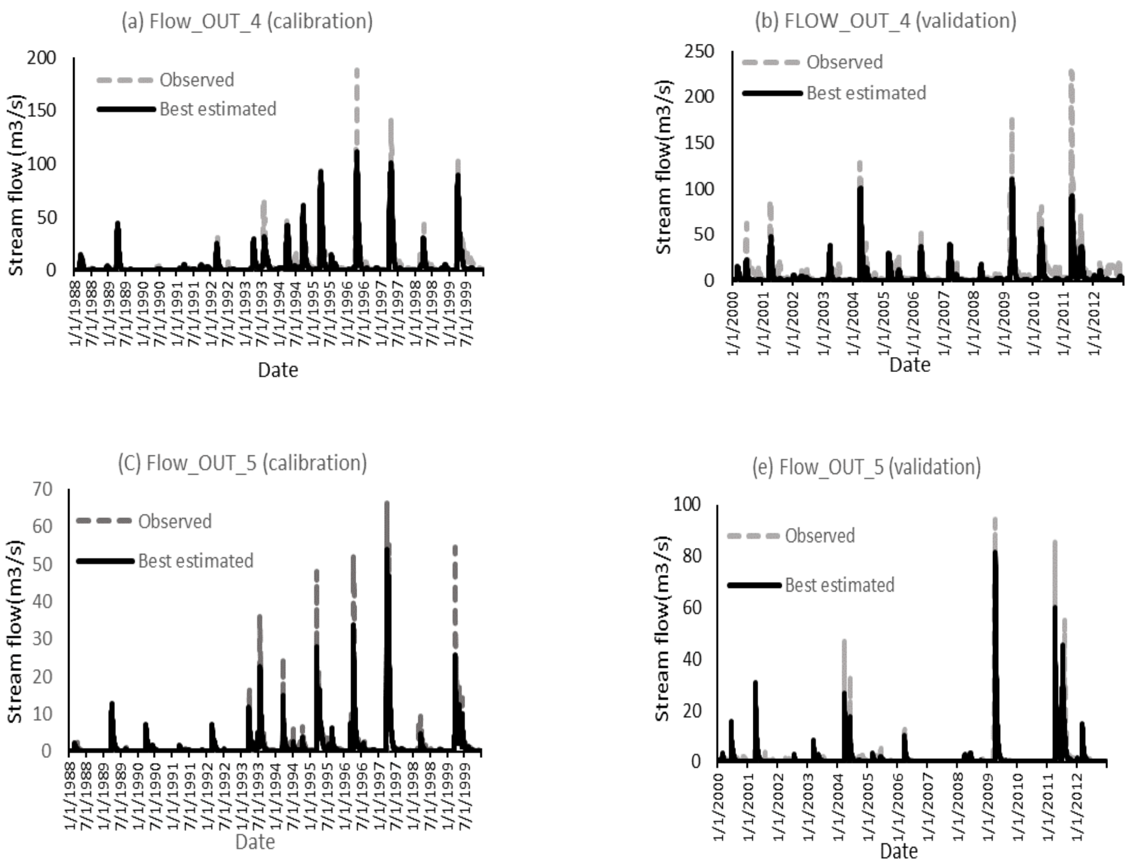


Figure10. Simulation of streamflow in watershed of Lake Ashtabula (calibration and validation by SWAT-CUP)

As it mentioned earlier, researchers put many efforts in to improvement of the SWAT performance in simulating streamflow series in the winter-spring period. But as it is described, the location of our study area doesn't warrant the use of those methods. On the other hand, in the northern region, melting of seasonal snow cover is one of the most important events in the water years. It is essential to know snowmelt hydrology well, not only for hydrological modeling, but also for other studies concerning nutrient dynamic and sediment transport in these regions.

All of these discrepancies related to the processes of melting are difficult to be resolved fully and SWAT could not adequately simulate the snowmelt runoff series well (Shoghli et al. 2017, Peterson and Hamlett, 1998, Chu and Shirmohammadi, 2004). These processes can be better understood by examining Figure 11 and Figure 12. In Figure 11, daily precipitation, mean daily temperature, maximum daily temperature, and minimum daily temperature during the winter-spring period of 1997 are delineated. As it can be seen in this figure, the mean temperature is below zero during the November to mid-March periods. This means that the possibility of having snow melting during this period is less. Simultaneously, with increasing rate of snow depth depletion in Figure 12, it can be deduced that there wasn't any melting until mid-Mach. During this period, as soon as the temperature goes up to zero, snow starts to melt. It should be noted that rainfall during the melting of snow will increase the melt-rate, and that was exactly the situation leading to the occurrence of a huge flood in April of 1997.

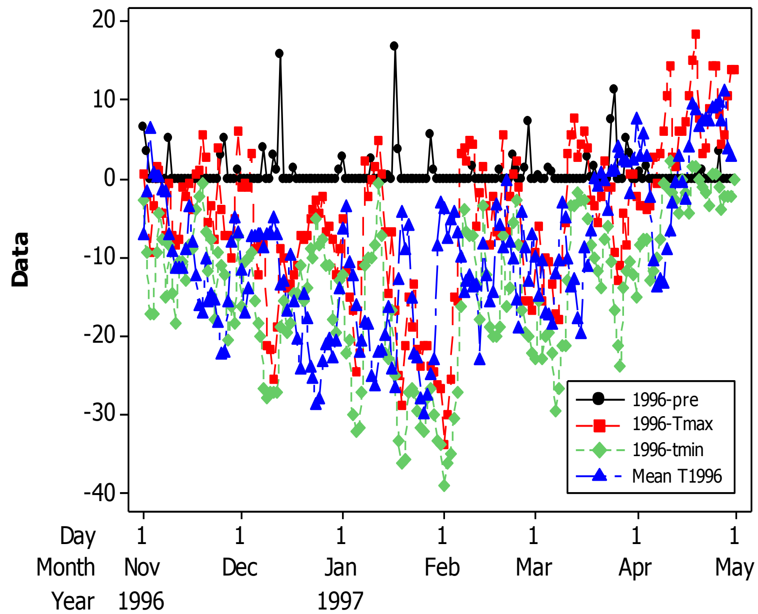


Figure11. Daily precipitation, daily mean temperature, daily maximum temperature and daily minimum temperature at Outlet 4 of Lake Ashtabula

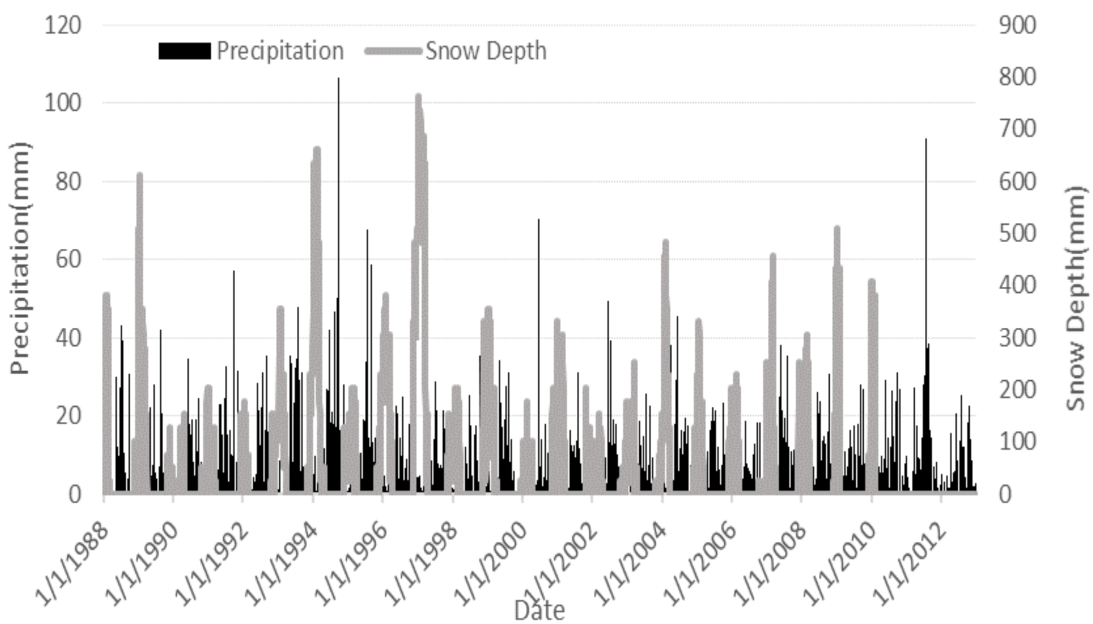


Figure 12. Precipitation against snow depth in Outlet 4 of watershed of Lake Ashtabula

There are large uncertainties in modeling of streamflow series because the process of snow melting is not fully modeled with limited number of parameters and the actual measurement of runoff that is generated by melting snow is often less than perfect .

To model the process well, it requires many different parameters, including the depth of the frozen layer of soil, the water content of the soil, level of ground water, amount of sublimation, and temperature of the different layer of the snow.

As it was described in the Method section for improving and enhancing SWAT simulation results, we coupled ANNs with SWAT. Among different types of ANN, BPNN were selected. The performance of BPNN in predicting streamflow was shown in Figure 12. It should be noted that the architecture of the applied BPNN has one hidden layer with one input layer which is included in seven nodes (precipitation, temperature max, temperature min, wind speed, relative humidity, snow depth, and simulated streamflow by SWAT) and one output layer (USGS measurement streamflow). The application of BPNN involved these steps:

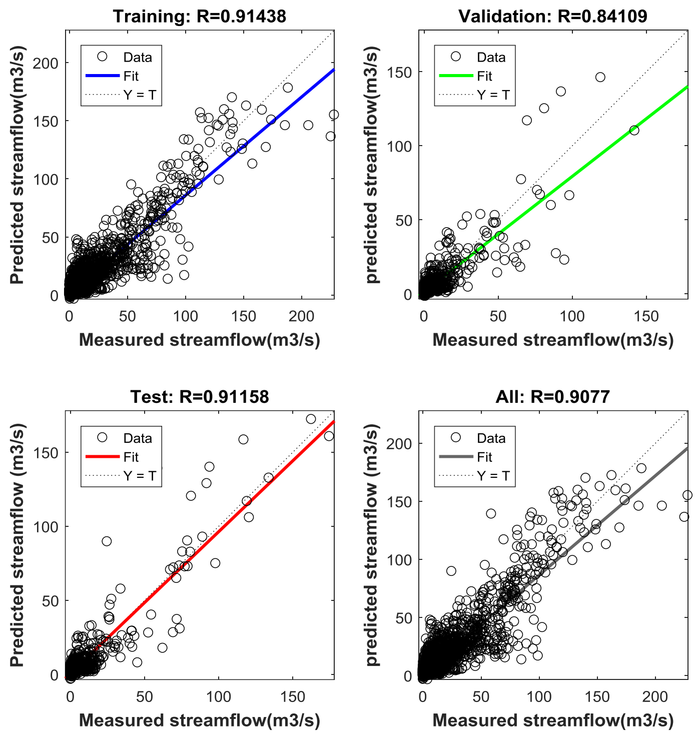
i) The data were normalized within the range of (-1, 1) as we used a tansig transfer function which only takes on the value in the internal of -1, 1.

ii) Since the number of the neurons in the hidden layer plays important role in the model performance, we tested 7-50 neurons.

iii) Epoch size was adjusted to 1000 as a result of the trail and errors application to the higher magnitude

In Figure 13, the predicted streamflow of BPNN with architecture 7-1-1 is compared with corresponding measured streamflow series in Outlet 4 with USGS station. It is obvious, that BPNN predicted values has less deviation from the measured data.

In order to assess the accuracy of performance, both the correlation coefficient (R) and MSE (mean square error) values are computed.



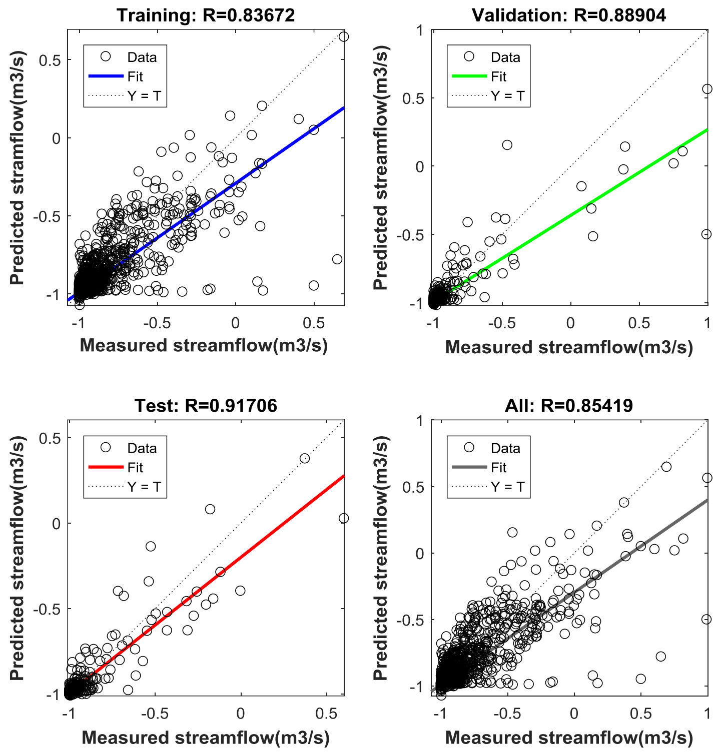


Figure 13. Performance of ANN in simulating streamflow in Outlet 4 and Outlet 5

In Table 5, the Nash-Sutcliff Coefficient of Efficiency for calibration and validation of SWAT model in Outlet 4 is evaluated as 0.75 and 0.64 respectively, and 0.76 and 0.61 for Outlet 5. These results indicate for the entire simulation periods, the SWAT simulations remain within an acceptable level.

However, looking at the peak streamflow separately, it is apparent that SWAT is unable to simulate daily streamflow series in the winter-spring period. Table 5 and Table 6 show the results of SWAT streamflow simulation and the improved SWAT by using ANNs.

Table 5. Statistical evaluation of SWAT in predicting streamflow series

Calibration (1985-1999)

Variable	R	NSE	PBIAS	RSR
Outlet 4	0.88	0.75	7.3	0.5
Outlet 5	0.87	0.76	7.9	0.49

Validation (2000-2008)

Variable	R	NSE	PBIAS	RSR
Outlet 4	0.83	0.64	43	0.6
Outlet 5	0.78	0.61	16	0.62

Table 6. Statistical evaluation of ANN in predicting of streamflow series

ANN streamflow prediction						
Number of Outlet	Prediction By BPNN(training)			Prediction By BPNN(test)		
	NSE	R	RMSE	NSE	R	RMSE
Outlet 4	0.85	0.92	0.0540	0.71	0.91	0.0901
Outlet 5	0.85	0.92	0.0457	0.62	0.72	0.0834

Summary of the performance statistics from the SWAT model, which is calibrated and validated by SWAT CUP with the improved SWAT-CUP result with ANN (which we will call SWAT-CUP-ANN), shows that the latter approach has improved the prediction accuracy, especially for the peaks of streamflow during extreme flood events. As described before, one of our concerns of SWAT was about the inability to simulate well peak discharges that has been generated by snow melting and rainfall in the early spring period.

The results of the calibration and validation of Outlet 4 and Outlet 5 using SWAT-CUP versus SWAT-CUP-ANNs is shown in Table 5 and Table 6, respectively. Results show that NSE statistical parameter that was used for the evaluation of hydrologic simulation for both outlets during the calibration and validation time period is greater than what we had with SWAT-CUP. Base on the previous study, the performance of the SWAT on simulation of the peak flow was weak. Figure 13 depicts BPNN prediction results against the SWAT simulation in Outlet 4 and Outlet 5

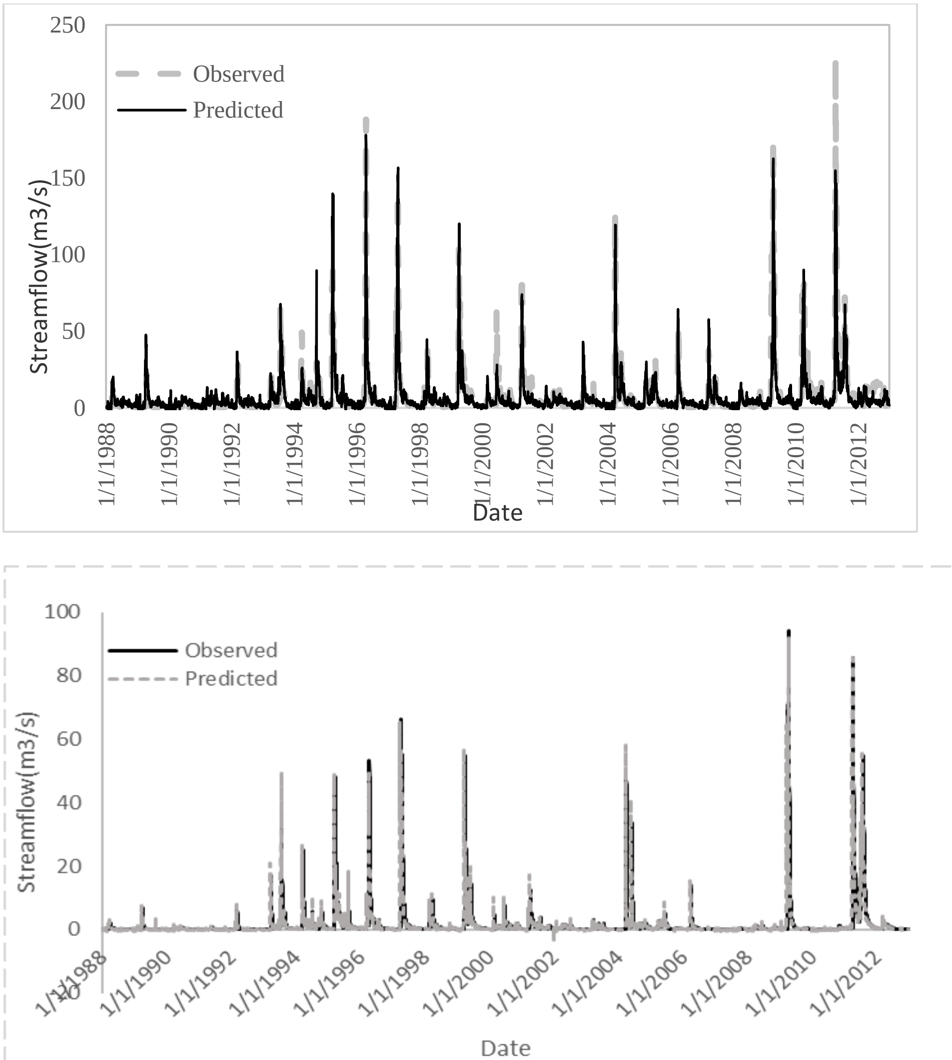


Figure 14. SWAT simulation against BPNN prediction streamflow a) Outlet 4 and b) Outlet 5

In Figure 14, for both outlets, the improvement method has removed the large differences between the simulated and the measured data. Hence, this method could be the way forward in simulating streamflow series in the winter-spring period and in the snow dominated regions.

Conclusion

Previous studies highlighted the need to improve the quality of SWAT in the simulation of peak streamflow in cold regions that spring flow has been generated by the melting of snow. In this study, the ability of ANN in improving the SWAT deficiency was investigated and methods were developed to overcome the problem.

The result of SWAT simulation at two-entrance locations of the reservoir of Lake Ashtabula was selected for a case study. Both of the simulated flow series of SWAT and results of the calibrated- validated flow series with SWAT CUP implementation were compared with the measured streamflow series at the same station. The comparison indicated that there are big differences in the peak streamflow values. The calibrated and validated streamflow series with SWAT-CUP implementation coupled with ANN for daily streamflow prediction showed the least differences. In this approach, ANN served essentially as an optimization tool to improve the simulated streamflow series by SWAT. Input data for the ANNs model were snow depth, precipitation, maximum temperature, minimum temperature, relative humidity, wind speed, and SWAT-CUP calibrated and validated streamflow series. *NSE* and *R* evaluated the predicted streamflow by ANN model using the metrics. Results of this predication show significant improvements in the peak streamflow magnitudes simulated for the cold region. The SWAT_CUP- ANNs is a good method to overcome the deficiencies of SWAT in modeling snow melt hydrology processes.

It can also be concluded that in the regions where the studied watershed is flat, and there is not any great difference in the upper and lower elevations for separating and dividing the temperature and precipitation with topographic elevation (Fontine et al).

Using the developed ANNs method in this study will improve the results of simulated model by SWAT. this is significant because modeling spring peak streamflow of cold regions accurately is required for the prediction of flood magnitudes in spring.

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ACKNOWLEDGMENTS

2015 and 2016 Fellowship Awards under the North Dakota Water Resource Research Institute (NDWRRI) supported this study, NSF EPSCoR RII SEED grant UND0021102, and College of Engineering and Mines (CEM), University of North Dakota.

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CHAPTER IV

CONCLUSION

Summary

Streamflow simulation and prediction is one of the important tasks in water management system. It is needed in flood prediction, the design of hydraulic structures and in management operation of the reservoir of dams. Therefore, an accurate prediction and simulation of streamflow is necessary for hydrologic management and decision-making. A lot of models and tools have been developed for simulating of streamflow series. One of the most applicable tools for predicting of streamflow series is SWAT. This model is widely used because of its ability in finding the effects of changes in different land use and climate in the simulated watershed area.

This study, along with the other studies that are mentioned in the literature review, show that SWAT and other similar tools have some deficiencies in simulating streamflow series.

SWAT simulation results show this software has performed well in simulating streamflow in the regions where streamflow are generated mainly by rainfall- runoff process. Results from this study has shown that SWAT has a deficiency in simulation peak streamflow in snow-dominated area.

In order to improve the simulation results of SWAT in snow-dominated area, two methods were developed. The principle focus of these two methods was on the effects of snow and snow melting process. In the first method for detecting the effect of snow, after simulation by SWAT in the calibration and validation step, the streamflow data was separated into winter and summer periods.

Separation of summer and winter periods produced two kinds of stream flow series: one in the summer which is mainly produced by the rainfall, and another in the winter which is produced by the combination of rainfall and snowmelt. It should be reminded that winter parameters such as snowfall temperature, snowmelt base temperature, and snowpack temperature were used just in the calibration and validation of winter data.

Simulation results have shown that there is an improvement in the simulation of peak streamflow events but still there is a discrepancy between the calculated peak streamflow and measure streamflow series.

The second method was performed by coupling ANNs model with SWAT-CUP results. In this method, the multilayer feedforward network (MFN) with back propagation (BP) training algorithm was selected. Since the disability of SWAT in the simulation of peak streamflow was because of the snow parameters. In this simulation, the snow depth and maximum and minimum temperature, precipitation, wind speed, and relative humidity along with calibrated and validated streamflow series were used as inputs of ANNs.

Simulation results of this method have shown smaller differences with the measured data. So it could be used as a way for predicting and simulating peak streamflow event in the snow-dominated area.

The other object of the research was to simulate and compute sediment entrance to the reservoir of Baldhill Dam in order to estimate the useful life of the reservoir based on the current climate data. The calibrated SWAT model predicted that the average rate of annual sediment accumulation within the Lake Ashtabula, reservoir of Bald Hill dams is varying between 3.73 (ton/ha/yr) and 0.058 (ton/ha/yr) from 1995 to 2011. Since the major land use in North Dakota is agricultural and snowmelt processes are causing more erosion, so by combining the result of the simulated streamflow series and TSS. It will be understood that snow and precipitation are important parameters in erosion, and after peak flood, the accumulation of sediment in the reservoir has been increased.

Research Limitations

This research has some limitations related to modeling and scenario assumptions. A limitation inherent to the current version of SWAT precludes us from modeling potholes, which are widely found in the Northern Great Plains where they from depression wetlands.

Further, the reservoir module in SWAT has limited utility, because only one reservoir can be included into a sub-basin and it can only have one outlet. These limitations over simplify the hydrology of the region and restrict the set of scenarios. Model verification is supported with the use of streamflow data but excluding sediment due to the lack of observed data in the watershed.

Possible Future Research Areas

Improving SWAT Program

One of the important concerns in the simulation of the streamflow was having the accurate prediction of peak streamflow in snow dominant area. As it was proposed, SWAT has difficulties in the simulation of peak streamflow event, which was generated by melting snow in short of time. However, this problem can be resolved by coupling of SWAT and ANNs were solved. However, using the proper snow parameters in the SWAT programs will directly improve simulation results. This suggest a potential method to be developed by considering the frequency of below zero temperature during winter, the beginning time of melting, complete melting process in the simulation algorithms.

Model Selection

Although SWAT is popularly used to simulate the effects of changes in climate and land use in thousands of watersheds across the world, it can be improved further by modeling of the potholes to quantify the water storage in the upper basin and the consequent delay/ reduction of surface runoff to the watershed of Lake Ashtabula.

APPENDIX A

1

In this Appendix the result Peak FQ is provided

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.003.000

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

--- PROCESSING OPTIONS ---

Plot option = None

Basin char output = None

Print option = Yes

Debug print = No

Input peaks listing = Long

Input peaks format = WATSTORE peak file

Input files used:

peaks (ascii) - C:\Users\bahareh.shoghli.AD\Desktop\OUTLET4_5.TXT

specifications - C:\Users\bahareh.shoghli.AD\Desktop\PKFQWPSF.TMP

Output file(s):

main - C:\Users\bahareh.shoghli.AD\Desktop\OUTLET4_5.PRT

1

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.001.001

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057000 SHEYENNE RIVER NR COOPERSTOWN, ND

I N P U T   D A T A   S U M M A R Y

Number of peaks in record	=	72
Peaks not used in analysis	=	0
Systematic peaks in analysis	=	72
Historic peaks in analysis	=	0
Beginning Year	=	1945
Ending Year	=	2016
Historical Period Length	=	0
Generalized skew	=	-0.400
Standard error	=	0.550
Mean Square error	=	0.303
Skew option	=	WEIGHTED
Gage base discharge	=	0.0
User supplied high outlier threshold	=	--
User supplied PILF (LO) criterion	=	--
Plotting position parameter	=	0.00
Type of analysis		BULL.17B
PILF (LO) Test Method		GBT
Perception Thresholds	=	Not Applicable
Interval Data	=	Not Applicable

********* NOTICE -- Preliminary machine computations.   *********

********* User responsible for assessment and interpretation. *********

WCF134I-NO SYSTEMATIC PEAKS WERE BELOW GAGE BASE. 0.0

WCF195I-NO LOW OUTLIERS WERE DETECTED BELOW CRITERION. 61.7

WCF163I-NO HIGH OUTLIERS OR HISTORIC PEAKS EXCEEDED HHBASE. 26064.1

Kendall's Tau Parameters

	TAU	P-VALUE	MEDIAN SLOPE	No. of PEAKS
SYSTEMATIC RECORD	0.149	0.065	12.747	72

1

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.001.002

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057000 SHEYENNE RIVER NR COOPERSTOWN, ND

ANNUAL FREQUENCY CURVE PARAMETERS -- LOG-PEARSON TYPE III

FLOOD BASE LOGARITHMIC

	DISCHARGE	EXCEEDANCE PROBABILITY	MEAN	STANDARD DEVIATION	SKEW
SYSTEMATIC RECORD	0.0	1.0000	3.1032	0.4522	-0.435
BULL.17B ESTIMATE	0.0	1.0000	3.1032	0.4522	-0.426

BULL.17B ESTIMATE OF MSE OF AT-SITE SKEW 0.0990

ANNUAL FREQUENCY CURVE -- DISCHARGES AT SELECTED EXCEEDANCE PROBABILITIES

ANNUAL EXCEEDANCE PROBABILITY	<-- FOR BULLETIN 17B ESTIMATES --> BULL.17B ESTIMATE	SYSTEMATIC RECORD	VARIANCE OF EST.	95% CONFIDENCE INTERVALS LOWER	UPPER
0.9950	57.4	56.9	----	33.4	87.4
0.9900	81.7	81.1	----	50.0	119.8
0.9500	203.6	203.1	----	141.5	272.8
0.9000	321.3	321.1	----	236.2	414.3
0.8000	543.2	543.6	----	421.9	676.7
0.6667	863.3	864.4	----	693.9	1058.0
0.5000	1365.	1367.	----	1115.0	1677.0
0.4292	1638.	1640.	----	1338.0	2024.0
0.2000	3091.	3092.	----	2476.0	3995.0
0.1000	4552.	4546.	----	3556.0	6125.0
0.0400	6681.	6658.	----	5060.0	9411.0

0.0200	8428.	8386.	----	6251.0	12230.0
0.0100	10280.	10210.	----	7484.0	15320.0
0.0050	12230.	12130.	----	8754.0	18660.0
0.0020	14940.	14790.	----	10480.0	23450.0

1

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.001.003

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057000 SHEYENNE RIVER NR COOPERSTOWN, ND

I N P U T D A T A L I S T I N G

WATER YEAR	PEAK VALUE	PEAKFQ CODES	REMARKS
1945	1000.0		
1946	964.0		
1947	1150.0		
1948	5600.0		
1949	2290.0		
1950	7830.0		
1951	989.0		
1952	1240.0		
1953	271.0		

1954	682.0
1955	1060.0
1956	2600.0
1957	280.0
1958	340.0
1959	360.0
1960	1340.0
1961	120.0
1962	900.0
1963	300.0
1964	795.0
1965	2320.0
1966	3040.0
1967	2160.0
1968	415.0
1969	5050.0
1970	964.0
1971	2310.0
1972	1120.0
1973	260.0
1974	2460.0
1975	1490.0
1976	1450.0
1977	136.0
1978	1460.0
1979	4680.0
1980	750.0
1981	500.0

1982	1900.0
1983	1610.0
1984	1850.0
1985	930.0
1986	1760.0
1987	4840.0
1988	389.0
1989	796.0
1990	159.0
1991	84.0
1992	1100.0
1993	2780.0
1994	1750.0
1995	3380.0
1996	6760.0
1997	5280.0
1998	1540.0
1999	3750.0
2000	2240.0
2001	3190.0
2002	418.0
2003	712.0
2004	4660.0
2005	1120.0
2006	1960.0
2007	1510.0
2008	392.0
2009	6280.0

2010	2870.0
2011	8460.0
2012	751.0
2013	4110.0
2014	1840.0
2015	1150.0
2016	964.0

Explanation of peak discharge qualification codes

PeakFQ CODE	NWIS CODE	DEFINITION
D	3	Dam failure, non-recurrent flow anomaly
G	8	Discharge greater than stated value
X	3+8	Both of the above
L	4	Discharge less than stated value
K	6 OR C	Known effect of regulation or urbanization
H	7	Historic peak

- Minus-flagged discharge -- Not used in computation

-8888.0 -- No discharge value given

- Minus-flagged water year -- Historic peak used in computation

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.001.004

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057000 SHEYENNE RIVER NR COOPERSTOWN, ND

EMPIRICAL FREQUENCY CURVES -- WEIBULL PLOTTING POSITIONS

WATER YEAR	RANKED DISCHARGE	SYSTEMATIC RECORD	B17B ESTIMATE
2011	8460.0	0.0137	0.0137
1950	7830.0	0.0274	0.0274
1996	6760.0	0.0411	0.0411
2009	6280.0	0.0548	0.0548
1948	5600.0	0.0685	0.0685
1997	5280.0	0.0822	0.0822
1969	5050.0	0.0959	0.0959
1987	4840.0	0.1096	0.1096
1979	4680.0	0.1233	0.1233
2004	4660.0	0.1370	0.1370
2013	4110.0	0.1507	0.1507
1999	3750.0	0.1644	0.1644
1995	3380.0	0.1781	0.1781
2001	3190.0	0.1918	0.1918
1966	3040.0	0.2055	0.2055
2010	2870.0	0.2192	0.2192
1993	2780.0	0.2329	0.2329
1956	2600.0	0.2466	0.2466
1974	2460.0	0.2603	0.2603

1965	2320.0	0.2740	0.2740
1971	2310.0	0.2877	0.2877
1949	2290.0	0.3014	0.3014
2000	2240.0	0.3151	0.3151
1967	2160.0	0.3288	0.3288
2006	1960.0	0.3425	0.3425
1982	1900.0	0.3562	0.3562
1984	1850.0	0.3699	0.3699
2014	1840.0	0.3836	0.3836
1986	1760.0	0.3973	0.3973
1994	1750.0	0.4110	0.4110
1983	1610.0	0.4247	0.4247
1998	1540.0	0.4384	0.4384
2007	1510.0	0.4521	0.4521
1975	1490.0	0.4658	0.4658
1978	1460.0	0.4795	0.4795
1976	1450.0	0.4932	0.4932
1960	1340.0	0.5068	0.5068
1952	1240.0	0.5205	0.5205
1947	1150.0	0.5342	0.5342
2015	1150.0	0.5479	0.5479
1972	1120.0	0.5616	0.5616
2005	1120.0	0.5753	0.5753
1992	1100.0	0.5890	0.5890
1955	1060.0	0.6027	0.6027
1945	1000.0	0.6164	0.6164
1951	989.0	0.6301	0.6301
1946	964.0	0.6438	0.6438

1970	964.0	0.6575	0.6575
2016	964.0	0.6712	0.6712
1985	930.0	0.6849	0.6849
1962	900.0	0.6986	0.6986
1989	796.0	0.7123	0.7123
1964	795.0	0.7260	0.7260
2012	751.0	0.7397	0.7397
1980	750.0	0.7534	0.7534
2003	712.0	0.7671	0.7671
1954	682.0	0.7808	0.7808
1981	500.0	0.7945	0.7945
2002	418.0	0.8082	0.8082
1968	415.0	0.8219	0.8219
2008	392.0	0.8356	0.8356
1988	389.0	0.8493	0.8493
1959	360.0	0.8630	0.8630
1958	340.0	0.8767	0.8767
1963	300.0	0.8904	0.8904
1957	280.0	0.9041	0.9041
1953	271.0	0.9178	0.9178
1973	260.0	0.9315	0.9315
1990	159.0	0.9452	0.9452
1977	136.0	0.9589	0.9589
1961	120.0	0.9726	0.9726
1991	84.0	0.9863	0.9863

1

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.002.001
Version 7.1 Annual peak flow frequency analysis Run Date / Time
3/14/2014 10/12/2017 18:21

Station - 05057200 BALDHILL CREEK NR DAZEY, ND

I N P U T D A T A S U M M A R Y

Number of peaks in record = 62
Peaks not used in analysis = 1
Systematic peaks in analysis = 61
Historic peaks in analysis = 0
Beginning Year = 1950
Ending Year = 2016
Historical Period Length = 0
Generalized skew = -0.400
  Standard error = 0.550
  Mean Square error = 0.303
Skew option = WEIGHTED
Gage base discharge = 0.0
User supplied high outlier threshold = --
User supplied PILF (LO) criterion = --
Plotting position parameter = 0.00
Type of analysis BULL.17B
PILF (LO) Test Method GBT
Perception Thresholds = Not Applicable
Interval Data = Not Applicable

********* NOTICE -- Preliminary machine computations. *********

********* User responsible for assessment and interpretation. *********

**WCF109W-PEAKS WITH MINUS-FLAGGED DISCHARGES WERE BYPASSED. 1

**WCF113W-NUMBER OF SYSTEMATIC PEAKS HAS BEEN REDUCED TO NSYS = 61

WCF134I-NO SYSTEMATIC PEAKS WERE BELOW GAGE BASE. 0.0

WCF195I-NO LOW OUTLIERS WERE DETECTED BELOW CRITERION. 6.2

WCF163I-NO HIGH OUTLIERS OR HISTORIC PEAKS EXCEEDED HHBASE. 22825.9

WCF002J-CALCS COMPLETED. RETURN CODE = 2

Kendall's Tau Parameters

	TAU	P-VALUE	MEDIAN SLOPE	No. of PEAKS
SYSTEMATIC RECORD	0.199	0.024	7.642	61

1

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.002.002

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057200 BALDHILL CREEK NR DAZEY, ND

ANNUAL FREQUENCY CURVE PARAMETERS -- LOG-PEARSON TYPE III

	FLOOD BASE		LOGARITHMIC		
	DISCHARGE	EXCEEDANCE PROBABILITY	MEAN	STANDARD DEVIATION	SKEW
SYSTEMATIC RECORD	0.0	1.0000	2.5740	0.6279	-0.210
BULL.17B ESTIMATE	0.0	1.0000	2.5740	0.6279	-0.257

BULL.17B ESTIMATE OF MSE OF AT-SITE SKEW 0.0981

ANNUAL FREQUENCY CURVE -- DISCHARGES AT SELECTED EXCEEDANCE PROBABILITIES

ANNUAL EXCEEDANCE PROBABILITY	BULL.17B ESTIMATE	SYSTEMATIC RECORD	<-- FOR BULLETIN 17B ESTIMATES --> VARIANCE OF EST.	95% CONFIDENCE INTERVALS LOWER	UPPER
0.9950	6.4	6.8	----	2.9	11.7
0.9900	9.9	10.4	----	4.8	17.2
0.9500	31.4	32.0	----	18.2	48.5
0.9000	56.8	57.1	----	35.6	83.0

0.8000	113.5	113.0	----	77.1	158.0
0.6667	211.9	209.9	----	151.8	288.1
0.5000	398.8	394.4	----	293.5	543.6
0.4292	514.7	509.3	----	379.6	708.3
0.2000	1284.	1282.	----	920.5	1897.0
0.1000	2288.	2308.	----	1575.0	3612.0
0.0400	4129.	4232.	----	2699.0	7055.0
0.0200	5964.	6190.	----	3761.0	10750.0
0.0100	8229.	8651.	----	5018.0	15560.0
0.0050	10970.	11680.	----	6484.0	21670.0
0.0020	15380.	16670.	----	8762.0	32060.0

1

Program PeakFq U. S. GEOLOGICAL SURVEY Seq.002.003

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057200 BALDHILL CREEK NR DAZEY, ND

I N P U T D A T A L I S T I N G

WATER YEAR	PEAK VALUE	PEAKFQ CODES	REMARKS
1950	-8888.0		
1956	767.0		

1957	248.0
1958	56.0
1959	30.0
1960	370.0
1961	40.0
1962	390.0
1963	24.0
1964	60.0
1965	1780.0
1966	880.0
1967	650.0
1968	210.0
1969	2510.0
1970	472.0
1971	305.0
1972	305.0
1973	100.0
1974	1130.0
1975	680.0
1976	400.0
1977	25.0
1978	560.0
1979	9000.0
1980	100.0
1981	28.0
1982	580.0
1983	650.0
1984	755.0

1985	88.0
1986	210.0
1987	960.0
1988	115.0
1989	303.0
1990	32.0
1991	50.0
1992	239.0
1993	1450.0
1994	1020.0
1995	1900.0
1996	1900.0
1997	2780.0
1998	355.0
1999	2300.0
2000	293.0
2001	453.0
2002	58.0
2003	146.0
2004	3250.0
2005	234.0
2006	502.0
2007	778.0
2008	52.0
2009	3470.0
2010	1700.0
2011	3200.0
2012	115.0

2013	1070.0
2014	1280.0
2015	854.0
2016	421.0

Explanation of peak discharge qualification codes

PeakFQ CODE	NWIS CODE	DEFINITION
D	3	Dam failure, non-recurrent flow anomaly
G	8	Discharge greater than stated value
X	3+8	Both of the above
L	4	Discharge less than stated value
K	6 OR C	Known effect of regulation or urbanization
H	7	Historic peak

- Minus-flagged discharge -- Not used in computation

-8888.0 -- No discharge value given

- Minus-flagged water year -- Historic peak used in computation

1

Version 7.1 Annual peak flow frequency analysis Run Date / Time

3/14/2014 10/12/2017 18:21

Station - 05057200 BALDHILL CREEK NR DAZEY, ND

EMPIRICAL FREQUENCY CURVES -- WEIBULL PLOTTING POSITIONS

WATER YEAR	RANKED DISCHARGE	SYSTEMATIC RECORD	B17B ESTIMATE
1979	9000.0	0.0161	0.0161
2009	3470.0	0.0323	0.0323
2004	3250.0	0.0484	0.0484
2011	3200.0	0.0645	0.0645
1997	2780.0	0.0806	0.0806
1969	2510.0	0.0968	0.0968
1999	2300.0	0.1129	0.1129
1995	1900.0	0.1290	0.1290
1996	1900.0	0.1452	0.1452
1965	1780.0	0.1613	0.1613
2010	1700.0	0.1774	0.1774
1993	1450.0	0.1935	0.1935
2014	1280.0	0.2097	0.2097
1974	1130.0	0.2258	0.2258
2013	1070.0	0.2419	0.2419
1994	1020.0	0.2581	0.2581
1987	960.0	0.2742	0.2742
1966	880.0	0.2903	0.2903

2015	854.0	0.3065	0.3065
2007	778.0	0.3226	0.3226
1956	767.0	0.3387	0.3387
1984	755.0	0.3548	0.3548
1975	680.0	0.3710	0.3710
1967	650.0	0.3871	0.3871
1983	650.0	0.4032	0.4032
1982	580.0	0.4194	0.4194
1978	560.0	0.4355	0.4355
2006	502.0	0.4516	0.4516
1970	472.0	0.4677	0.4677
2001	453.0	0.4839	0.4839
2016	421.0	0.5000	0.5000
1976	400.0	0.5161	0.5161
1962	390.0	0.5323	0.5323
1960	370.0	0.5484	0.5484
1998	355.0	0.5645	0.5645
1971	305.0	0.5806	0.5806
1972	305.0	0.5968	0.5968
1989	303.0	0.6129	0.6129
2000	293.0	0.6290	0.6290
1957	248.0	0.6452	0.6452
1992	239.0	0.6613	0.6613
2005	234.0	0.6774	0.6774
1968	210.0	0.6935	0.6935
1986	210.0	0.7097	0.7097
2003	146.0	0.7258	0.7258
1988	115.0	0.7419	0.7419

2012	115.0	0.7581	0.7581
1973	100.0	0.7742	0.7742
1980	100.0	0.7903	0.7903
1985	88.0	0.8065	0.8065
1964	60.0	0.8226	0.8226
2002	58.0	0.8387	0.8387
1958	56.0	0.8548	0.8548
2008	52.0	0.8710	0.8710
1991	50.0	0.8871	0.8871
1961	40.0	0.9032	0.9032
1990	32.0	0.9194	0.9194
1959	30.0	0.9355	0.9355
1981	28.0	0.9516	0.9516
1977	25.0	0.9677	0.9677
1963	24.0	0.9839	0.9839
1950	-8888.0	--	--

1

End PeakFQ analysis.

Stations processed : 2

Number of errors : 0

Stations skipped : 0

Station years : 134

Data records may have been ignored for the stations listed below.

(Card type must be Y, Z, N, H, I, 2, 3, 4, or *.)

(2, 4, and * records are ignored.)

For the station below, the following records were ignored:

FINISHED PROCESSING STATION: 05057000   USGS SHEYENNE RIVER NR COOPERSTOWN

For the station below, the following records were ignored:

FINISHED PROCESSING STATION: 05057200   USGS BALDHILL CREEK NR DAZEY, ND

For the station below, the following records were ignored:

FINISHED PROCESSING STATION:

For having good understand about the peak streamflow in the watershed of Lake Ashtabula, annual peak discharge for outlet 4 and outlet 5 were delineated in figure 15 and figure 16 respectively. As it was shown in both outlet the after building dam the increasing trend of peak flow was decreased. But after 1990 the regim of the streamflow changed and it could be because of the land use change and climate change in this area. what is understandable from figure is after 1990 peak stramflow is going to raised.

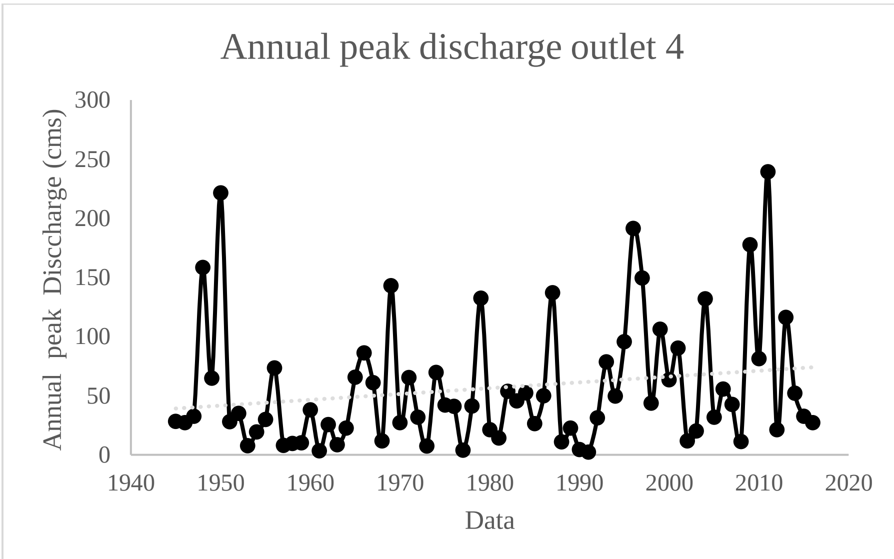

Figure 15. Annual peak discharge in Outlet 4 of watershed Lake Ashtabula

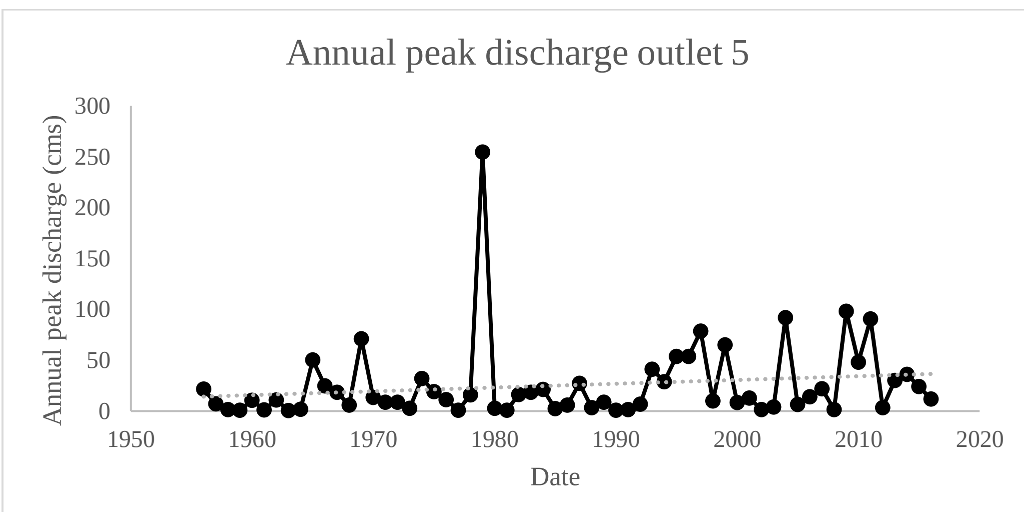

Figure 16. Annual peak discharge in Outlet 5 of watershed Lake Ashtabula

Flood Frequency Analysis

For have good understanding about flood prediction in the watershed of Lake Ashtabula, flood frequency analysis were performed with the help of PeakFQ program. This program was developed by USGS, Program PeakFQ implements both the Bulletin 17B and Expected Moments Algorithm (EMA) procedures for flood-frequency analysis of streamflow records. Providing estimates of flood magnitudes and their corresponding variance for a range of 15 annual exceedance probabilities, including 0.6667, 0.50, 0.4292 0.20, 0.10, 0.04, 0.02, 0.01, 0.005, and 0.002 (recurrence intervals 1.5, 2, 2.33, 5, 10, 25, 50, 100, 200, and 500 years, respectively.

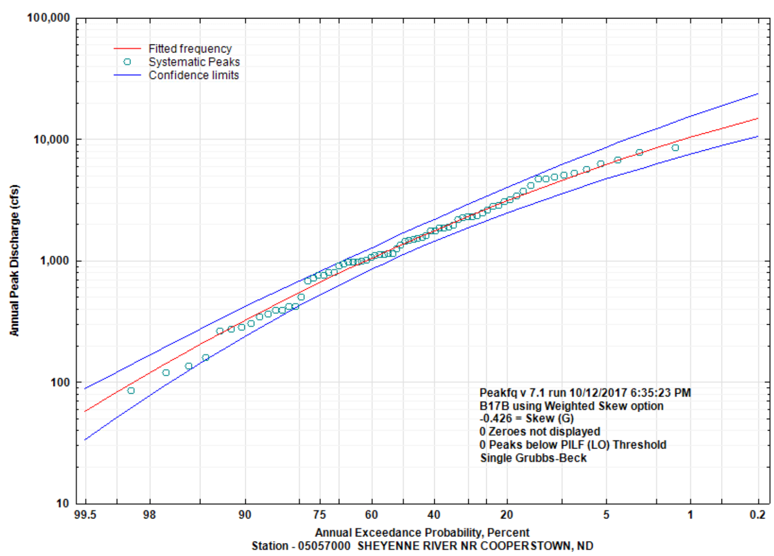

Figure 17. Probability of annual peak discharge in Outlet 4

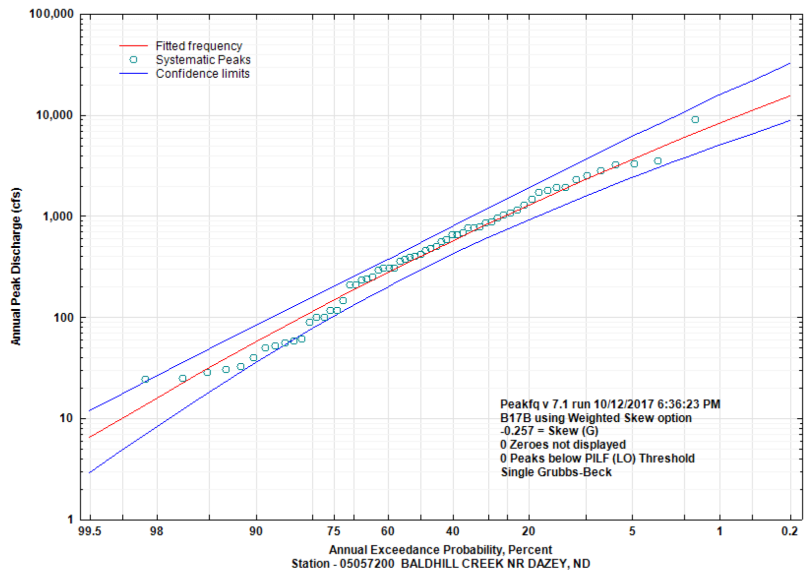

Figure 18. Probability of annual peak discharge in Outlet 5

These figures help us to understand what is the peak discharge with the probability of 1% or in the other words with the return periods of 100 years that that most small embankment dams are designed based on that.

APPENDIX B

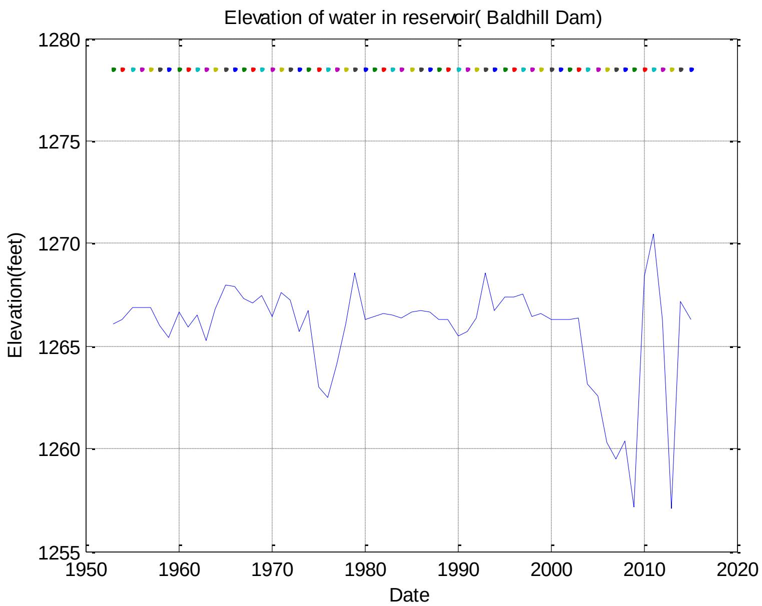

Figure 19. Elevation of the water in the reservoir of Baldhill Dam

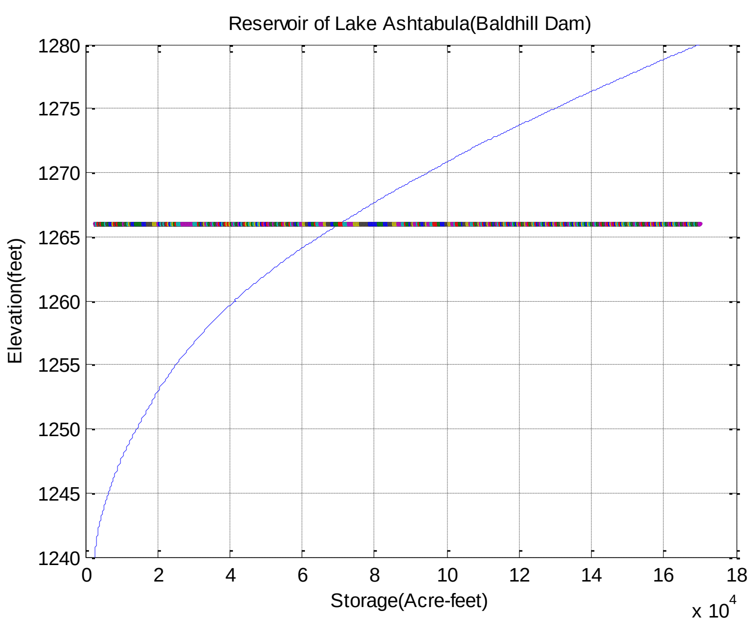

Figure 20. Storage capacity of reservoir of Baldhill Dam

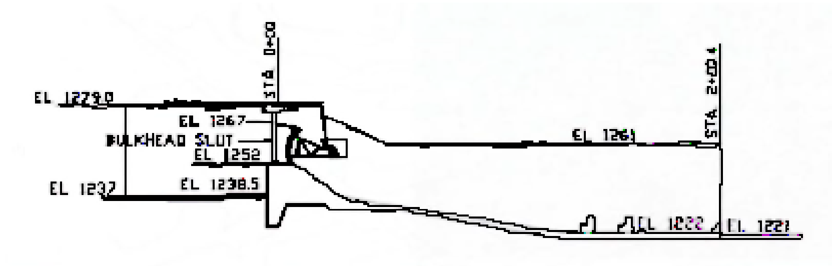

Figure 21. Layout of Baldhill Dam structure

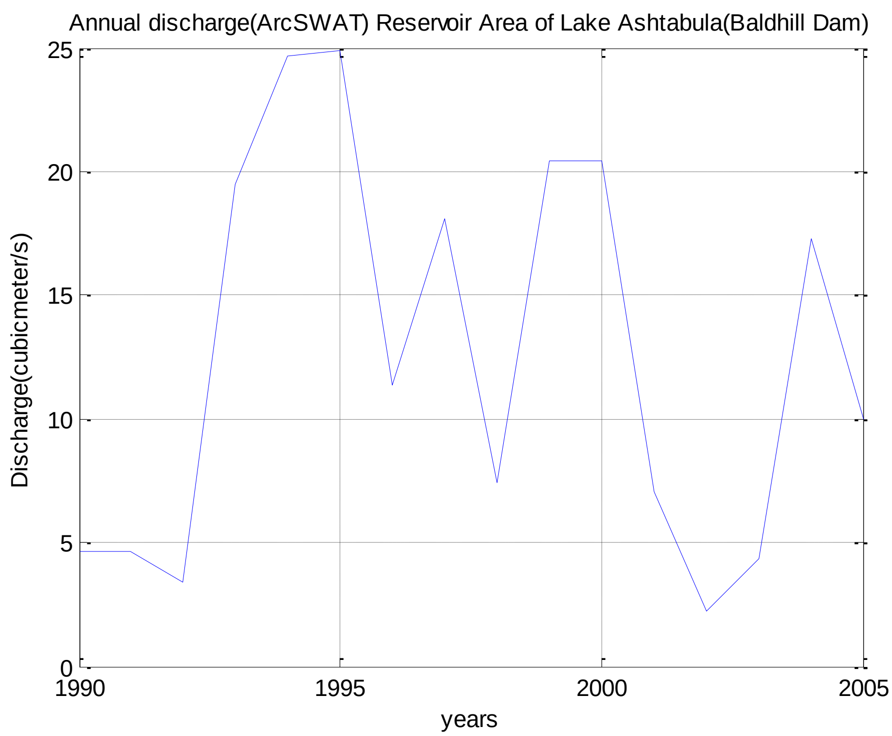

Figure 22. Annual discharge in the reservoir of Baldhill Dam

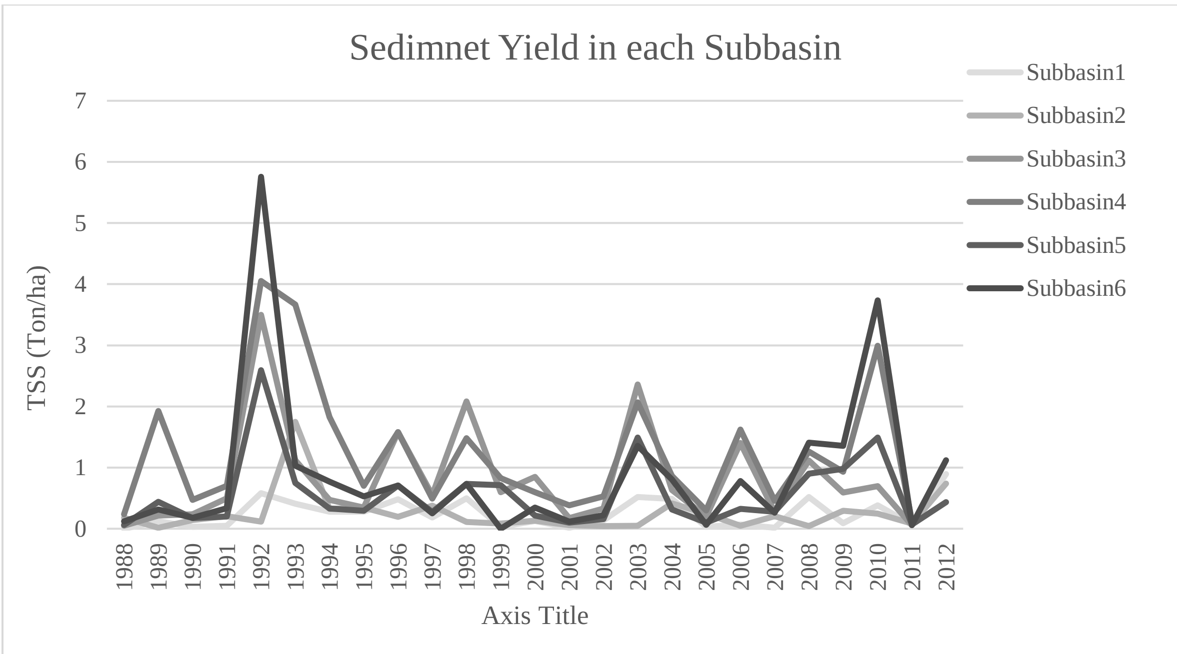

Figure 23. Sediment yield in sub basins of watershed Lake Ashtabula

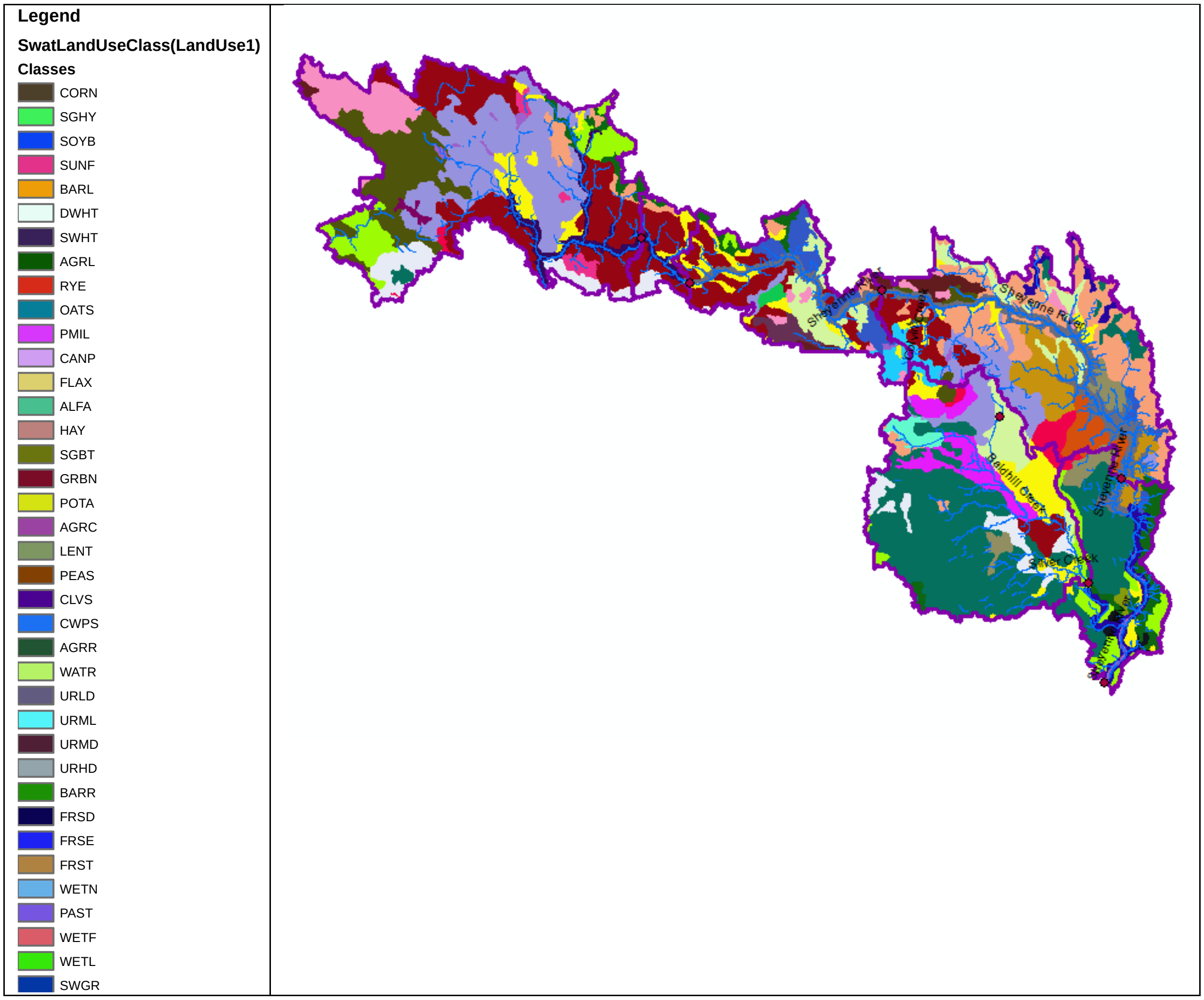

Figure 24. Land use of watershed Lake Ashtabula

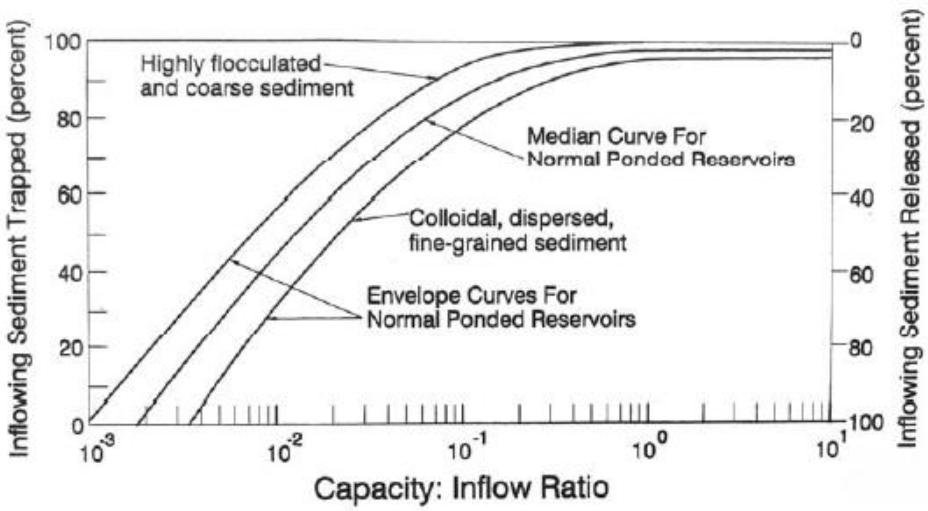

Figure 25. Brune curve for estimating sediment trapping or release efficiency in conventional impounding reservoirs

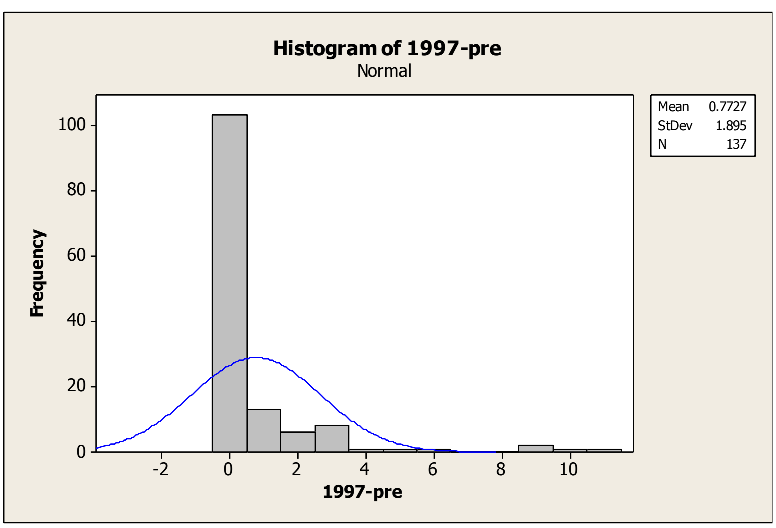

Figure 26. Frequency of precipitation in 1997

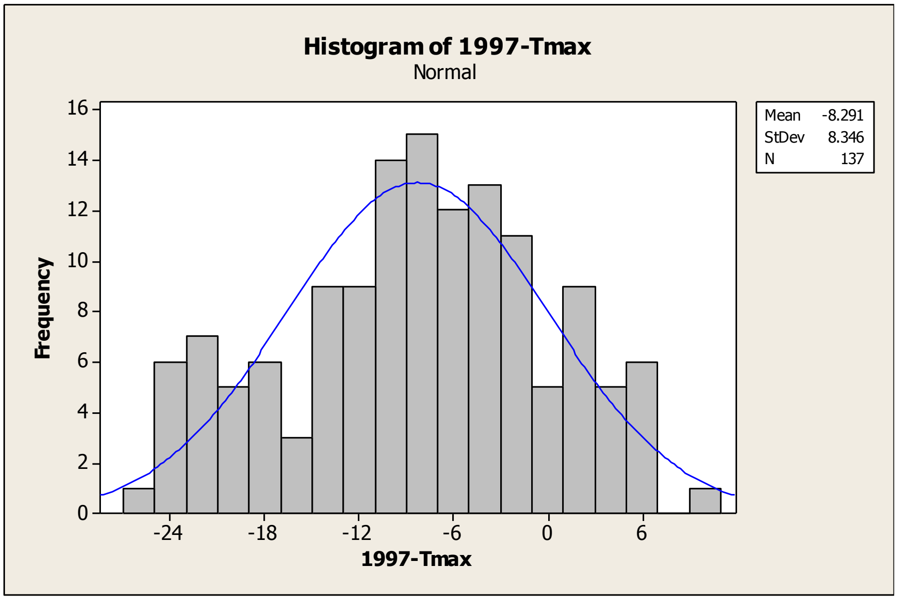

Figure 27. Frequency of maximum temperature in 1997

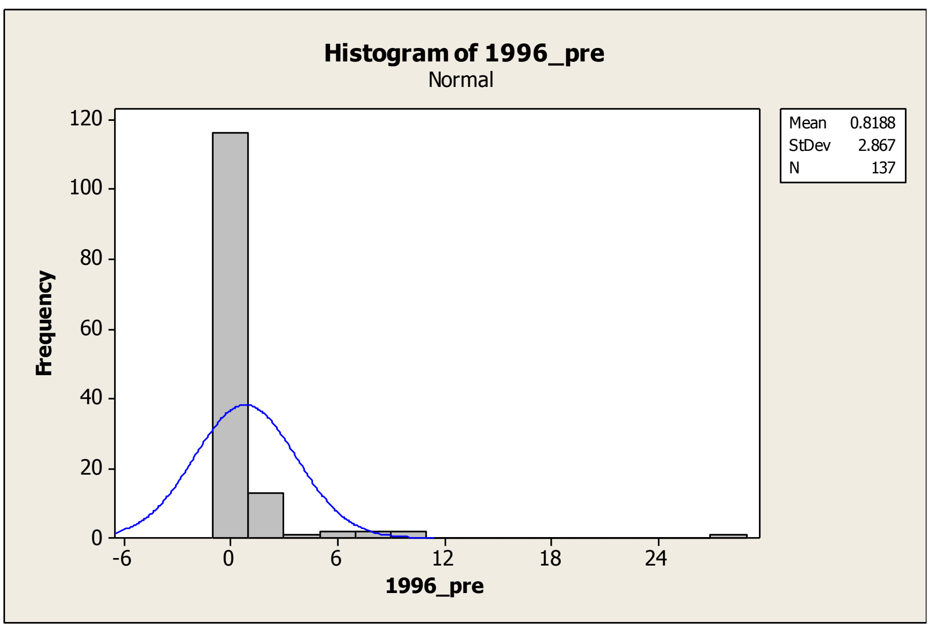

Figure 28. Frequency of precipitation in 1996

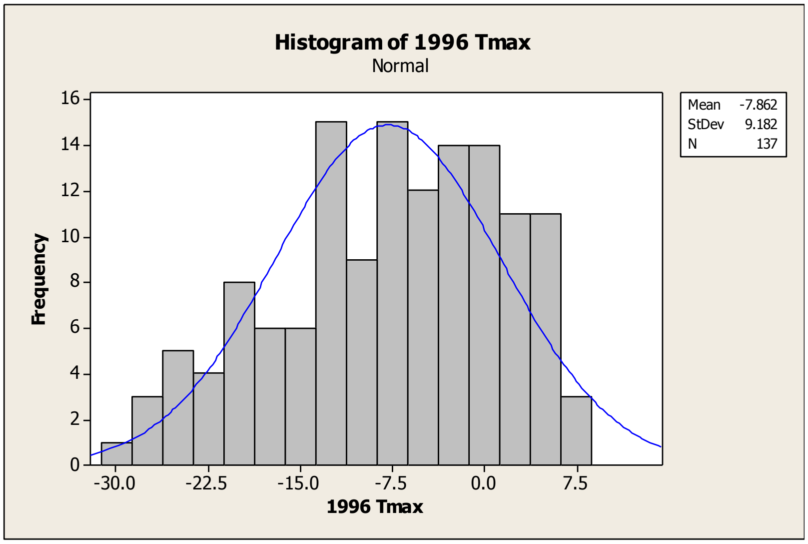

Figure 29. Frequency of maximum temperature in 1996

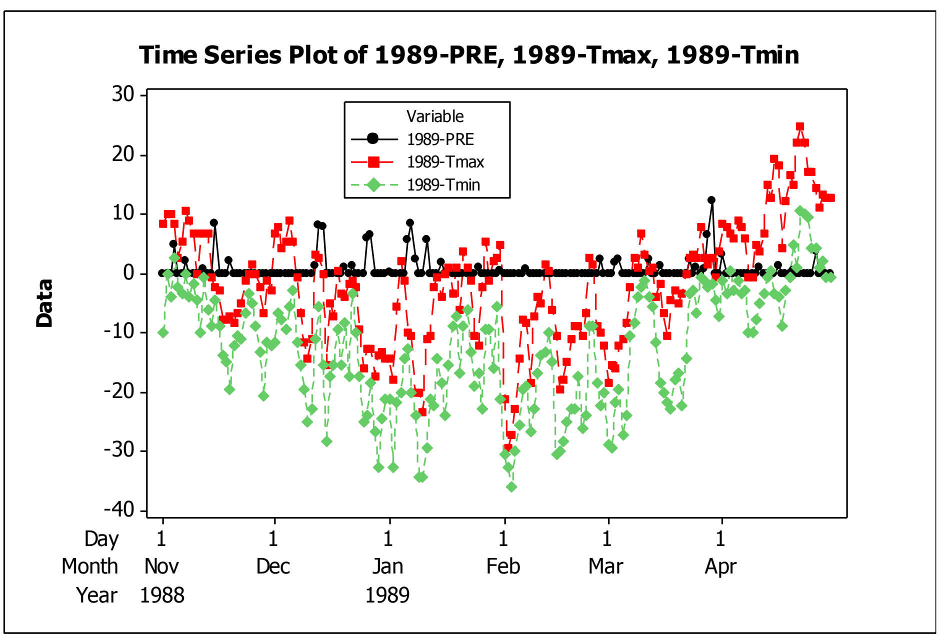

Figure 30. Time series of precipitation against maximum and minimum temperature of winter 1989

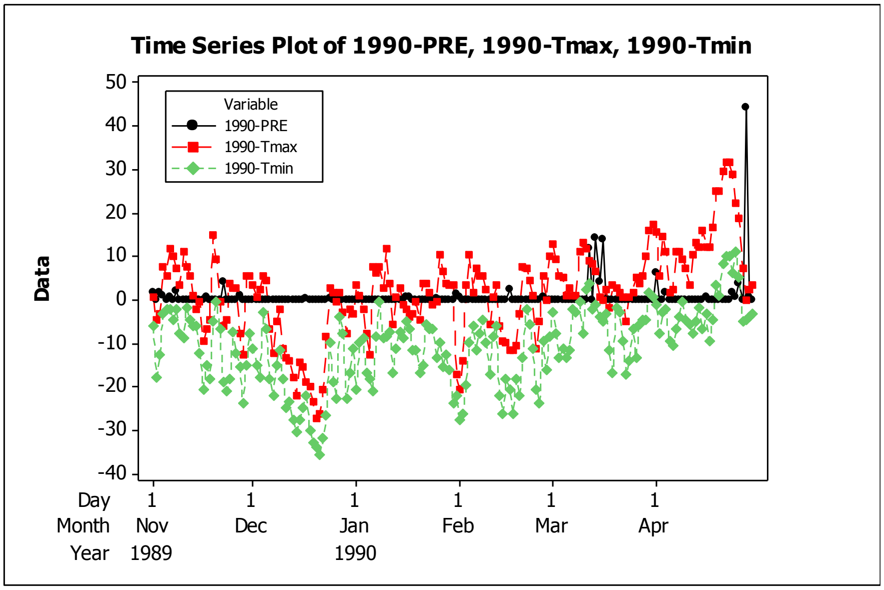

Figure 31. Time series of precipitation against maximum and minimum temperature of winter 1990

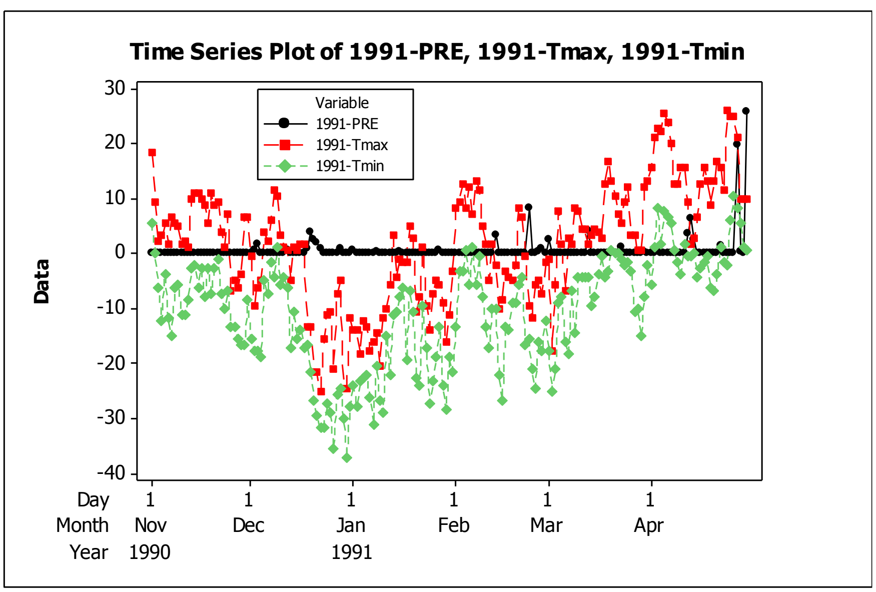

Figure 32. Time series of precipitation against maximum and minimum temperature of winter 1991

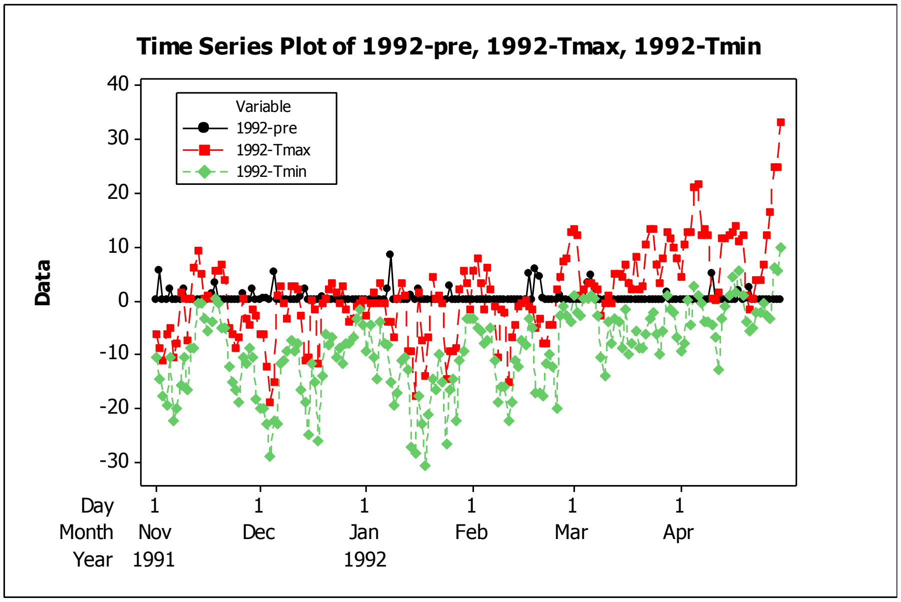

Figure 33. Time series of precipitation against maximum and minimum temperature of winter 1992

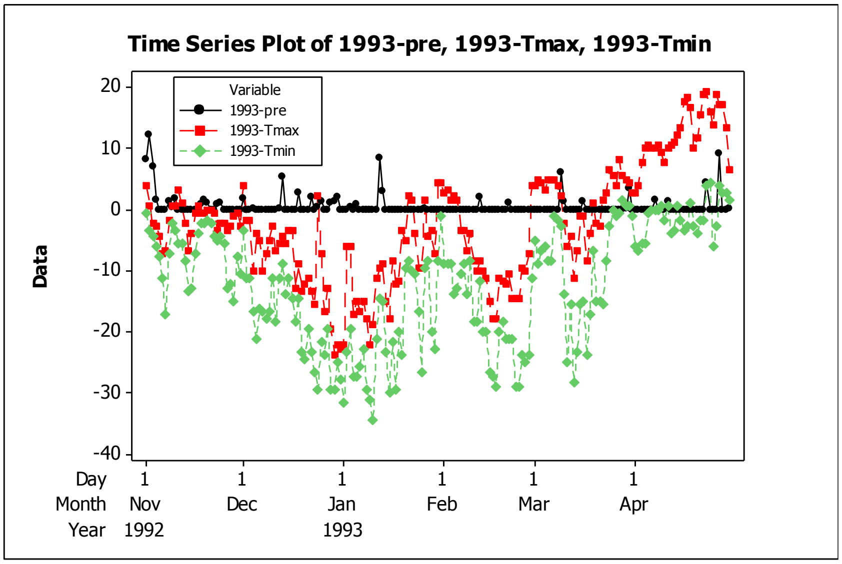

Figure 34. Time series of precipitation against maximum and minimum temperature of winter 1993

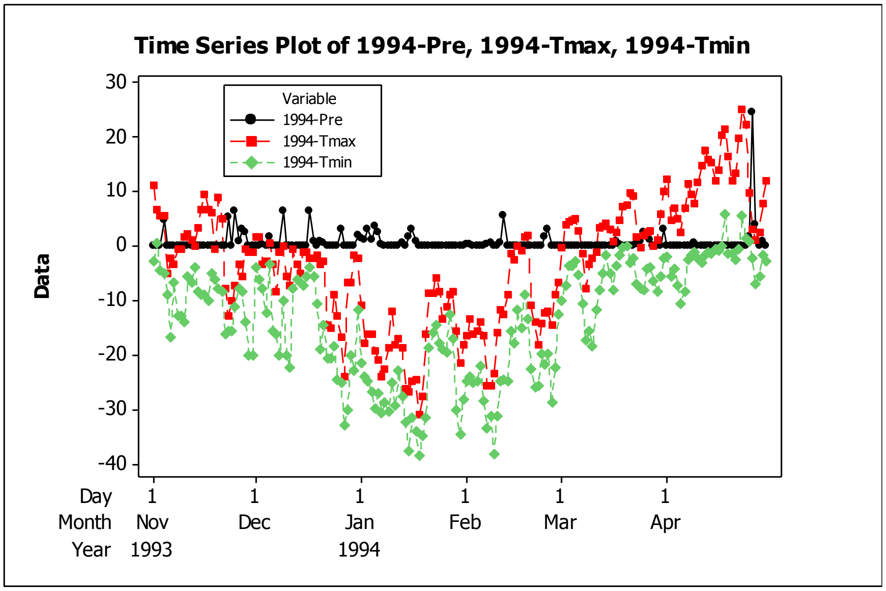

Figure 35. Time series of precipitation against maximum and minimum temperature in winter of 1994

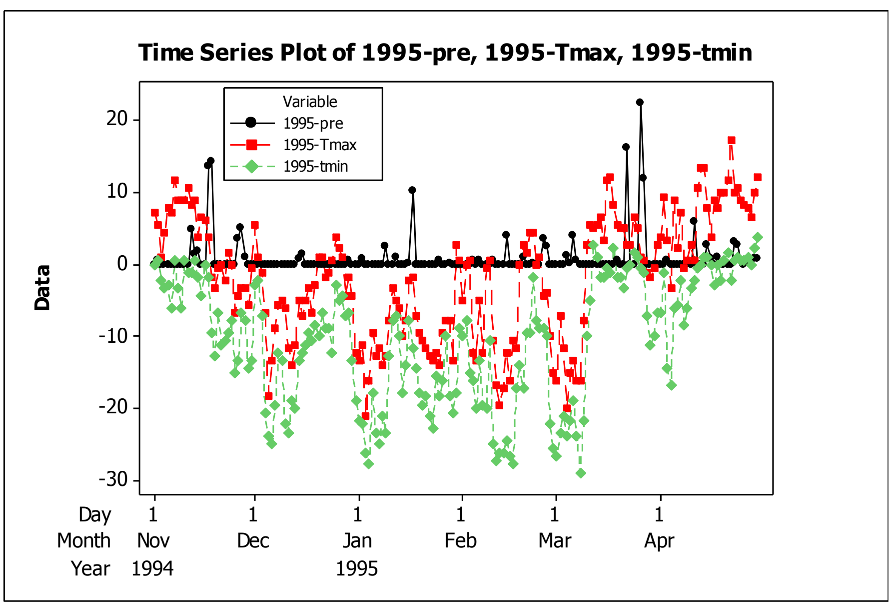

Figure 36. Time series of precipitation against maximum and minimum temperature in winter of 1995

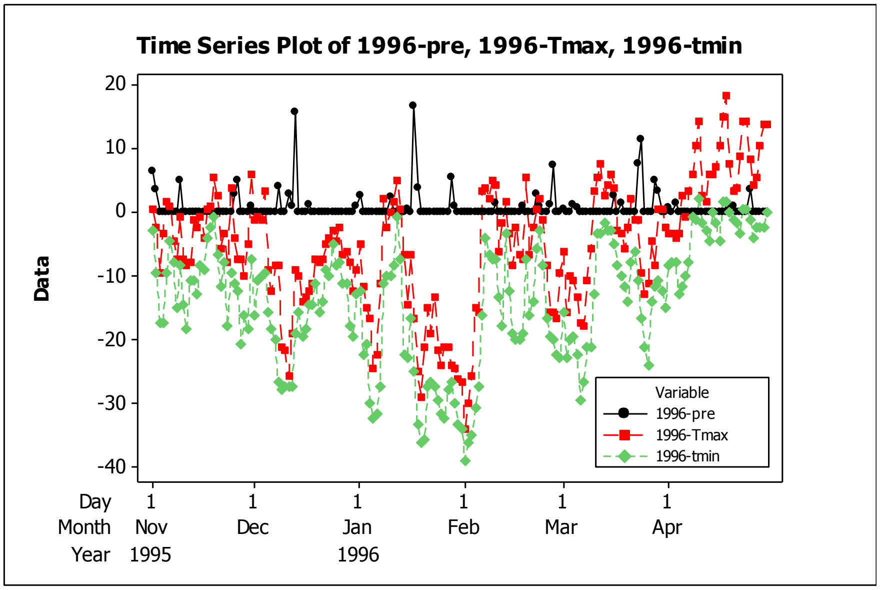

Figure 37. Time series of precipitation against maximum and minimum temperature in winter of 1996

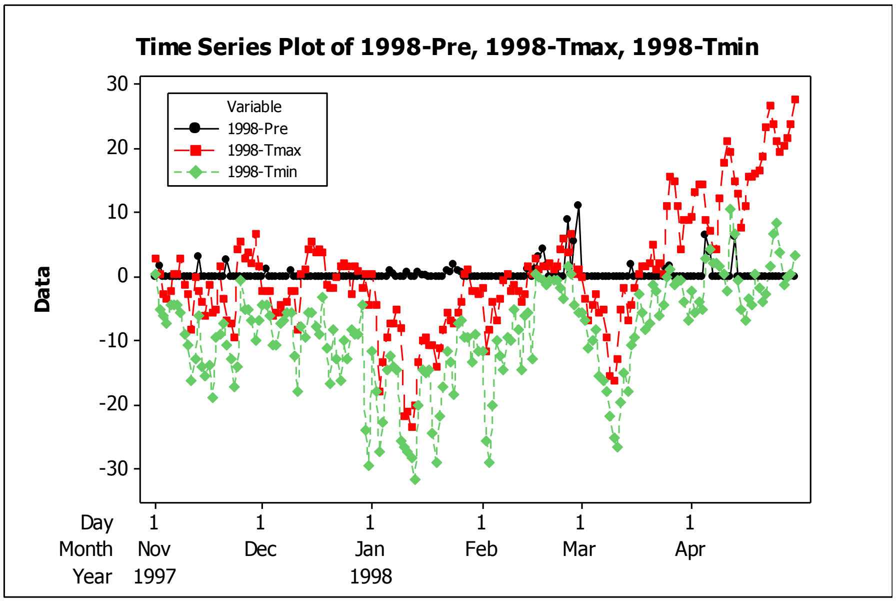

Figure 38. Time series of precipitation against maximum and minimum temperature in winter of 1998

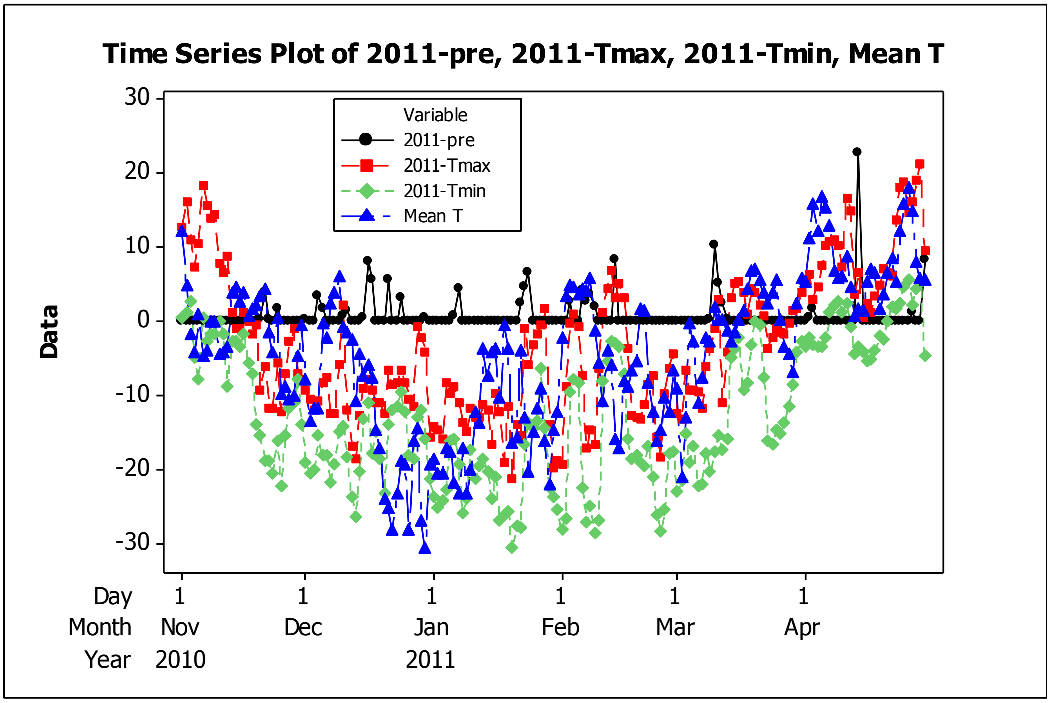

Figure 39. Time series of precipitation against maximum, minimum, and mean temperature in winter of 2011