Investigating the Temporal and Spatial Variability of Flow and Salinity Levels in an Ungaged Watershed for Ecological Benefits: A Case Study of the Mentor Marsh Watershed

by

Hari Dhungel

Submitted in Partial Fulfillment of the Requirements

for the Degree of

Master of Science in Engineering

in the

Civil and Environmental Engineering Program

YOUNGSTOWN STATE UNIVERSITY

August, 2018

Investigating the Temporal and Spatial Variability of Flow and Salinity Levels in an Ungaged Watershed for Ecological Benefits: A Case Study of the Mentor Marsh Watershed

Hari Dhungel

Signature:

Hari Dhungel, Student — Date

Approvals:

Suresh Sharma, Thesis Advisor — Date

Tony Vercellino, Committee Member — Date

Peter Kimosop, Committee Member — Date

Dr. Salvatore A. Sanders, Dean of Graduate Studies — Date

ABSTRACT

The Mentor marsh was the first declared a National Natural Landmark in 1966 and became a nature preserve in 1971 in the State of Ohio. Despite being affected by salt pollution and other physical challenges, it still has a tremendous economic value, and will rise if it is restored. The Marsh was specifically dominated by catastrophic salt pollution due to the development of different human and industrial activities, especially between the late 1950's and late 1970's. The water salinity of the marsh varied from oligosaline (500 to 5,000) mg/L to hypersaline (above 40,000 mg/L) during that period. Salinity is a crucial environmental problem in the Mentor Marsh leading to profound consequences in wetland plants and aquatic habitats; including the rapid development of *Phragmites australis* in the downstream marshland. These *Phragmites australis* were very vulnerable to capture fire. While several studies were conducted in the past in the Mentor marsh, hydrologic investigation of the watershed has not been conducted yet, due to the lack of monitoring stations and long-term data records. Since the Mentor marsh watershed is a small ungaged watershed, and data is only being collected for a short duration, the prediction of flow with limited data invites certain degree of uncertainty. Therefore, monitoring stations were established in two small tributaries of Blackbrook Creek and Marsh Creek, for real time data recording of flow stage, water conductivity, water temperature, and atmospheric pressure in hourly mode using Levelogger and Barologger data logging devices. Similarly, the creek cross-section, water velocity and water stage were recorded intermittently with direct field observation to develop a rating curve and generate the continuous streamflow data.

The hydrologic model, Soil and Water Assessment Tool (SWAT), was developed using climate data from National Climatic Data Center (NCDC) and Digital Elevation Model (DEM), land cover and soil data from the United States Department of Agriculture (USDA). The model was calibrated on the monthly scale with a Nash Sutcliffe Efficiency (NSE) of 0.86, the Root Mean Square Error (R^2) of 0.87, and Percentage bias (PBIAS) of -2.9% using the observed data from Blackbrook monitoring station from the period of November 2016 to August 2017. Similarly, it was validated with NSE (0.78), R^2 (0.87) and PBIAS (-13%), respectively, using the observed data records from the period of September 2017 to March 2018. The total monthly salinity loading from Blackbrook Creek was in the range of 10.23 ton to 163.98 ton, whereas it was in the range of 65.63 ton to 2028.13 ton in Marsh Creek. The median monthly salinity loading in Blackbrook Creek and Marsh Creek were 55 ton and 329 ton, respectively. The analysis showed that the Marsh creek had higher salinity loading than that of Blackbrook creek during direct field observation. This was mainly because of the relatively large size of Marsh Creek catchment compared to Blackbrook Creek. However, the salinity concentration was higher in Blackbrook Creek compared to the Marsh Creek except in the month of winter and early spring seasons. The salinity loading was linearly correlated with streamflow in daily ($R^2 = 0.72$) and monthly scale ($R^2= 0.83$) in Blackbrook Creek. Similarly, the daily and monthly R^2 of streamflow with salinity in Marsh Creek was 0.86 and 0.76, respectively. Furthermore, the correlation of salinity loadings with simulated streamflow from the SWAT model was utilized to generate the salinity loadings in streamflow events of various years at historical period. The monthly simulated salinity loading in Blackbrook and Marsh Creek in the historical period (2000-2016) illustrated that Marsh Creek contributed more than 10 times higher salinity loading than that of Blackbrook Creek. Similarly, the results showed that Blackbrook and Marsh Creek had higher median salinity loading in spring season. The salinity loading simultaneously decreased in summer and fall in both creeks and vice versa in winter season, most likely due to road salt application. The result also showed that wet years such as 2008 and 2011, experienced higher salinity loading in both creeks. Likewise, the analysis showed that annual median salinity loading in a historical period of 2000 to 2016 from Blackbrook and Marsh Creek were 620 ton and 8334 ton salt load respectively, which contributed to downstream marsh.

ACKNOWLEDGMENTS

First, I would like to express my sincere gratitude to Dr. Suresh Sharma, my advisor, for his continuous guidance and encouragement during the development of this thesis work. I am indebted to Dr. Tony Vercellino and Dr. Peter Kimosop for their willingness to serve on my thesis committee and provide valuable suggestions and feedbacks. I am also thankful to the Department Chair, Dr. Anwarul Islam for his valuable guidance and support.

I would like to acknowledge Youngstown State University for providing wonderful learning experiences and research environment throughout the study period. I would like to acknowledge to Ohio Sea Grant, Lake Erie Protection Fund, University Research Council at YSU, City of Mentor and Lake County Soil and Water Conservation District (LCSWCD) for providing the funding support for this research work. Sincere appreciation is extended to Mr. Chad Edgar from LCSWCD for providing necessary data, information and continuous help for data collection throughout the study. Also, I am much obliged to Mr. Abe Bruckman, City of Mentor and Ms. Maurine Orndorff, LCSWCD and Mr. Gregory Orr, Ohio EPA for their valuable inputs.

I am very much thankful to Linda Adovasio for her support and assistance at YSU. I am immensely grateful to all my friends, who helped and encouraged me at various stages during the research works and thesis writing.

Last but not the least, I am highly obliged especially to my family for their unwavering love, support and encouragement throughout my education and life. Also, I would like thank to my Uncle Toya Nath Dhungel and Aunt Puja Dhungel for their continuous financial support and encouragement to complete this research.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ARS	Agricultural Research Service
DEM	Digital Elevation Model
GIS	Geographic Information System
HRU	Hydrologic response units
LCSWCD	Lake County Soil and Water Conservation District
NCDC	National Climatic Data Center
NLCD	National Land Cover Dataset
NOAA	National Oceanic and Atmospheric Administration
NPDES	National Pollutant Discharge Elimination System
NSE	Nash-Sutcliffe's Efficiency
ODOT	Ohio Department of Transportation
OEPA	Ohio Environmental Protection Agency
PBIAS	Percentage Bias
PSU	Practical Salinity Unit
RMSE	Root Mean Square Error
RSR	RMSE Standard Deviation Ratio

SSURGO	Soil Survey Geographic
STATSGO	State Soil Geographic
SWAT	Soil and Water Assessment Tool
TEOS	Thermodynamic Equation of Sea Water
USACE	United States Army Corps of Engineers
USDA	United States Department of Agriculture
USGS	United States Geological Survey

Chapter 1. Introduction

A wetland is a type of land that is inundated by surface or ground water for longer durations of time, either seasonally or permanently. It develops a unique characteristic of a biologically diverse ecosystem, which becomes problematic for all plants and animals except for those which are adapted for such conditions. Different scientists classify wetlands according to their hydrologic characteristics, relative contribution of a water source, the water quality and flooding regime, the landform, etc. Bog, fen, marsh, swamp, and shallow water are five commonly recognized wetland types presented by the Canadian system (Allakhverdiev et al., 2000). Typically, marsh land is classified into three categories: a Freshwater marsh, Intermediate marsh and Brackish marsh (Lu and Kwoun, 2008). Marsh falls under the wetland that is mostly dominated by herbaceous rather than woody plant species with standing water for most part of the year. Mostly, Marsh is covered by the growth of grasses*, phragmites* and *typha*. In most of the wetland communities, salinity is a priority environmental concern (Twilley et al., 2001). High levels of salt stress are the major environmental factor restraining plant growth and productivity (Allakhverdiev et al., 2000). Intrusion of salt water in the marsh can heavily damage or destroy delicate plant populations (Pezeshki et al.,1990; Krauss et al., 2000). However, some salt tolerant plant species undergo changes in their growth, development and productivity and complete their life cycle in the area despite the existing high concentration of soluble salt. Therefore, it is very critical to identify the critical sources or hot spots of salinity in the marsh (Seliskar et al., 2000).

Past studies have suggested that recovery of marshes damaged by human actions like improper waste disposal, accidental spills of petroleum products and other toxic chemicals are slow under natural conditions (Broome et al., 1988). However, currently, Marsh restoration technology has been applied at many countries all around the world to protect natural marshes, which were damaged and destroyed by human activities (Zedler and Kercher, 2005).

The Mentor Marsh, located adjacent to Lake Erie in the Northern part of Ohio, once was an exceptional Natural Landmark (Bernstein, 1977) . It was deemed as a first National Natural Landmark in 1966 and became a first state nature preserve on the Great Lakes shoreline in 1971 (Matson et al., 2017). In the last few decades, the Mentor Marsh has experienced catastrophic salt pollution as a result of different human and industrial activities, specifically from 1959 to the late 1970's. In this period, it was reported that water salinity varied from oligosaline (500 to 5,000) mg/l to hypersaline (above 40,000 mg/l) (Fineran, 2003). This led to disastrous loss of natural vegetation leading to the growth of *Phragmites australis* (commonly called reed, giant reed and giant reed grass), which can withstand the highly concentrated saline water condition. The earlier study conducted by researchers (Rand 1968; Hauser 1972 Jones, 1975; Lass, 1984, Fineran, 2003) in Mentor Marsh showed that the rapid growth and development of phragmites were due to the salt pollution by different anthropogenic activities within the vicinity of marsh land. The major pollution sources, which triggered the fresh water marsh into a salt stressed marsh, are likely wind-blown salt, old brine well fields at the upstream of Blackbrook Creek, downstream salt fill over Blackbrook Creek and road salt application (used as a deicing agent during winter season).

For the first time in 1959, Headland Beach State Park rangers observed the wind-blown salt coating over the forest trees of the marsh and noticed that those plants were started dying (Fineran, 2003; Whipple, 199). Later, it was investigated and resulted that the Fairport Harbor salt mine associated with Mortan salt company was the source for wind-blown salt (Fineran, 2003).

The second source of salt pollution was from Diamond Shamrock's Alkali facility. At the beginning of 1955, the company built their brine well fields outside the Mentor Marsh watershed adjacent to Grand River but later around 1955, they started constructing brine wells inside the Mentor Marsh watershed. During the mining process, they encountered with weak brine with almost zero industrial value, and the brine was dumped near by the facility. As a result, the waste brine entered Blackbrook Creek and flowed into the Marsh (Fineran, 2003). This facility announced the shutdown of their brine mining near the Blackbrook Creek in 1977 (Bernstein, 1977).

The third source of salinity intrusion in marsh was from salt dumping site over Blackbrook Creek. In between the first half of the 1960's, this salt dumping site was built on a local owner's land to deposit the low-grade salt ore generated by the Fairport Harbor salt mine (Ohio EPA, 1980). A culvert was laid under the salt fill to collect and route the flow to dispose the water in to the Mentor Marsh as well. The leachate coming from the salt fill was collected in the same culvert and routed through the Blackbrook flow to the Mentor Marsh. After 22 years of continued public concerns and appeals, Blackbrook was rerouted from the salt fill in 1988 (Fineran, 2003).

However, the study conducted by Rand (1969) and Jones (1975) suggested that the intrusion of salinity in Blackbrook Creek was primarily from two sources. One of which was from the location, where brine well fields were drilled, whereas the second source of salt was from a previous salt dumping site. In each study, the salt fill site was examined as the primary source of salinity in marsh. As per Rand (1969), the maximum chloride levels of 97×10^{3} mg/L was captured at salt fill site during the study. Similarly, Jones (1975) reported that the chloride concentration varied significantly when the Blackbrook Creek flowed through the culvert. This was because the culvert cap was broken and allowing salt contaminated seepage water to be discharged into the Blackbrook Creek. At the time when water passes through this soil layers, the salt concentration increased significantly up to twenty times (Rand, 1969). Therefore, it was assumed that the major source of salinity in Mentor Marsh was only due to salt fill dumped over Blackbrook Creek. Currently, a housing development is built over the salt fill area.

Whipple (1999) conducted a study after Blackbrook was rerouted in 1988 and found a reduction in water salinity. However, the leaching from the brine well still persists and contributes to the stream salinity via storm water and ground water movement through salt fill.

While salinity investigations with continuous dataset were difficult to conduct in ungaged watersheds, several scientists have studied the salinity relationship with flow using various modeling approaches across the world. Some researches in the past have been conducted to comprehend salinity modelling by using various empirical models (Wang et al., 1992; DeSilet et al., 1992), statistical models (Gibson and Najjar, 2000; Prairie et al., 2005), hydrologic models (Gibbs et al., 2011; Michot et al., 2015; Mittelstet et al., 2015) and hydrodynamic models (Mohd et al., 2015; Meselhe and Noshi, 2001). These models are composed of many variables that are difficult to analyze and execute (Gibson and Najjar, 2000). Moreover, developing a model to predict salinity in an ungaged catchment is a challenging job due to the lack of information about water quality and quantity. Since the hydrological model does not simulate salinity, the development of a regression equation between streamflow and salinity could be a better option to predict salinity loading with respect to model predicted flow. Dawes et al. (2004) conducted a study in the unregulated catchment and concluded that the salt load from the small upland catchment was linearly related to the streamflow rate. Similarly, Mittelset et al. (2015) conducted a study in the North Fork river basin of the United States using a SWAT model and developed a regression equation between streamflow and electrical conductivity to predict salinity level. Similarly, Somura et al. (2009) used SWAT model and regression equation to study the salinity in Lake Sinji, Japan. Likewise, Gassman and Yingkuan (2015) also supported the fact that salinity modelling could be done by using simulated flow values from a SWAT model.

Several studies which were conducted across the world (Gikas et al., 2009; Piman et al., 2013) also used model simulated flow from SWAT with other salinity modelling tools, and a regression equation to predict salinity loading. These studies showed that simulated streamflow values derived from the model was successful to correlate the salinity level, and to predict salinity loading for various climates from different parts of the world (Akhbari et al., 2014). Therefore, a hydrological model (Soil and Water Assessment Tool) SWAT has been utilized in this study to predict the salinity variation with respect to the streamflow in both current, and historical time.

Scope and Objectives

The marsh water and surrounding area have relatively high salt content, which is not a natural condition of the Mentor Marsh (Rand, 1969). As a result, Phragmites austrails has developed in the Mentor Marsh and has become a dominant species in the last few decades due to its resilience saline water conditions. The maximum level of salt tolerance by these species was reported in the range from 12 ppt to 40 ppt (Finlayson et al., 1983). These dry Phragmites led several fires and burnt several parts of the Mentor Marsh since 1979 (Fineran, 2003; Edgar, 2017).

To restore the Marsh into to its original form, the restoration of native plant species and native wildlife is very important. More importantly, the risk for marsh fires needs to be monitored to protect the native plants and wildlife species. For this, *Phragmites* should be controlled and the salinity should be within the permissible limit in marsh water. Therefore, two major monitoring sites were established inside the watershed to record electrical conductivity, water level, and water temperature. Most of the earlier studies conducted in this watershed were focused only on hydrological and topographic characteristics including water quality and vegetative dynamics. On top of this, no research has been conducted so far in the Mentor Marsh to correlate the salinity level with daily and monthly flow datasets. Past research studies across the world suggested that a simulated streamflow derived from the model was successful to correlate the salinity level to predict salinity for various climates from different parts of the world. Therefore, a hydrologic modelling approach was incorporated in this study to correlate the salinity level with respect to streamflow in current and historical time for all seasonal and climatic conditions.

The specific objectives of this research project are:

1. To develop a hydrologic model to predict salinity loadings from the upland watersheds in various temporal scales such as hourly, daily, monthly, seasonal and annual.
2. To determine the salinity loading from the two tributaries of the Marsh in various temporal scales in the historical period with the help of simulated streamflow from the SWAT model.

The following methodology was used to accomplish objective 1.

I. Download digital elevation model (DEM) to delineate the study area;

II. Delineate the watershed including land catchments, flow direction and accumulation, the stream network, subbasin parameters, outlets in monitoring station, and the outlet of whole watershed;

III. Download the necessary land use data, soil data and meteorological data and prepare the input data for SWAT simulation;

IV. Run the SWAT model for simulated stream flow;

V. Measure the stream cross-section, velocity and stage for observed flow;

VI. Prepare a stage discharge curve to interpolate daily and monthly flow calculation;

VII. Compare the observed and simulated flow and re-run the model if necessary for the model calibration and validation;

VIII. Install the Levelogger in Blackbrook creek and Marsh creek to record the real-time data of water level, stream temperature, and conductivity;

IX. Install the Barologger in Blackbrook creek to monitor the atmospheric pressure and temperature for the barometric correction on water level measured by Levelogger;

X. Download the data from the Levelogger and Barolloger to prepare daily and monthly discharge records and salinity values;

XI. Compare and analyze the hourly, daily and monthly salinity in both streams;

XII. Develop a correlation equation between the observed discharge and salinity loading in both streams.

The following methodology was followed to accomplish specific objective 2.

I. Download the historical rainfall and temperature data from nearest weather station;

II. Re- run the calibrated and validated SWAT model in a historical time;

III. Compare and analyze the daily, monthly, seasonal and annual salinity loading in both streams for the historical time period.

Thesis Structure

This thesis is categorized into three different chapters. Chapter 1 describes the background of the study area, the scope and objectives of the research, the brief methodology for each specific objective, and the thesis structure.

Chapter 2 describes the material and methods involved in determining the spatial and temporal variability of flow using hydrologic modelling in the ungaged Mentor Marsh watershed. A physically based dynamic watershed SWAT model (Arnold et al., 1998) was used in this small ungagged catchment for salinity prediction. It included a field survey, instrument setup, and cross-section and velocity measurement during each field visit for observed flow estimation as a field work. All these works and scenarios are described briefly in chapter 2.

Chapter 3 discusses the process of watershed delineation, preparation of input data, calibration and validation of simulated flow as a modelling work. Similarly, the calculation of salinity loading using observed data in Blackbrook creek and Marsh creek using Levelogger and Barologger device is explained in detail. This chapter also uses the SWAT model to simulate historical stream flows and to generate the salinity loading in historical time using salinity and the observed discharge correlation equation. The third chapter is organized in a journal paper format; therefore, readers may find some repetition in the content.

Chapter 2. Materials and Experimental Methods Used for Discharge and Salinity Prediction

The monitoring sites were established in Blackbrook and Marsh Creek by installing the Levelogger and Barologger instruments in order to record the real time data of stage, stream temperature, atmospheric pressure and conductivity. Additionally the stream cross sections and flow velocity were recorded intermittently to develop a rating curve of observed flow vs stage datasets. These observed data values were utilized to calibrate and validate the SWAT model. In the next step, the simulated flow from the SWAT model was utilized to develop a correlation equation between streamflow and salinity loading, and to predict the salinity loadings in current and historical time.

Study Area

The Mentor Marsh watershed (Figure 2.1) is located at southern margin of Lake Erie in Lake County, Ohio. The watershed covers an area of approximately 20.32 square miles. It is the largest marsh in northeast Ohio, and covers 1.08 square miles (Whipple, 1999). The marsh is 4.28 miles long, and 0.5 mile wide at its widest point, and has an approximate perimeter of 12.42 miles (Matson et al., 2015). The watershed lies between latitudes 41^0 39' 18" N to 41^0 45' 3.6" N and longitudes 81^0 22' 26.4" W to 81^0 14' 52.8" W. Similarly, the elevation of the watershed ranges from 172ft to 411ft above mean sea level.

The climate of the watershed is humid continental with an annual average precipitation of 39 inches, whereas the average snowfall is 36 inches. The average annual high and low temperature are 58.90 ^{o} F and 43.60 ^{o}F, respectively. The marsh can be physically characterized into three basins such as east, west and middle. The hydrological flow within and between these basins involves inputs from Lake Erie and two sub-watersheds Blackbrook and Marsh creek with tributaries that enters the marsh. However, this study will be constrained to the upland sub-watersheds of the Mentor Marsh watershed. This watershed is further divided into two sub watersheds: Blackbrook and Marsh Creek. Blackbrook is the smallest watershed amongst the two, which drains 2128.11 acres, whereas Marsh Creek the larger watershed, which drains 8859.26 acres. In addition, Marsh Creek has two large tributaries, Heisley Creek and Martin Ohm Creek, which drains 1766.9 acres and 1459.2 acres, respectively (Edgar, 2017).

The Mentor Marsh watershed along the Lake Erie coastline is an under-appreciated and underutilized tourist area. From the late 1950s, this fresh water marsh has been severely impacted, due to salt intrusion from upstream brine well fields and downstream salt fill over Blackbrook Creek. As a result, these negative impacts began affecting the forest and plant community in most parts of the Lake Erie region (Fineran, 2003). The vegetative dynamics of the Mentor Marsh was changed from an ash-elm-maple swamp forest to a current wetland dominated by *Phragmities austrailis (Cav.) Trin. Ex Steudel* (Poznik, 2003) resulting into the largest *Phragmities* marsh in Ohio.

Moreover, the impacts of elevated salinity levels in the marsh watershed led to the loss of the economic growth in the region due to substantial alteration or elimination of the habitat (Xie, 2012). The introduction of elevated levels of salinity has created a condition that has caused native plant species to be crowded out by other more salt tolerant plant species. Due to the extreme level of salinity in the marsh and swamp forest, the majority of trees in the marsh began to die. One consequence of this die off was the condition that led to the rapid establishment of *Phragmites*, resulting in an increased potential for fire.

Despite being affected by pollution and other physical challenges, the Marsh still attracts hikers, bird and nature loving people. The Marsh has significantly contributed to the local economy and will have a tremendous potential for future economic development via eco-tourism related activities if it can be restored. The economic return from eco-tourist activities, such as bird watching, has already been documented to have some impact to the local economy of this region (Xie, 2012).

Ungaged Watershed

A watershed is a hydrologic unit which produces discharge as an end product from a certain boundary. Finally, discharge is produced by the interaction of precipitation and the land surface through a common outlet. The aim of watershed modelling is to seek different results such as flow analysis, sediment analysis, nutrient analysis, or groundwater modelling, among many more. In some watersheds, the aim of watershed modelling may be to determine the maximum and minimum flow for water supply, or to analyze nutrient loading for the establishment of a NPDES (National Pollutant Discharge Elimination System) permit. In this study flow was simulated using a watershed model to predict salinity loading from an area upstream of the Mentor Marsh watershed.

In order to conduct a simulation study, observed streamflow data is crucial for appropriate model calibration and validation. However, streamflow data is not readily available from this ungaged catchment. While there are several stream gauging stations (>60,000) installed worldwide (Blöschl, 2005), most watersheds do not have observed streamflow data, since the United States and Geological Services (USGS) doesn’t typically install gauging stations in small tributaries. Since the Mentor Marsh watershed is an example of ungaged watershed, a development of a rating curve was necessary to obtain continuous stream flow data.

Field Study

A preliminary survey was conducted in October 2016 by a joint field survey team from Youngstown State University, the City of Mentor, and the Lake County Soil and Water Conservation District to identify the appropriate location for the installation of the equipment. The most suitable locations for both tributaries, Blackbrook Creek and Marsh Creek, were identified. The water sampling site for Blackbrook Creek was finalized on the upstream side of the culvert on Blackbrook road near a pump station. Similarly, the water sampling site in Marsh Creek was identified on the downstream side of Marsh Creek Bridge on Lake Shore Boulevard.

Hydrologic Model Used

SWAT is one of the most advanced watershed models with a capacity to represent the complex watershed characteristics in terms of land use, soil, slope and digital elevation model. More importantly, the SWAT model has been widely used for various ranges of watershed conditions, especially in watersheds with limited data; therefore, SWAT model has been selected for this study.

Instrument Used

Levelogger

The LTC Levelogger Junior was used in this study (Figure 2.2-a). It provides an inexpensive, helpful and convenient method which includes all sensors in one device to measure conductivity, depth, and temperature of water. The device normally operates in the temperature range between - 20°C to 80°C and an altitude range between -980 to 16400 ft. (-300 to 5,000 m). It is capable of storing a maximum of 16000 readings (Solinist, 2016).

Piezoresistive Silicon with a Hastelloy sensor were used in this device to measure water depth up to 30,100 ft. The level sensor of this probe works with an accuracy of ±0.1% Full Scale (FS). Similarly, a Platinum Resistance Temperature Detector (RTD) was used to sense the water temperature. The temperature resolution and accuracy of this sensor are 0.1 °C and ± 0.1 °C respectively. Likewise, a 4-Electrode Platinum conductivity sensor was used inbuilt to measure conductivity from 0 to 80,000 μS/cm. The accuracy of this sensor is ±2% reading or 20μS/cm and works on the resolution of 1μS.

Barologger

The Barologger model 3001 (Figure 2.2-b) was used in this study to monitor the fluctuations that occur in barometric pressure. It was used to barometrically compensate the Levelogger readings of water depth. It can compensate any Leveloggers in 20 mile (30 km) radius with the change in elevation of 1000 ft. (300 m) (Solinist, 2016). The size of this device is 22mm × 154mm and weighs 179 gm. The device normally operates in the temperature range of -20°C to 80°C.

Two sensors were used in this probe to measure air temperature and atmospheric level. Piezoresistive Silicon in 316L Stainless Steel was used to measure the barometric level. The level sensor of this probe works on the accuracy of ±0.05% Full Scale (FS). Similarly, a Platinum Resistance Temperature Detector (RTD) was used to sense the water temperature. The temperature resolution and accuracy of this sensor were 0.003°C and ±

0.05°C respectively. It is capable to storing a maximum 40,000 of pressure and temperature readings.

Flow Probe

To develop the rating curve, the velocity of the stream is required to be measured. For this, a hand-held flow probe (FP111-S Global Water Flow Probe) (Figure 2.2-c), a velocity measurement device, was used for measuring water velocity in both Blackbrook and Marsh Creek. The Global water flow probe measured the instantaneous velocity to the nearest 0.33 ft/s (Global Water, 2016). The actual range of velocity measurement for this device was (0.33-20 ft/s).

Similarly, a self levelling laser, level rod, engineering tape, chaining pins, metal pipe, cable lock, and metal rods were used for assisting instrument setup, and discharge measurement.

Levelogger Calibration

The LTC Levelogger Junior conductivity calibration was performed by using a liquid solution, with a known conductivity value of 1,413 µS/cm, and the calibration data wizard in the Levelogger software. The data wizard was helpful to convert conductivity readings to salinity and are expressed in Practical Salinity Units (PSU). The sensor was calibrated at room temperature (68 degrees Fahrenheit or 25 degrees centigrade) for the reliability of the measured conductivity before installation. In general, the calibration of the LTC Levelogger instrument was performed before the instrument setup and at least twice a year at the beginning of the seasons for better performance (Figure 2.3).

Instrument Setup

The monitoring sites were established at the Black Brook Creek (at 41º 43' 22.85''N, 81 º 17' 28.1'' W) and Marsh Creek (at 41º43'12.33'' N, 81º20''19.9''W) within the watershed (Figure 2.4). Automated LTC Levelogger junior and Barologger devices were installed at the water-monitoring location in October 2016. The first set of instruments (Levelogger and Barologger) were established at the first water sampling site on the upstream side of the culvert on Blackbrook road near pump station (Figure 2.5). Similarly, the second Levelogger instrument was established at the second water sampling site on the downstream side of Marsh Creek Bridge on Lake Shore Boulevard (Figure 2.6). These stations were selected in such a way that the site was accessible for data download, and the stream cross-section was almost straight for measurement of river cross-sections.

Measurement of Cross-Section, Stage and Velocity

The Levelogger device continuously measured the water stage throughout the year of every hour interval at both Blackbrook and Marsh Creek gauging stations. The site for cross section measurement for Blackbrook (Figure 2.7) and Marsh Creek (Figure 2.8) were established at the instrument locations. Flow velocity and water stage were measured using a hand-held flow probe and level rod, respectively, in both Creek. The Creek cross-section were measured with the help of levelling laser and level staff in both creeks. The cross-section, stage, and velocity were measured at least twice a month by field measurement. The flow depth and velocity recorded in the field observation were converted into streamflow for the development of the rating curve.

Development of Rating Curve

USGS develops its rating curve at every gauging station to convert the water stage (ft) into volume of water (ft^3/s). It is developed by measuring frequent discharge measurements at monitoring stations. USGS regularly measures the stage and discharge measurements to ensure various ranges of stage and discharge are measured correctly in order to represent high and low flows well in the rating curve.

The rating curve was developed at Blackbrook Creek water monitoring station at the same place on the upstream side of culvert located on Blackbrook road (Figure 2.9). The stage discharge (rating) curve was developed with 40 observed discharges, and its corresponding stage datasets. In fact, USGS calculates flow at gauging stations throughout the United States using the same approach of stage discharge relationship. The flow depth recorded in the stream were converted into streamflow values after developing the stage discharge (rating) curve. The developed rating curve was utilized to predict the water flow in the Blackbrook Creek.

Working Principle of Levelogger and Barologger

The submerged Levelogger always gives the readings combining both the data for barometric pressure and water pressure above their sensor. These Leveloggers are non-vented loggers that require the use of a barometric pressure logger, and the Leveloggers data must be barometrically compensated to obtain true water level (Figure 2.10). In order to evaluate the actual water pressure, the Barologger was installed separately nearby Black Brook Creek. The actual water pressure was calculated by subtracting the data obtained from the Levellogger to the data obtained from Barolloger. The Levelogger Software Data

Wizard automatically calculate the true water level after providing Barologger and Levelogger .xle file. However, manual calculation can also be done with the help of equation 2.

$$A = L - B \tag{2}$$

Where,

A= Actual water column height

L= Total pressure reading from Levelogger

B= Barometric pressure measured by Barologger

D = Depth to water level, below reference datum

Conversion of Conductivity into Salinity

The salinity of water is expressed as the total of all non-carbonate salts dissolved in water. It is usually expressed in parts per thousand (1 ppt = 1000 mg/L). The Solinst levelogger windows software uses the equation given in the UNESCO Technical Paper (Fofonoff and Millard Jr., 1983) to convert Conductivity (μS/cm) readings to Salinity (psu). However, according to modern oceanography, the conversion equation of Salinity (ppt) to Salinity (psu) is explained by the following equation 3 (Millero, 2010).

$$S\ (ppt) = S\ (psu) * 1.004715 \tag{3}$$

Parts-per thousand are the pseudo-units for absolute (reference) salinity, defined by (Thermodynamic Equation of Sea Water) TEOS-10 and expressed in g/kg, i.e. ppt. In this study Blackbrook and Marsh Creek salinity both are classified as either fresh (< 0.5 ppt), oligosaline (0.5 to 5 ppt) (a subcategory of mixosaline), eusaline (30 to 40 ppt) and hypersaline (> 40 ppt) on the basics of salinity present in the water (Cowardin et al., 1979; Fineran, 2003).

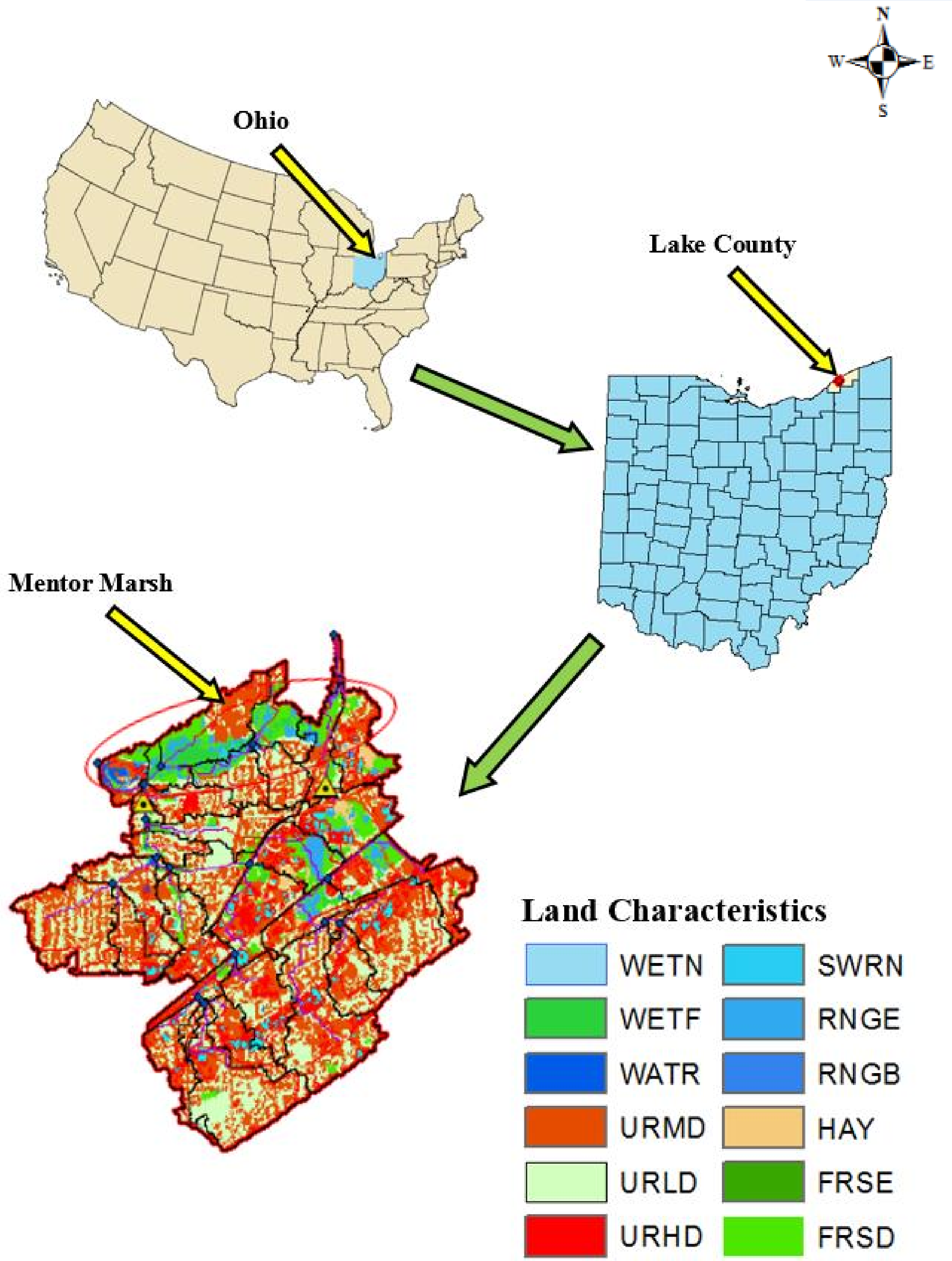


Figure 2-1: Study area of the Mentor Marsh watershed consisting sub-basins and water monitoring stations

(a) (b) (c)

Figure 2-2: Levelogger (a), Barologger (b) and Flow Probe (c)

Figure 2-3: Calibration of Levelogger before instrument installation

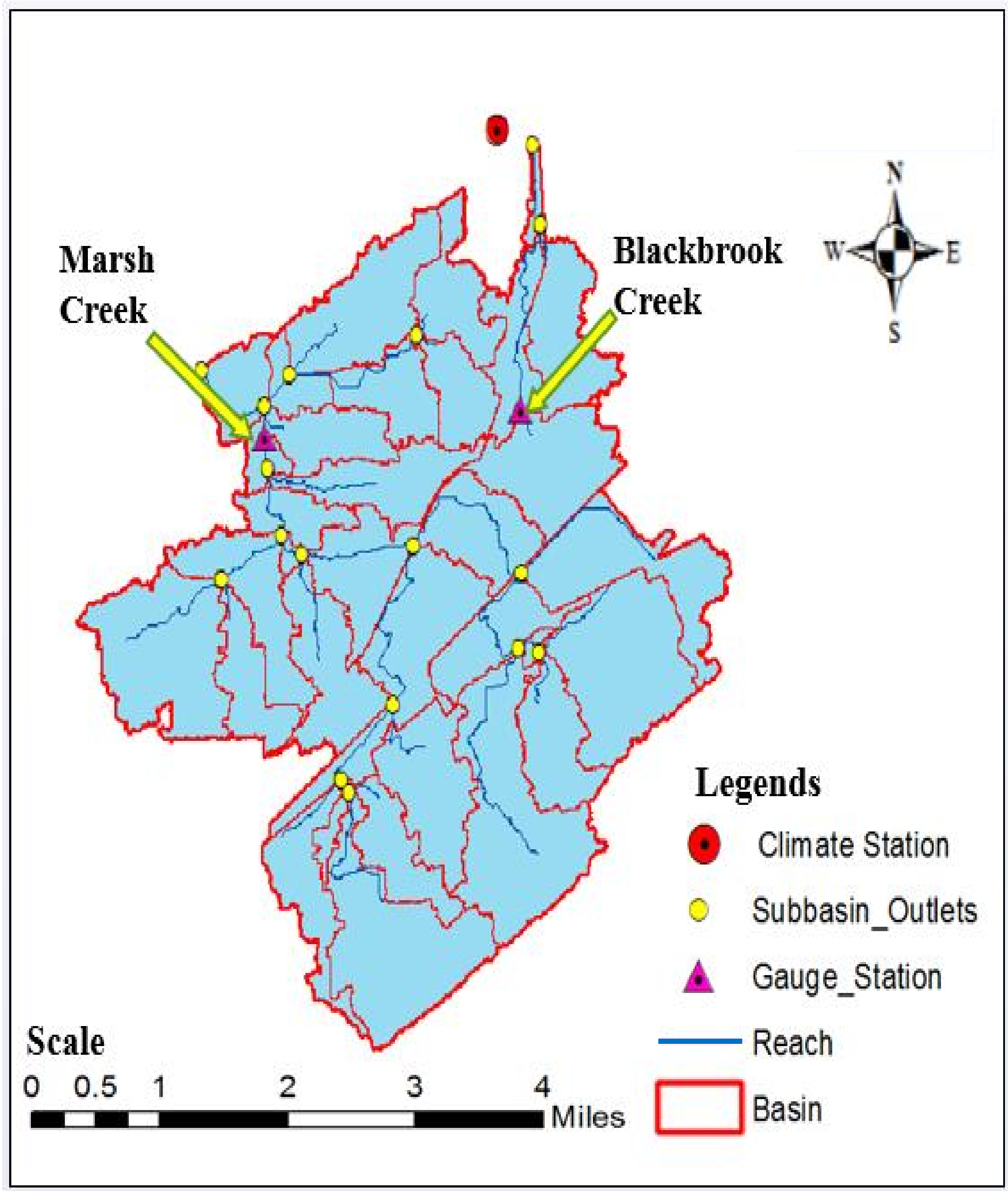


Figure 2-4: Location of gauging station at Blackbrook Creek and Marsh Creek

Figure 2-5: Levelogger instrument setup on the upstream side of culvert and Barologger at pump station (top left corner) on Blackbrook road

Figure 2-6: Levelogger instrument setup on the downstream side of Marsh Creek Bridge on Lake Shore Boulevard

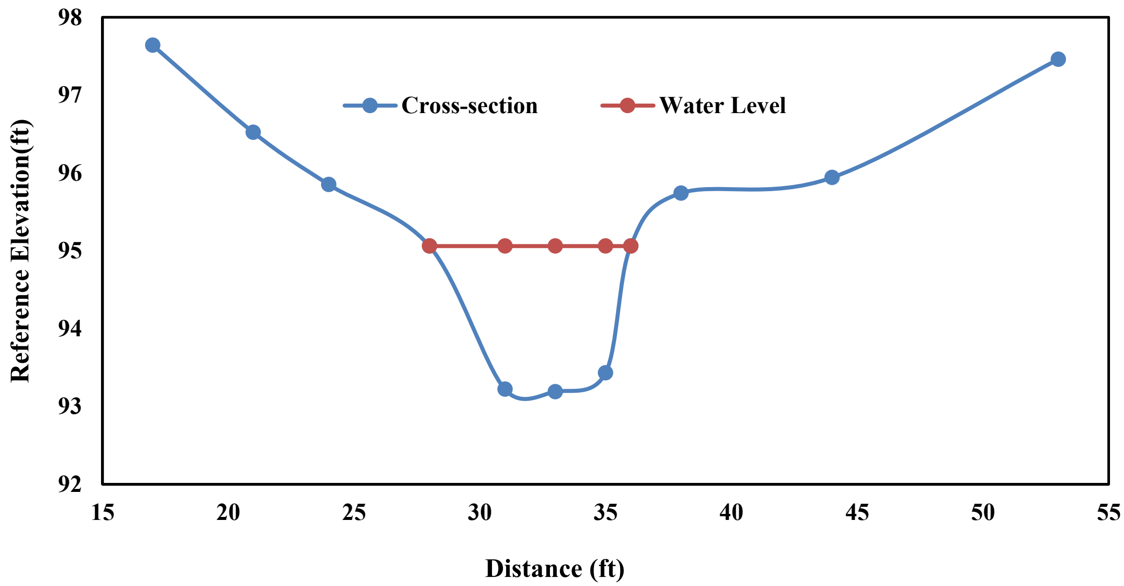


Figure 2-7: Blackbrook Creek cross-section at flow monitoring site

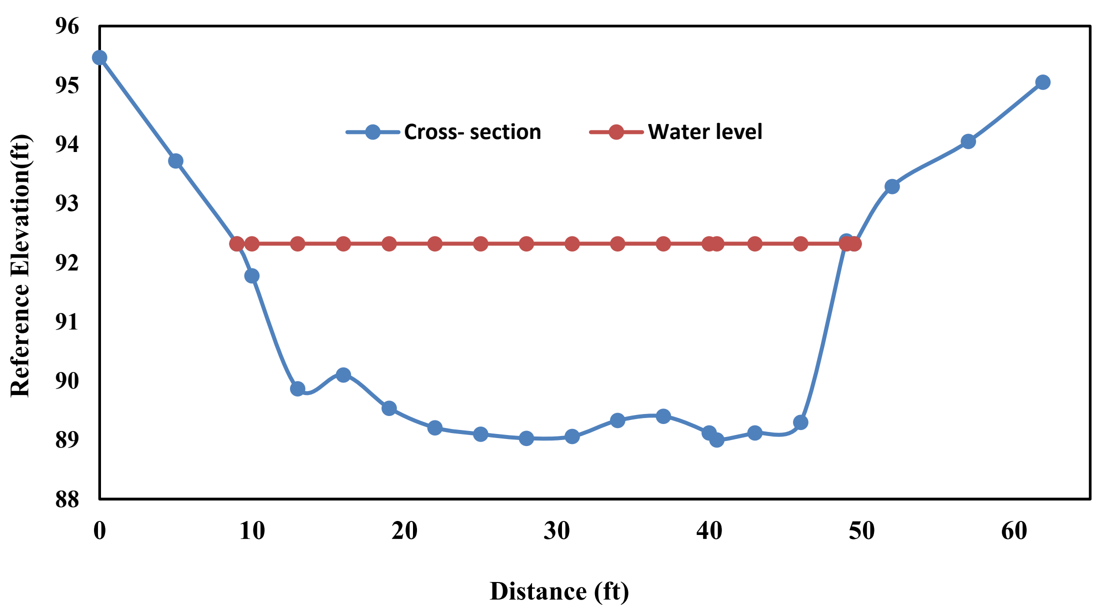


Figure 2-8: Marsh Creek cross-section at flow monitoring site

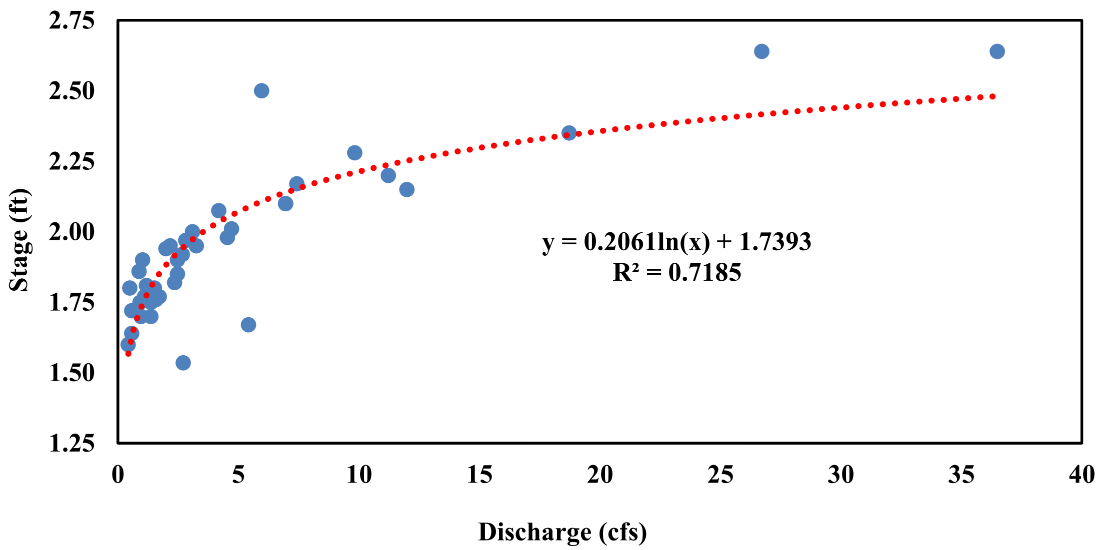


Figure 2-9: Development of Stage Discharge (rating) curve at Blackbrook Creek monitoring site

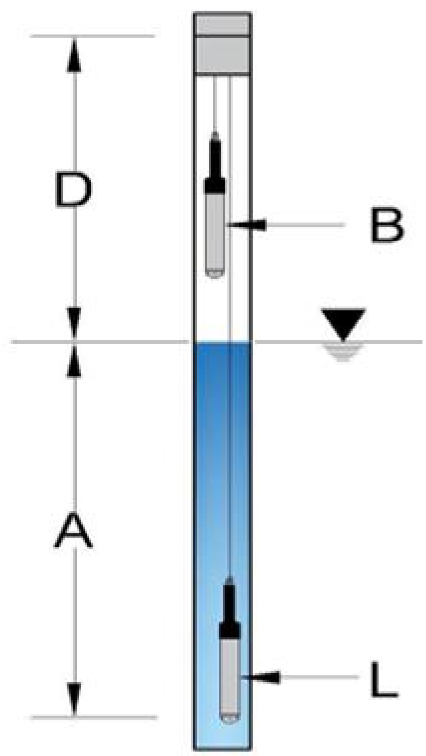


Figure 2-10: Working principle of Levelogger and Barologger

Chapter 3. Hydrologic Modelling Using SWAT in Small Ungaged Catchment for Salinity Prediction

Abstract

In this study, the flow stage and electrical conductivity data were recorded using a Levelogger and Barologger to investigate the critical sources of salinity. Similarly, stream cross-sections and velocity of the streamflow were recorded intermittently in the ungaged Blackbrook Creek to develop a rating curve and generate continuous streamflow data. The watershed model, Soil and Water Assessment Tool (SWAT), was calibrated and validated to a monthly scale with good model performance. The analysis suggested that the total monthly observed salinity loading from Blackbrook and Marsh creek was in the range of (10.23 ton to 163.98 ton) and (65.63 ton to 2028.13 ton), respectively. While salinity concentration was higher in Blackbrook, the salinity loading contribution was 10 times higher from Marsh Creek. Daily and monthly Salinity loadings were linearly correlated with streamflow, which was utilized to generate the salinity loadings in streamflow events of various years of the historical period. The result shows that wet years in the historical period experienced higher salinity loading in both Creeks. The total annual median salinity loading shows that Blackbrook Creek and Marsh Creek transport nearly 9,000 ton salt load towards the marsh.

Keywords: Creek, Phragmites, Salinity, Marsh, SWAT, Levelogger, Barolloger, Mentor Marsh Watershed

Introduction

The collection and deposition of soluble salts from different point and nonpoint sources are the major factors for wetlands pollution (Herbert et al., 2015; Fujioka, 2001; McElroy,1976). Increase of the salinity level in wetlands is a widespread environmental problem in many parts of the world in terms of profound consequences in wetland plants and aquatic habitats (Fennessy,2013; Herbert et al.,2015; Williams, 199). Even though the wetlands are protected by environmental acts issued by the regulating agencies, the possibility of disturbance by the accidental spillage of harmful pollutants into water sources is always possible (Broome et al., 1988). The different sources of salt pollution on wetlands are from agricultural drainage (Khalil et al., 1967), construction of highway and road salt application (Novotny et al., 2008), leakage from offshore petroleum pipelines (Broome et al., 1988), port construction (Muniz et al., 2005), power generation facilities (Carlson et al., 1993), and urbanization and industrialization (National Wetlands Working Group, 1988). Moreover, many other factors including rise in groundwater table (van der Kamp and Hayashi, 2009), evaporation, acid rain (Baker, 1992), sediment type, and water logging also have an influence on wetlands (Huckle et al., 2000).

As the standing water on the marshland does not flush easily, the deposited salts remain for a longer period of time, which has a potential to detrimental impact on wetland ecosystem and landscape dynamics (Fineran, 2003; Herbert et al., 2015). These impacts play a crucial role on degradation of biodiversity, change in their natural habitat, functional integrity and destroy delicate plant populations (Lövei, 1999; Mack et al, 2000.; Fineran, 2003; Pezeshki et al,1990.; Krauss et al.,2000). Moreover, these problems replace the native plant species having low salt tolerance ability with more salt tolerant plants such as *Phragmites australis* (Cav.) *Trin ex Steud* (common reed) (Mauchamp et al., 2001).

Phragmites is a common example of a dominant and nuisance species in North American wetland plant communities in the past century (Cronk and Fuller, 1995; Chambers et al. 1998; Orson et al., 1987). Several researchers in the past have conducted studies to comprehend the invasion of *phragmites* in United States North America (Lissner and Schierup, 1997; Chambers, 1998; Meyerson, et al., 2000; Galatowitsch et al., 1999; Vasquez et al., 2006) and throughout the United States (Roman et al., 1984; Mack et al., 1994). It was found that salinity is a major factor for increasing the population of *phragmites* in both tidal and inland marshes (Meyerson et al., 2000; Chambers et al., 1998). The maximum level of salt tolerance by these species was reported in the range between 12 ppt to 40 ppt (Finlayson et al., 1983). These plants can grow about two to four meters in height, and will stand with dead culms and dry leaves in the winter (Orson et al.,1987; Poznik, 2003). These dry *Phragmites* led to several major fire incidents in the marsh (Thompson and Shay, 1985). Therefore, controlling *phragmities* has turned into a priority concern for wetland administrators (Marks et al., 1994). In this context, identifying the hot spots of salinity loading and its concentration with respect to flow using watershed modeling is essential to investigate salinity intrusion.

Many researches in the past have been conducted to comprehend salinity modelling by using various empirical models (Wang et al., 1992; DeSilet et al., 1992), statistical models (Gibson and Najjar; Prairie et al., 2005), hydrologic models (Gibbs et al., 2011; Michot et al., 2015; Mittelstet et al., 2015) and hydrodynamic models (Mohd et al., 2015; Meselhe and Noshi, 2001). Those modeling studies were typically conducted to correlate the streamflow with salinity loadings. For example, the study conducted by Dawes et al., 2004, in the unregulated catchment showed that the salt load from the small upland catchment was linearly related to the streamflow rate. The study conducted by various scientists (Mittelset et al., 2015; Somura et al., 2009; Gikas et al., 2009; Piman et al., 2013) in Japan, Greece, and Southeast Asia suggested that model predicted flow from SWAT with the combination of other salinity modelling tools or regression equation, were proven the best tool and methods to predict salinity loading. Similarly, the study conducted by Gassman and Yingkuan (2015) and Tomas et al. (2014) supported the fact that simulated flow from SWAT model was useful for salinity modelling.

The majority of these studies did not directly simulate the salinity loadings, rather, they simulated the flow and correlated the model generated flow with salinity loadings. Even though watershed model does not simulate salinity, the simulated flow from the model can be utilized to develop a regression equation between streamflow with salinity, which is potentially useful to predict salinity loading. Nevertheless, simulation of the flow in an ungaged catchment is crucial (Deckers, 2006) due to the lack of observed data. Prediction of flow in an ungaged catchment is relatively more complicated as compared to a gauged catchment leading to the higher degree of uncertainty (Sivapalan et al., 2003). While there are several stream gauging stations (> 60,000) installed worldwide, most of the catchments around the world are ungaged (WMO, 1995). The United States and Geological Services (USGS) also doesn't have gaging stations to record continuous flow data in all streams. Therefore, the development of rating curve using the stage data recorded from Levelogger and occasional recording of streamflow could be easy, viable and more economical option to record the streamflow in an ungaged catchment.

In this study, a widely used watershed model, Soil and Water Assessment Tool (SWAT), has been developed using observed streamflow through the stage rating curve established in a creek section based on the continuously measured stage in the Levelogger and occasional flow rate measurement in the site.

SWAT Model

The Soil and Water Assessment Tool (SWAT) is a semi-distributed hydrologic model jointly developed by the USDA-ARS and Agricultural Experiment Station in Temple, Texas in the early 1990s (Arnold et al., 1998). This model has a capacity to address the complexity of the watershed in terms of land use, soil and slope (Arnold et al., 2001). SWAT can simulate various components water flow, nutrient cycling, crop growth and sediment transport as physical process (Jain et al., 2010).

SWAT was originally developed to predict the long-term impact of watershed management in terms of hydrologic and water quality response of large watershed (Moriasi et al., 2007). The hydrologic modeling is conducted by using either Green or Ampt or SCS curve number method (Arnold et al., 1988). The Green and Ampt equation is used for hourly flow estimation whereas an empirical SCS curve number (CN) method is used for daily flow computation.

SWAT modeling work consists of two different modelling phases called the land phase of the hydrological cycle, and water routing of runoff through the reaches. The land phase of hydrological simulation of SWAT is represented by following water balance equation (Neitsch et al., 2011).

$$SW_t = SW_0 + \sum_{i=1}^{n}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_w) \quad (1)$$

Where, SW_t and SW_o are the initial and final water content expressed in millimeters of water column at 4^o C pressure unit (mm H_2O) at n time (days). R_{day}, Q_{surf} and Q_{gw} are the amount of rainfall, surface runoff, and return flow respectively on day i expressed in millimeters of water column at 4^oC pressure unit (mm H_2O). Similarly, E_a and w_{seep} are the amount of evapotranspiration and water entering the vadose zone from the soil profile on day i expressed in millimeters of water column at 4^o C pressure unit (mm H_2O).

A watershed is delineated into sub-watersheds including land catchments, flow directions and stream network inland phase modeling. These sub-watersheds are further divided into hydrologic response units (HRUs), which are further subdivided into homogeneous land use, soil type, and slopes also called management characteristics. Finally, loadings from each sub-basin are connected together with stream networks and routed towards the outlets through different channels and reservoirs in their routing phase (Arnold et al., 2001) .

Material and Methods

The detail methodology is explained in chapter 2 in detail.

SWAT Model Inputs

SWAT was used to model the entire hydrologic process, which included the evapotranspiration, shallow infiltration, deep aquifer percolation, and lateral flow study (Olivera et al., 2006). Since it can represent the complexity of the watershed using various model inputs, digital elevation model (DEM), land use, slope length, soil type, stream network, temperature, precipitation and reservoir were utilized for SWAT modelling. ArcGIS interface was used to extract necessary information from these different available datasets to conduct further analysis.

In order to accurately represent the topography of the sites, high resolution DEM of 3m were downloaded from the USGS National Elevation Dataset (NED) in raster format, which contain topographic information such as stream networks, slope length and slope gradient. These DEM datasets were used to delineate the watershed into 35 sub-basins by using SWAT automatic watershed delineation. Similarly, the most recently available land use dataset with a spatial resolution of 30 m was used from the USDA. The distribution of land use in the watershed is presented in Table 3.1. Soil plays a crucial role while modelling different hydrological processes. Therefore, high resolution, Soil Survey Geographic (SSURGO) data sets were downloaded from USDA. Since the catchment size is relatively small, the detailed soil datasets such as SSURGO was selected, which high resolution has compared to the State Soil Geographic (STATSGO) data. Since runoff generated from the watersheds depends on the actual hydrologic conditions of soil, land cover and topographic conditions of the watershed, appropriate threshold of land use, soil and slope should be provided in the model in order to better represent the different flow predictions in the watershed. Therefore, the threshold value for land use (5%), soils (10%) and slope (15%) were subsequently used to generate 346 hydrological response units (HRUs).

The climate data including precipitation, and maximum and minimum temperature were downloaded from the National Climatic Data Center (NCDC) website for Painesville station (USC00336389). However, the remaining climatic datasets such as solar radiation, wind speed, and relative humidity were simulated using the weather generator function in the SWAT model. Daily and monthly streamflow data needed for model calibration and validation were generated from developed rating curve and installed Levelogger instrument at Blackbrook Creek.

Model Setup, Calibration, and Validation

The SWAT model was set up and run from 2012 to 2018 in monthly time steps using a 4-year warm up period (2012-2015). Since hydrologic modeling is associated with certain degree of uncertainties, the model needs to be properly calibrated and validated before conducting any analysis (Engel et. al., 2007). Therefore, the model was calibrated by using continuous observed streamflow record derived from rating curve established with in the watershed at Blackbrook Creek. The streamflow records were obtained for a 17-month period from November 2016 to Mar 2018 at Blackbrook Creek station. For the model calibration, multiple parameters were adjusted manually by an iterative process to produce the best fit result between the observed and simulated data. For this, various sets of model parameters were selected by observing watershed characteristics (Table 3.2).

The model was calibrated on a monthly time scale from November 2016 to August 2017. These model parameters were then independently validated using observed streamflow data from September2017 to March 2018 with respect to coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE) and percent of bias (PBIAS).

Model Evaluation Criteria

Though the SWAT model is a powerful tool for simulating the effect of different watershed processes, (Rafiei Emam et al., 2017), the simulated results from the model cannot be expected to match 100% with the observed data for ungaged watershed. Therefore, the performance of the model is always evaluated through the various statistical and graphical model evaluation techniques. However, there is not a single statistical measure to evaluate the performance of the model; therefore, typically multiple objective functions are used to calibrate and validate the model. Among them four major statistical indicators are used to assess model performance are R^2, NSE, RMSE and PBIAS.

The first statistical measure used to assess model performance is the coefficient of determination (R^2) which is one of the frequently used criteria and was employed to measure the degree of collinearity between observed and simulated data. The R^2 values vary from 0 to 1, and indicates the variances in the observed and simulated data sets. The higher values approaching 1 indicates less error variance and 0 indicates no linear relationship exists. In most of the modeling work, the values greater than 0.5 are typically considered good and accepted as a workable model (Santhi et al. 2001; Van Liew et al. 2003).

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_{obs}^{mean}\right)\left(Y_i^{sim} - Y_{sim}^{mean}\right)}{\left[\sum_{i=1}^{n}(Y_i^{obs} - Y_{obs}^{mean})^2 \sum_{i=1}^{n}(Y_i^{sim} - Y_{sim}^{mean})^2\right]^{0.5}} \right)^2 \quad (3)$$

The second statistical measure to assess model performance is the Nash Sutcliffe Efficiency (NSE) and is widely used to test the model performance with values ranges from -∞ to 1. The values between 0 and 1 generally indicate an accepted level of performance, whereas values less than 0 indicates the unacceptable performance. According to (Moriasi et al., 2007), the model is considered as good if its values range from 0.5 and 1. NSE with value 1 being the optimal value and accepted as the perfect model.

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n}(Y_i^{obs} - Y^{mean})^2} \right] \quad (4)$$

The third statistical measure to assess model performance is RMSE-observations standard deviation ratio (RSR). RSR is calculated as the ratio of root mean square (RMSE) and standard deviation of observed data. The lower RSR value indicates the better model simulation performance. The RSR with 0 value indicates the perfect model.

$$\mathrm{RSR} = \left[\frac{\sqrt{\sum_{i=1}^{n}(Y_i^{obs} - Y_i^{sim})^2}}{\sqrt{\sum_{i=1}^{n}(Y_i^{obs} - Y_{obs}^{mean})^2}}\right] \tag{5}$$

The fourth statistical measure to assess model performance is percent bias (PBIAS). It indicates whether the tendency of simulated data is larger or smaller than the observed data (Gupta et al., 1999). The optimal value for PBIAS is 0 which indicates the perfect model simulation whereas positive and negative value represents the model underestimation or overestimation respectively.

$$\mathrm{PBIAS} = \left[\frac{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right) \times 100}{\sum_{i=1}^{n}(Y_i^{obs})}\right] \tag{6}$$

In above equations, Y_i^{obs} and Y_i^{sim} are i$^{th`}$ values represent the observed and simulated values. Similarly, Y_{obs}^{mean} and Y_{sim}^{mean} are mean observed and simulated flows, respectively, and "n" indicates the total number of observations.

Results and Discussions

SWAT Model Performance

The model performance was evaluated with the help of different statistical indicators based on daily and monthly time scale at Blackbrook Creek station. The various model parameters selected for the calibration of the model are reported in Table 3.2. The model was performing well in both the calibration and validation period with reasonable accuracy and within the recommended ranges (NSE > 0.50, PBIAS ±25% and RSR ≤ 0.70) given by

(Moriasi et al., 2007). In this study, the performance indicators R^2, NSE, RSR, and PBIAS for monthly flows at the outlet were 0.87, 0.86, 0.37 and -2.9% respectively in the calibration phase. Similarly, for the validation phase, the value for different model indicators were 0.87, 0.78, 0.35 and -13% respectively. Furthermore, the performance of the model was evaluated using graphical plotting of observed and simulated flow. The average monthly-observed vs simulated flow during the calibration period (Nov-2016 to Aug-2017) and the validation period (Sep-2017 to Mar- 2018) at the Blackbrook outlet was graphically plotted in (Figure 3.1).

SWAT commonly underestimates the daily and monthly simulated peak flows (Bieger et al., 2014; Santhi et al., 2014). Similarly, the developed model also failed to capture few simulated low and peak flows during calibration and validation phase. This could be due to the differences between SWAT simulated discharge and the manually observed discharge obtained from rating curve. Similarly, there might be the various potential errors in input data such as weather, land use, soil, observed flow etc. (Santhi et al., 2001).

Observed Variability of Flow and Salinity Level in Marsh

This study was conducted from late 2016 to early 2018 to predict water salinity level with respect to flow. Similarly, the salinity data were also recorded and separately analyzed in hourly, daily, monthly, and seasonal scale throughout the study period. The study was primarily focused to quantify the salinity level from upper part of Mentor Marsh watershed. At the downstream of watershed, the Blackbrook creek was flowing below the salt fills through concrete culvert (Figure 3.2) before being rerouted in 1988 (Fineran, 2003).

Figure 3.3 shows the comparison between the monthly observed salinity level and streamflow discharge in both Blackbrook and Marsh Creek. The analysis shows the trend of increase in salinity (mg/L) with decrease in discharge (cfs) and vice versa. However, positive correlation was detected during the months of winter season.

The hourly, daily and monthly salinity records are essential to analyze temporal and spatial variability of salinity level within the watershed. Figure 3.4 depicts the comparison of hourly salinity level in Marsh and Blackbrook Creek. It captured some higher salinity value at the particular moment of the day. This is not surprising to experience such an abrupt variation in salinity especially in hourly scale because the leakage of brine well fields was still observed in the recent field visits. The water salinity in Blackbrook fluctuated between 234 mg/L to 3668 mg/L. However, water salinity in Marsh Creek varied between 77 mg/L to 2940 mg/L.

Similarly, Figure 3.5 shows the comparison of daily salinity level in Marsh Creek and Blackbrook Creek. The variability of water salinity in daily scale was relatively less compared to hourly scale. The daily salinity in Blackbrook ranged from 275 mg/L to 2837 mg/L. The lowest salinity was observed in the month of November, whereas the highest was recorded in the month of February. Likewise, the water salinity in Marsh Creek oscillated between 111 mg/L to 2585 mg/L with lowest record in November and highest in the month of January. The graphical analysis suggested that the salinity in Blackbrook and Marsh creek followed the consistent pattern except during winter season. However, this trend changed by the second half of April due to the back-water effects from Lake Erie and continued until the beginning of early May. Backwater effect was not anticipated on the monitoring site based on the of several years records of Lake Erie level.

Similarly, there was a large fluctuations of salinity level in Marsh Creek and Black Brook Creek from early December 2017 to the second half of February 2018. During this period, Marsh Creek continuously exceeded the salinity level than that of Blackbrook Creek. This trend reversed from the second week of January 2018 and continued up to the second half of February 2018.

The monthly salinity level in Marsh Creek and Blackbrook Creek is presented in Figure 3.6. The water salinity at Blackbrook and Marsh Creek varied between 419 mg/L to 1538.43 mg/L and 275.57 mg/L 2017 to1398.26 mg/L, respectively. The lowest salinity level was captured in the month of November and the highest salinity level was captured in the month of February. It is interesting to note that higher salinity level was detected consecutively from December to March as compared to the other months of a year. The higher concentration of salinity during this period might be due to the excessive application of road salt for deicing purpose. Similarly, seasonal salinity variation is shown in Figure 3.7. The graph shows winter and spring seasons captured higher salinity level in both year 2017 and 2018. While the salinity level was higher in both creeks on other seasons as well, the significant variability of salinity level was not detected.

Furthermore, the observed salinity concentration and flow were computed and changed into salinity loading in both Creeks. The instrument was disturbed at the monitoring site in the month of February to early March in 2017. Therefore, actual salinity loading was not computed. Figure 3.8 shows the monthly observed salinity loading in Blackbrook and Marsh Creek. The analysis shows both Creeks had higher monthly salinity loading as compared to fresh water Creeks indicating that Marsh Creeks received significant salinity loading in the months of winter and spring seasons. Similarly, the Blackbrook Creek received significant salinity loading in the months of spring season and some months of fall and winter seasons. Regardless, Marsh Creek contributed more salinity loading compared to Blackbrook in downstream Marsh land. Figure 3.9 shows the box plot of observed median salinity loading in Marsh creek and Blackbrook creek throughout the study period. The monthly median salinity loadings in Blackbrook and Marsh Creek were 55 ton and 329 ton, respectively. The result showed that Marsh Creek contributed 10 times higher salinity loading compared to Blackbrook Creek.

Historical Salinity Loading

After calibration and validation, the SWAT model was re- run in the historical time period from 2000 to 2016 using climate data from Painesville station (USC00336389) to generate historical discharge. The correlation equation between salinity loading and discharge in daily (R^2 = 0.71) and monthly (R^2 = 0.82) scale was established in Blackbrook Creek (Figure 3.10). Similarly, the daily and monthly R^2 of streamflow with salinity in Marsh Creek was 0.86 and 0.76, respectively (Figure 3.11). The developed correlation equation and model predicted flow was utilized to compute the salinity loading in the historical time period.

The monthly simulated salinity loadings averaged for each month, during the historical period of 2000 to 2016, shows that Marsh creek had nearly 10 times higher salinity loading than that of Blackbrook creek (Figure 3.12). Similarly, seasonal salinity loading into the Marsh creek for historical period, computed average for each season from 2000 to 2016, was found higher than that of Blackbrook creek, which was consistent with our observed data (Figure 3.13). It shows that Marsh creek had higher seasonal median salinity loading in spring season (3792 ton), which successively decreased in summer (1236 ton) and fall (1103 ton) and increased in winter (2286 ton). This is not surprising because the flow was relatively higher in winter and spring season and the salinity loadings were primarily generated using the regression equations established between flow and salinity. Similarly, Blackbrook creek also had higher seasonal median salinity loading in spring season (246 ton) and successively decreased in summer (118 ton) and fall (110 ton) with a slight increase in winter season (161 ton). Likewise, Figure 3.14 shows that both creek received higher salinity loading in year 2008 and 2011, and the smaller salinity loadings in year 2000 and 2001 indicating the consistent trend of loadings and the degree of variability from year to year.

Figure 3.15 shows the annual salinity loading in Blackbrook and Marsh creek from (2000-2016). The box plot suggests that the Marsh creek contributed more salinity loading compared to Blackbrook Creek. The annual median salinity loading shows that Blackbrook Creek and Marsh Creek transported 620 ton and 8334 ton of salt, respectively towards marsh. The higher salinity loading from Marsh could be mainly due to the size of catchment which contributes more road salt from relatively large catchment size as compared to Blackbrook Creek. Road salt has been widely practiced as a deicing agent at pavement surface from departments of highway since the early 1960's (Demers and Sage, 2003). According to the study done by Murray and Ernst (1976), approximately 8.2 x 10^6 tons of salt are applied every year in the country's road and out of the which, 70% used in Northeast (Hanes et al., 1970).

Conclusion

There is an increasing need of in-depth salinity study in Mentor Marsh watershed to protect first natural preserve of Ohio. Therefore, this study was aimed to investigate the impacts of long term variation of salinity loading with respect to flow from two tributaries, Blackbrook and Marsh Creek. For this purpose, we developed a watershed model to simulate daily Creek flow from Mentor Marsh watershed using SWAT model. Although some modeling studies were conducted across the world specially to correlate the salinity loading with simulated flow, correlating salinity with model simulated flow to predict the salinity loading particularly in an ungaged catchment such as Mentor Marsh was a great challenge. More importantly, none of the prior research have been performed using a watershed model to investigate salinity level in Mentor Marsh. Therefore, two monitoring stations were established in Blackbrook and Marsh Creek for real time data recordings of stage, stream temperature and electrical conductivity. The measured conductivity was converted into salinity using Solinist Levelogger data wizard. Since the watershed model do not directly simulate the salinity level, we utilized the observed streamflow data to calibrate and validate the SWAT model and the correlation equation between flow and salinity was established to predict the salinity loading.

The analysis suggested that the salinity level captured in both Creek was consistently higher with most of the data values within oligosaline i.e. (500 to 5000 mg/L) category. It also indicated that Blackbrook Creek continued to experience higher level of salinity (mg/l) than that of Marsh Creek. Initially, we expected the lower salinity level in Blackbrook Creek as the monitoring station was located in the upstream from the salt fill and the salt fill tailings was not included. From the field investigation it is was clear to us that old brine fields which were closed decades ago are still leaking continuously. Another important finding of this research study was the variation of salinity level during winter and early spring season in both Creeks. Marsh Creek salinity level was observed higher than that of Blackbrook Creek for certain interval of time in winter season and kept fluctuating. However, rest of the year salinity level was found higher in Blackbrook compared to Marsh Creek.

The historical daily and monthly salinity loading also showed that Marsh creek had higher salinity loading than that of Blackbrook Creek. Similarly, both Creeks had higher median salinity loading in spring and winter season. The result showed that both Creek received higher salinity loading in wet year 2008 and 2011.

The continuous deposited salt increased the growth and development of phragmites in the downstream marsh land. As a matter of fact, it led to the rapid establishment of phragmites and increase the potential for fire hazard for community near the marsh. In order to avoid the Marsh fire, the sources of salt pollution for phragmites growth must be controlled. Therefore, an immediate action should be taken to rectify the old brine fields before rapid urbanization occurs. We also recommend ODOT to come up an alternative approach for deicing the salt or to use the limited amount around the area during winter season. Even though the complete removal of phragmites from Marsh land does not seem to be feasible, we recommend the managers, policymakers and different conservation agencies to come up with long-term research for further analyses to understand the salinity sources and loading pattern in the downstream Marsh.

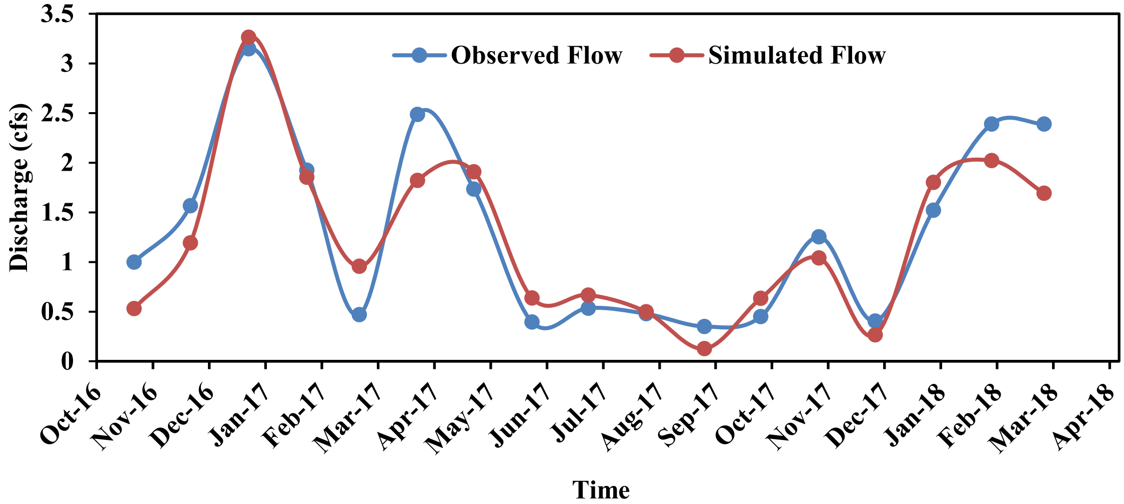


Figure 3-1: Calibrated and validated streamflow at the watershed outlet at Blackbrook Creek

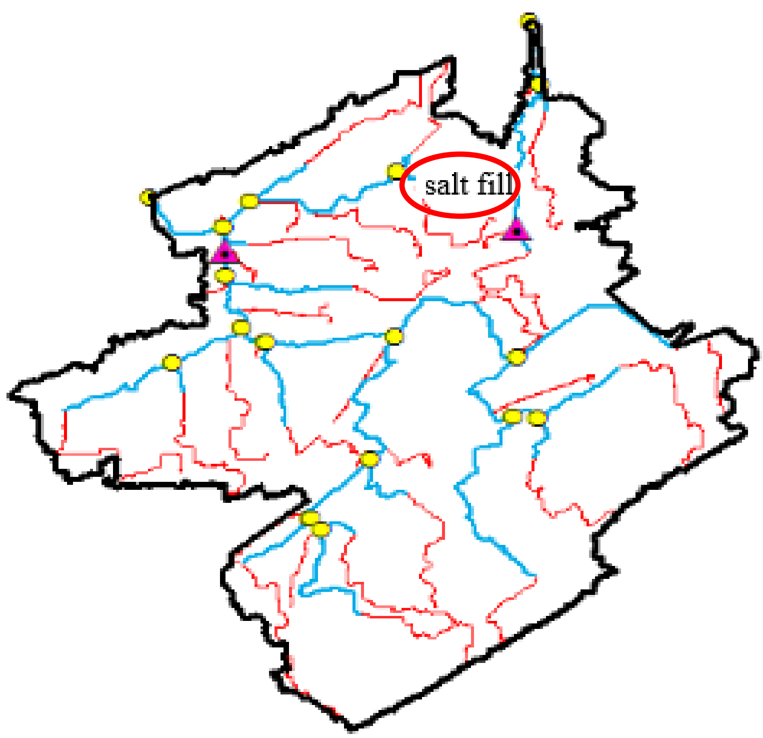
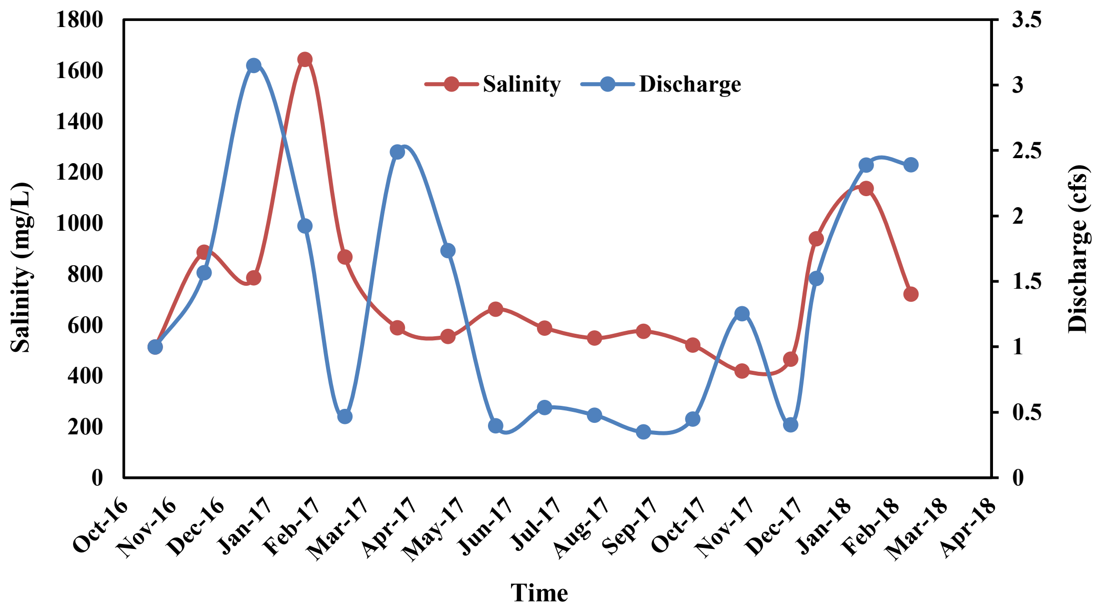
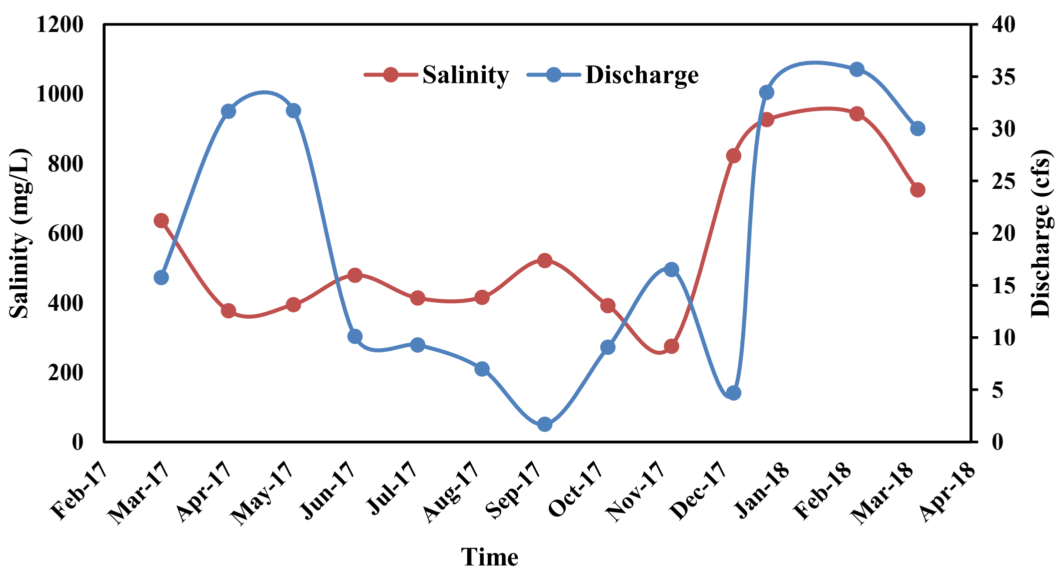


Figure 3-2: Saltfill site over Blackbrook Creek before rerouted



(a)



(b)

Figure 3-3: Monthly salinity and Discharge comparison at Blackbrook Creek (a) and Marsh Creek (b)

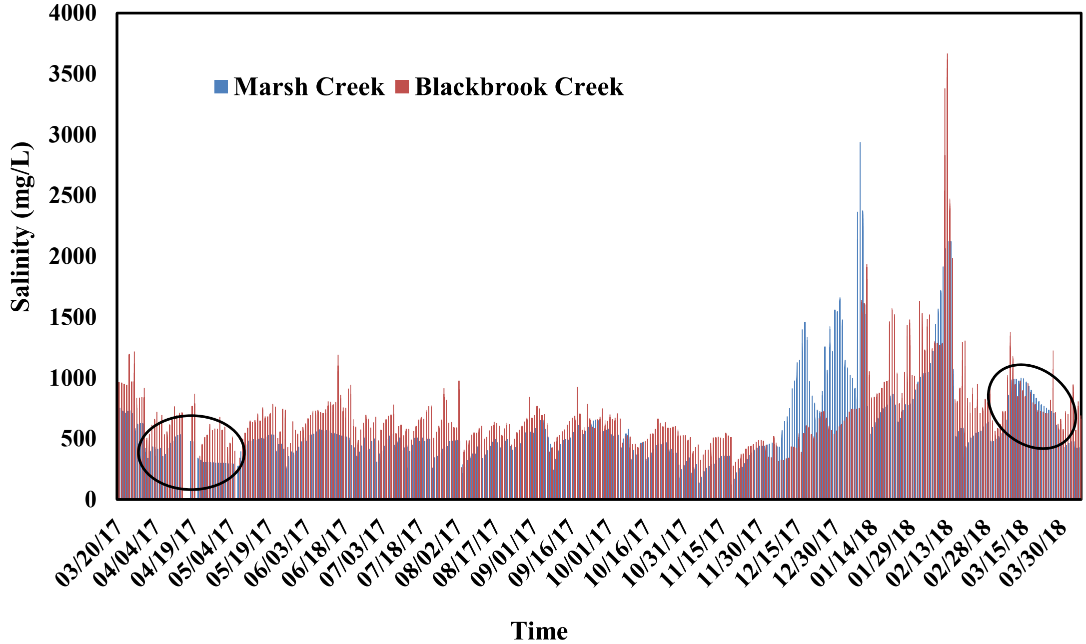


Figure 3-4: Hourly salinity comparison at Blackbrook Creek and Marsh Creek

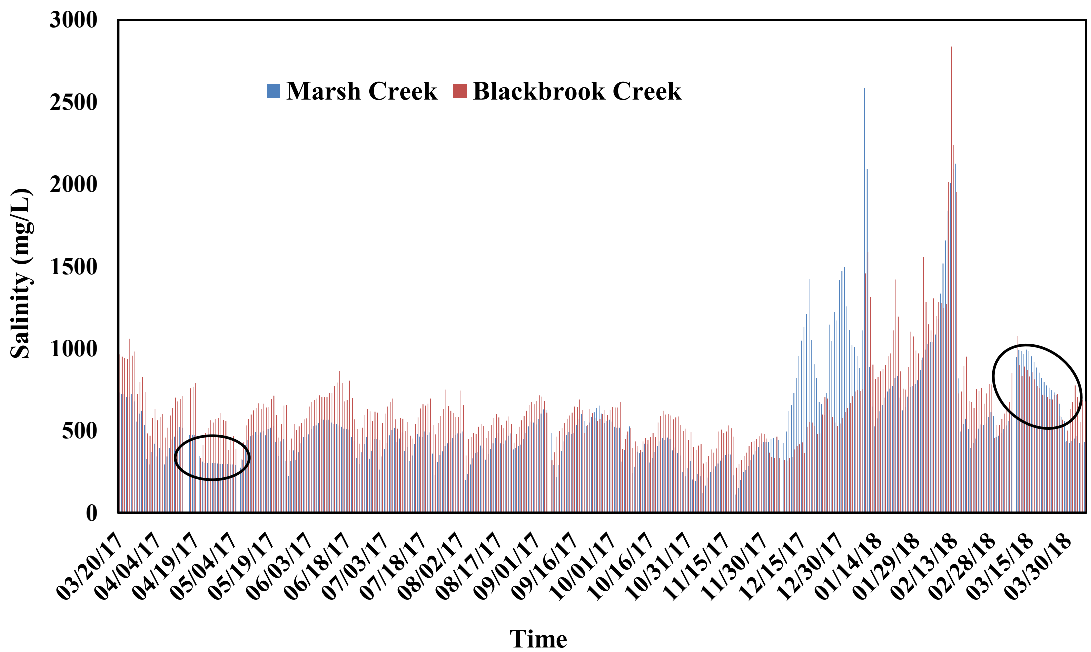


Figure 3-5: Daily salinity comparison at Blackbrook Creek and Marsh Creek

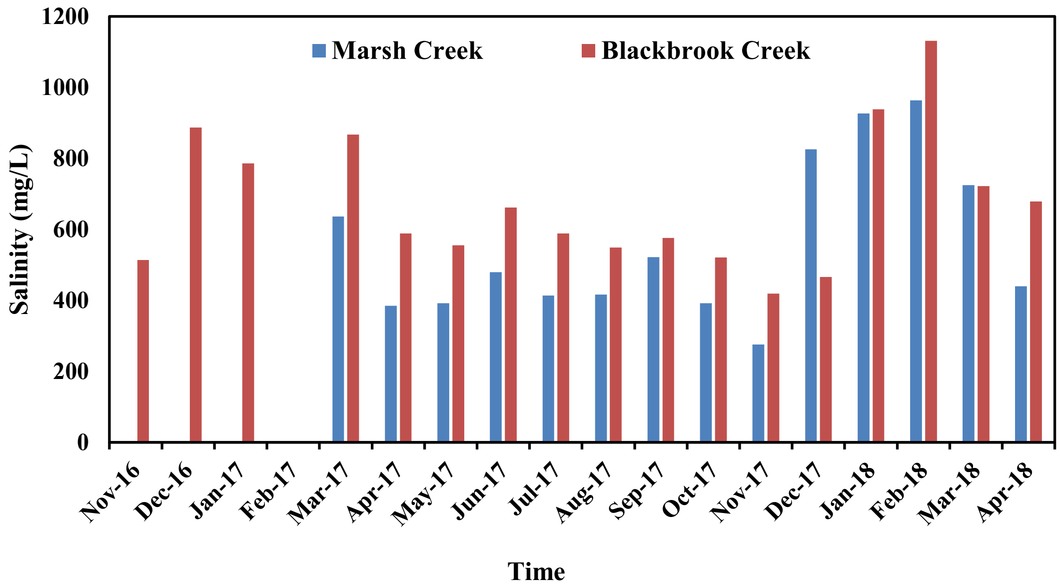


Figure 3-6: Monthly salinity comparison at Blackbrook Creek and Marsh Creek

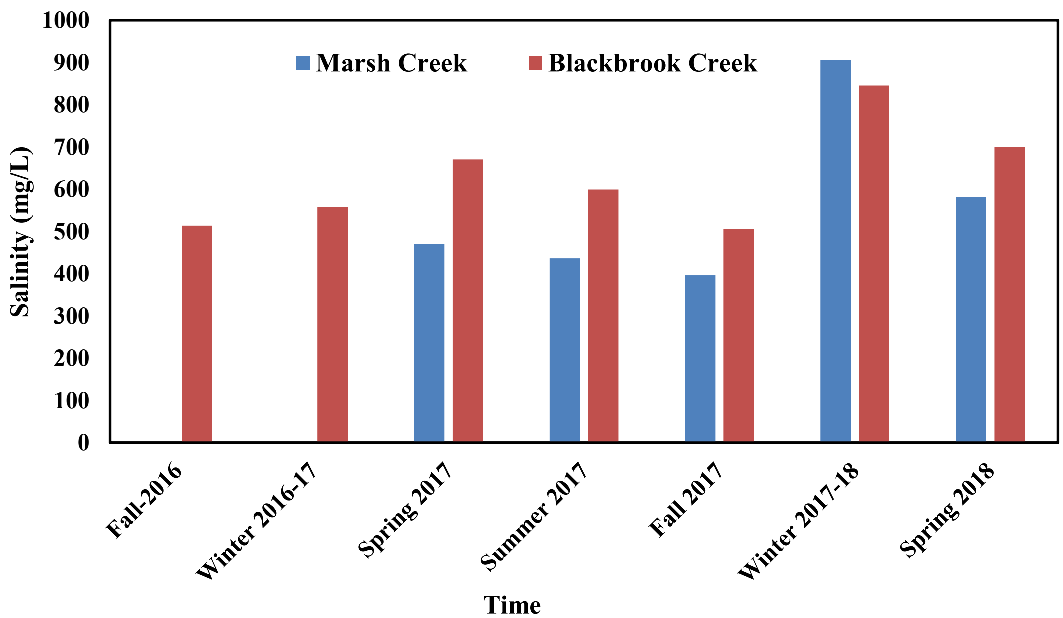
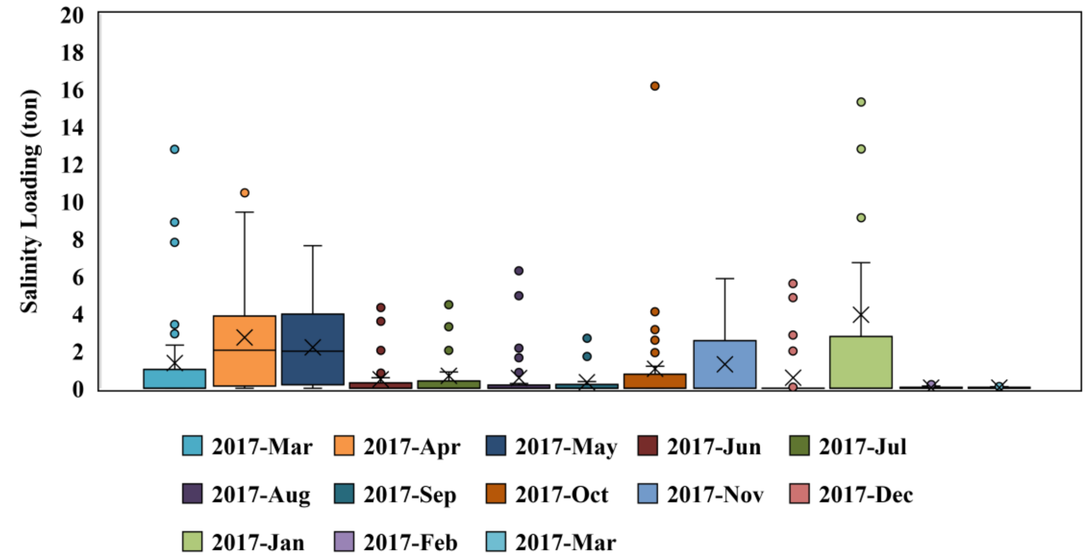
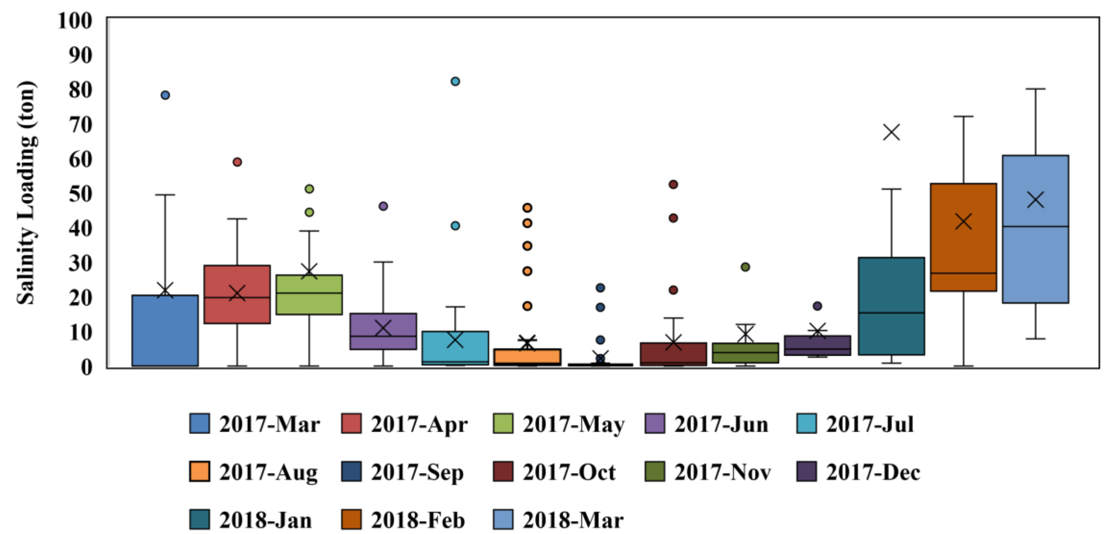


Figure 3-7: Seasonal salinity comparison at Blackbrook Creek and Marsh Creek

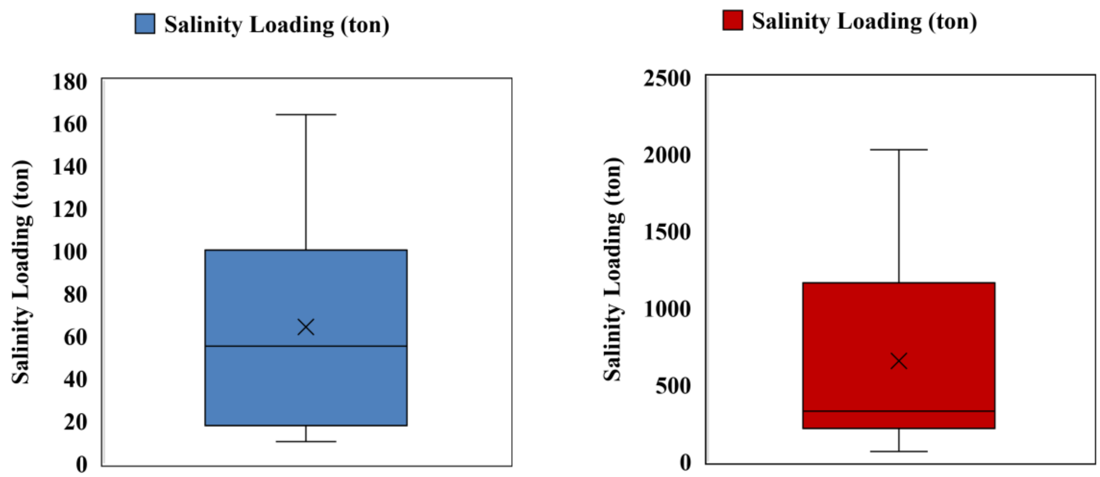


(a)



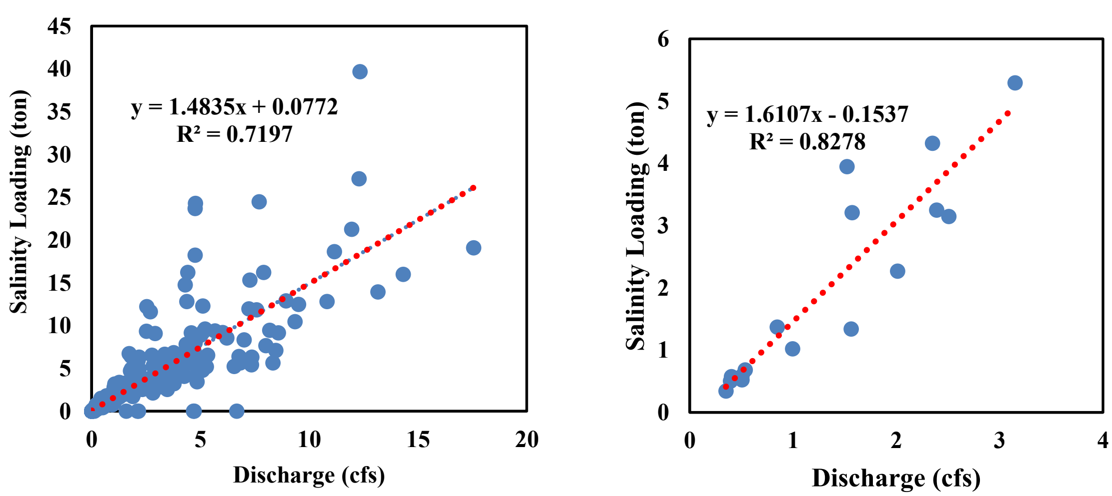
(b)

Figure 3-8: Observed monthly salinity loading at Blackbrook Creek (a) and Marsh Creek (b)



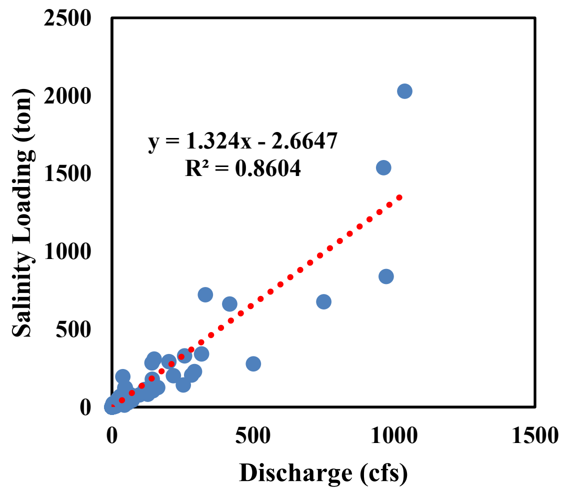
(a) (b)

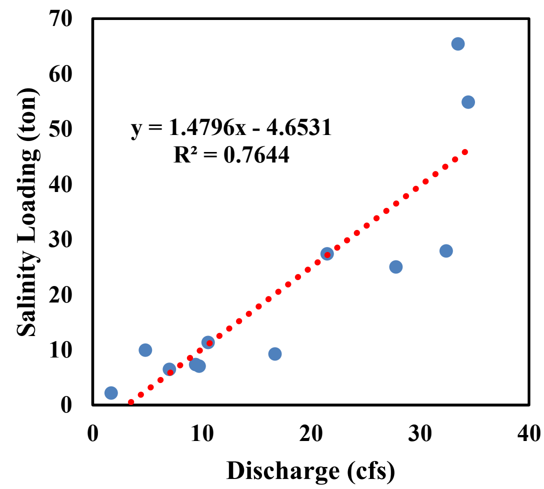
Figure 3-9: Total observed monthly salinity loading at Blackbrook Creek (a) and Marsh Creek (b)



(a) (b)

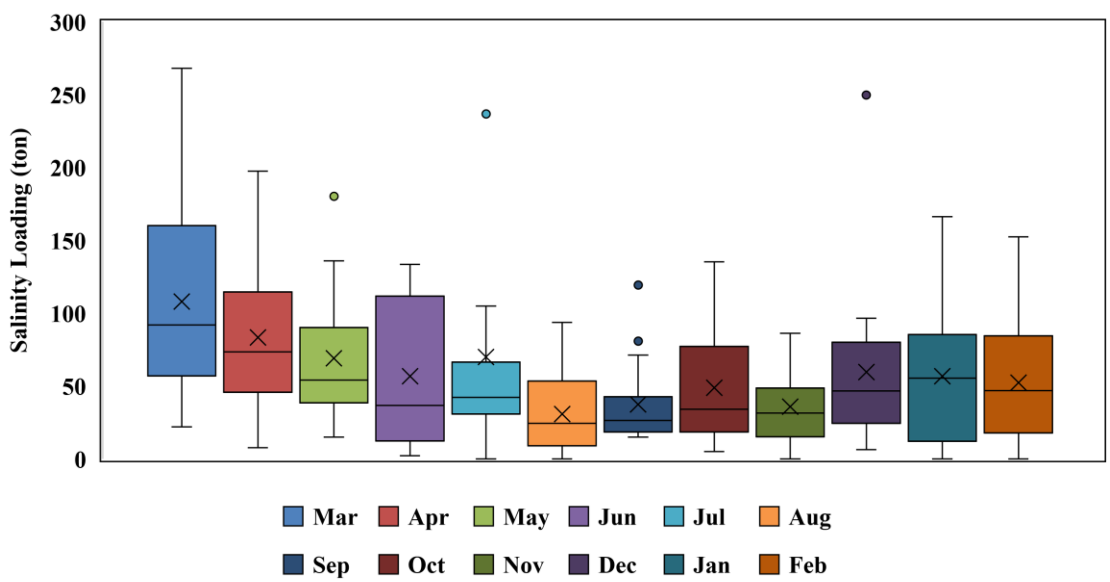
Figure 3-10: Correlation between salinity loading versus streamflow at Blackbrook Creek on Daily Scale (a) and Monthly Scale (b)



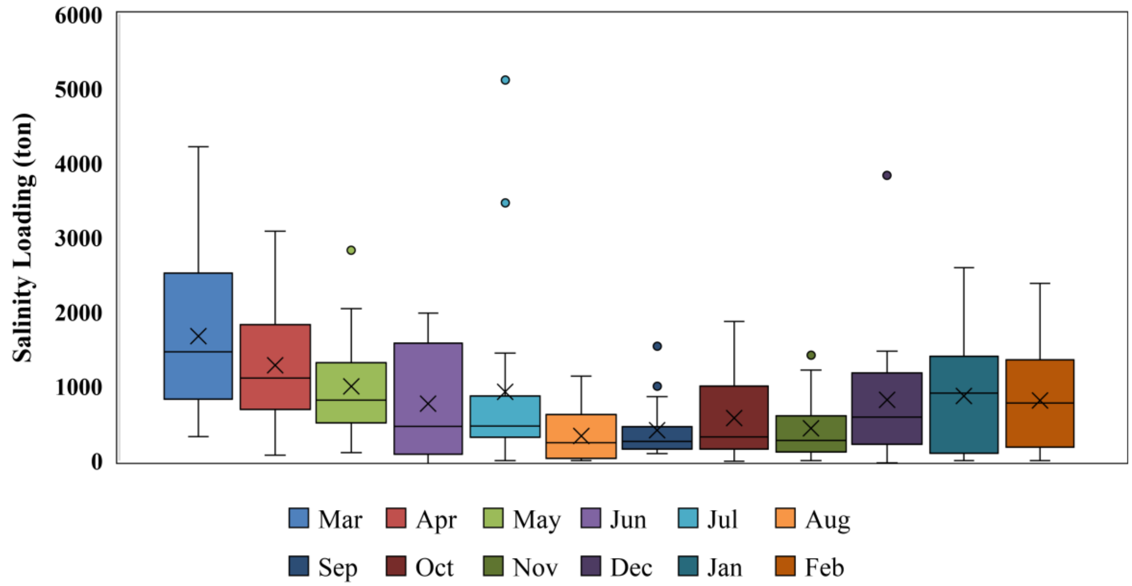


(a) (b)

Figure 3-11: Correlation between salinity loading versus streamflow at Marsh Creek on Daily Scale (a) and Monthly Scale (b)

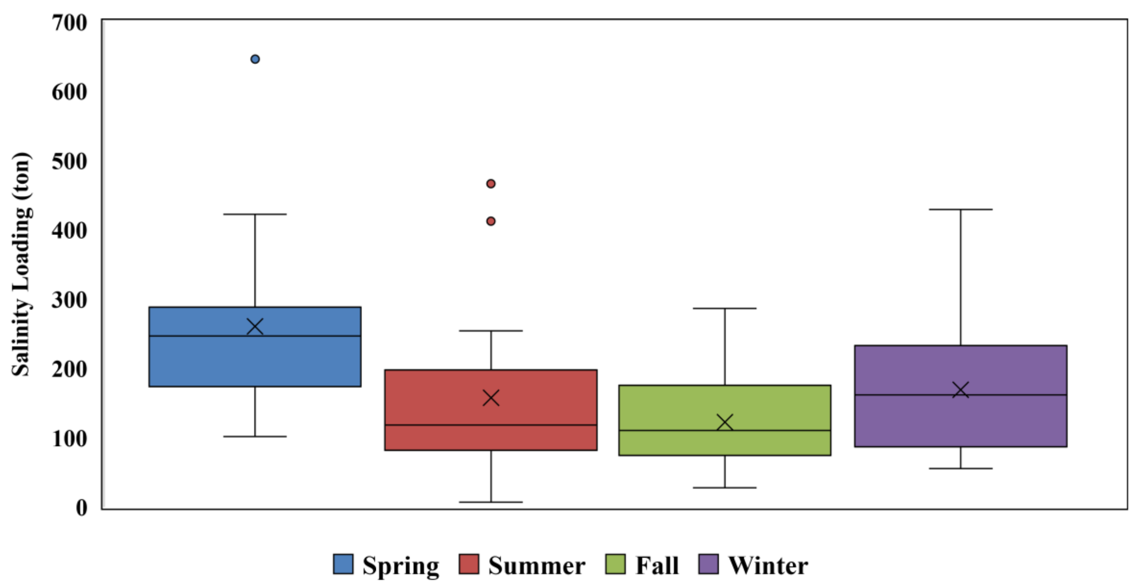


(a)

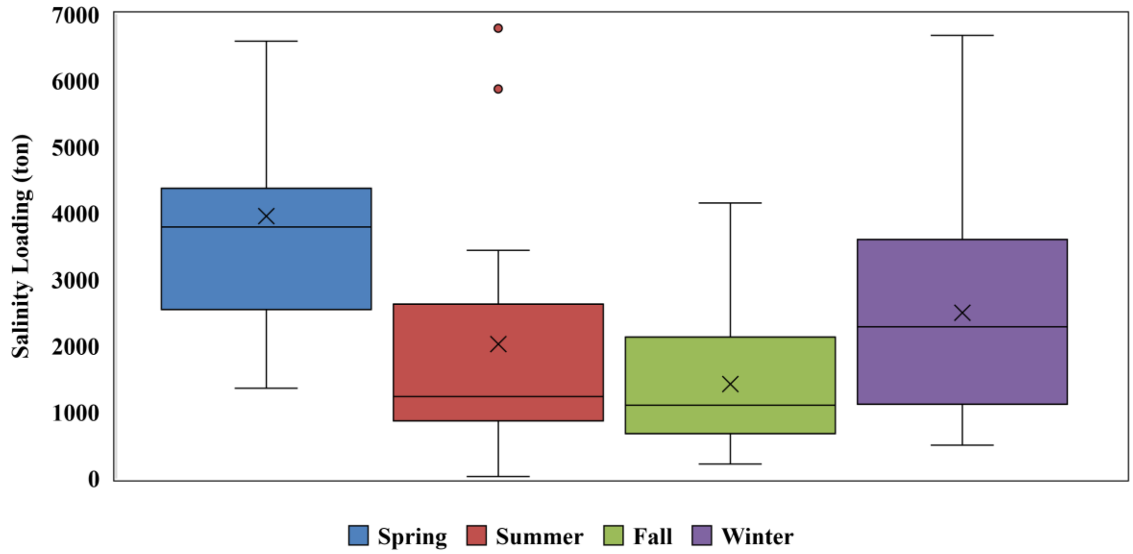


(b)

Figure 3-12: Monthly simulated salinity loading at Blackbrook Creek (a) and Marsh Creek (b)

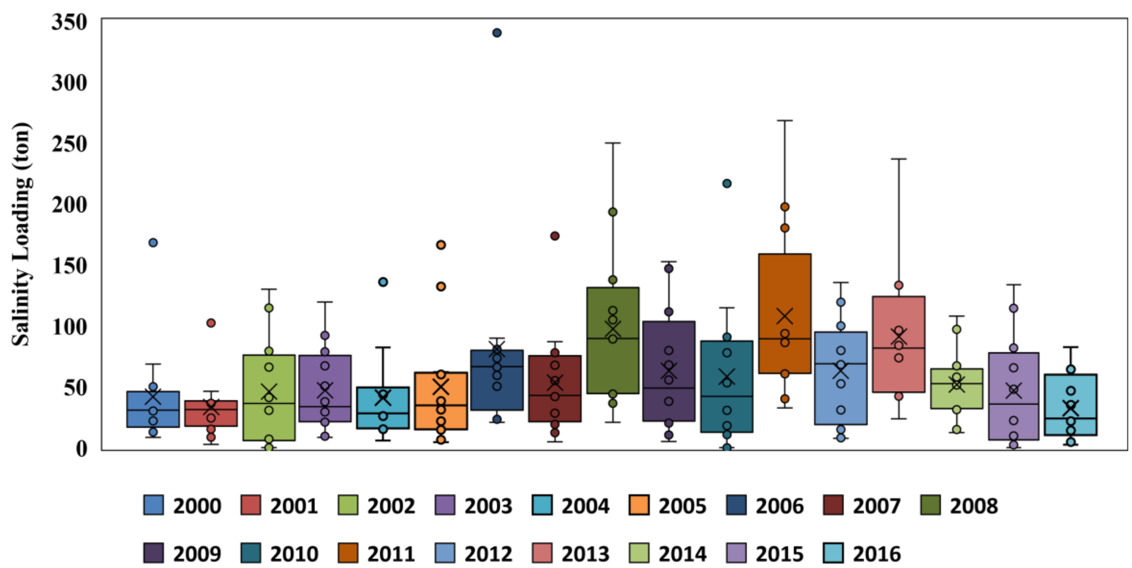


(a)

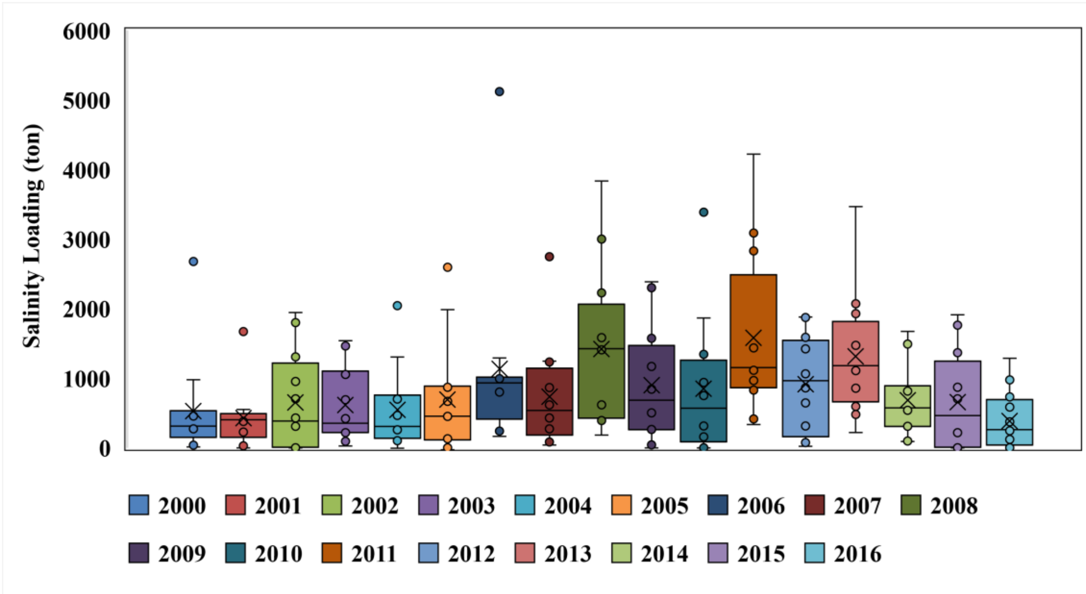


(b)

Figure 3-13: Seasonal simulated salinity loading at Blackbrook Creek (a) and Marsh Creek (b)

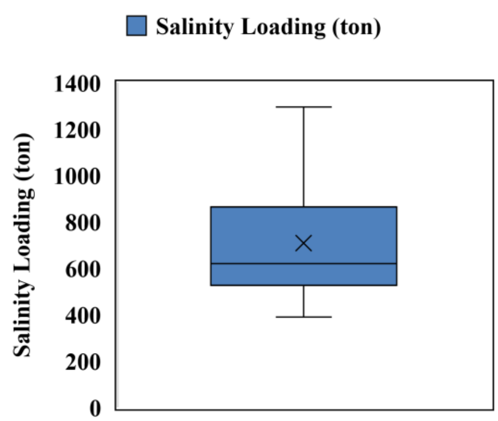


(a)

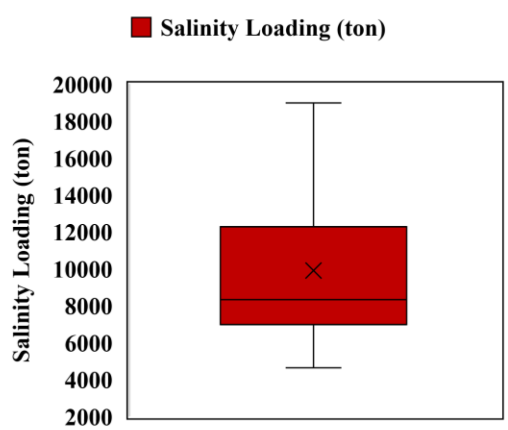


(b)

Figure 3-14: Annual simulated salinity loading at Blackbrook Creek (a) and Marsh Creek (b)



(a)



(b)

Figure 3-15: Total annual simulated salinity loading at Blackbrook Creek (a) and Marsh Creek (b)

Table 3.1 Percentage of land cover in Mentor Marsh watershed

Land Cover	Percentage
Open Water	0.23
Developed, Open Space	32.33
Developed, Low Intensity	40.55
Developed, Medium Intensity	9.5
Developed, High Intensity	2.4
Barren Land	0.32
Deciduous Forest	8.79
Evergreen Forest	0
Shrub/Scrub	0.03
Grassland/Herbaceous	3.11
Hay/Pasture	1.07
Woody Wetlands	1.66
Emergent Herbaceous Wetlands	0.03

Table 3.2 Model parameters used in SWAT calibration

Parameters	Calibrated Value
CN (relative)	65.3
ESCO	0.98
EPCO	0.98
GW-delay	10
Alpha-bf	0.5
Gw-Revap	10
Sol- Awc	0.118
SMFMX	3
TIMP	0.75
SMFMN	3
SMTMP	4
SFTMP	2.51

References

Akhbari, Masih, and Neil S. Grigg. “Water Management Trade-Offs between Agriculture and the Environment: A Multiobjective Approach and Application.” Journal of Irrigation and Drainage Engineering, vol. 140, no. 8, 2014, p. 05014005.

Allakhverdiev, Suleyman I., et al. “Ionic and Osmotic Effects of NaCl-Induced Inactivation of Photosystems I and II in Synechococcus Sp.” Plant Physiology, vol. 123, no. 3, July 2000, pp. 1047–56.

Arnold, J. G., et al. “Large Area Hydrologic Modeling and Assessment Part I: Model Development1.” JAWRA Journal of the American Water Resources Association, vol. 34, no. 1, Feb. 1998, pp. 73–89.

Arnold, Jeffrey G., Peter M. Allen, and David S. Morgan. "Hydrologic model for design and constructed wetlands." Wetlands 21.2 (2001): 167-178.

Baker, Lawrence A. “Introduction to Nonpoint Source Pollution in the United States and Prospects for Wetland Use.” Ecological Engineering, vol. 1, no. 1–2, 1992, pp. 1–26.

Bieger, Katrin, Georg Hörmann, and Nicola Fohrer. "Simulation of streamflow and sediment with the soil and water assessment tool in a data scarce catchment in the three Gorges region, China." Journal of environmental quality 43.1 (2014): 37-45.

Bernstein, Neil P. Red-Winged Blackbird Ecology and Environmental Change in Mentor Marsh. John Carroll University, 1977.

Blöschl, Günter. Rainfall-Runoff Modeling of Ungauged Catchments.

Broome, Stephen W., et al. “Tidal Salt Marsh Restoration.” Aquatic Botany, vol. 32, no. 1, Oct. 1988, pp. 1–22.

Carlson, Claire L., and Domy C. Adriano. “Environmental Impacts of Coal Combustion Residues.” Journal of Environmental Quality, vol. 22, no. 2, 1993, pp. 227–247.

Chambers, Randolph M., Thomas J. Mozdzer, et al. “Effects of Salinity and Sulfide on the Distribution of Phragmites Australis and Spartina Alterniflora in a Tidal Saltmarsh.” Aquatic Botany, vol. 62, no. 3, 1998, pp. 161–169.

Chambers, Randolph M., Laura A. Meyerson, et al. “Expansion of Phragmites Australis into Tidal Wetlands of North America.” Aquatic Botany, vol. 64, no. 3–4, 1999, pp. 261–273.

Cowardin, Lewis M., et al. Classification of Wetlands and Deepwater Habitats of the United States. US Department of the Interior, US Fish and Wildlife Service, 1979.

Cronk, Q. C. B., and J. L. Fuller. Plant Invaders. People and Plants Conservation Manual. London, Chapman & Hall, 1995.

Dawes, Warrick, et al. Flow Regime, Salt Load and Salinity Changes in Unregulated Catchments. Interpretation for Modelling the Effects of Land-Use Change. p. 32.

Deckers, D. L. E. H. Predicting discharge at ungauged catchments: parameter estimation through the method of regionalisation. MS thesis. University of Twente, 2006.

Demers, Charlotte L., and Richard W. Sage. “Effects of Road Deicing Salt on Chloride Levels in Four Adirondack Streams.” Water, Air, and Soil Pollution, vol. 49, no. 3–4, 1990, pp. 369–373.

DeSilet et al. “Predicting Salinity in the Chesapeake Bay Using Backpropagation.” Computers & Operations Research, vol. 19, no. 3–4, Apr. 1992, pp. 277–85.

Edgar, Chad. Mentor Marsh Watershed Action Plan. http://www.lakecountyohio.gov/swcd/Projects/MentorMarsh.aspx. Accessed 27 Jan. 2017.

Engel, Bernard, et al. "A Hydrologic/Water Quality Model Applicati1 1." JAWRA Journal of the American Water Resources Association 43.5 (2007): 1223-1236.

Fineran, Stacey A. Assessing Spatial and Temporal Vegetative Dynamics at Mentor Marsh, 1796 to 2000 A.D. The Ohio State University, 2003.

Finlayson, C. M., et al. "The Biology of Australian Weeds. II. Typha Domingensis Pers. and Typha Orientalis Presl." Journal of the Australian Institute of Agricultural Science, vol. 49, no. 1, 1983, pp. 3–10.

Fofonoff, P., and R. C. Millard. "JR. 1983. Algorithms for computation of fundamental properties of seawater." Unesco Technical Papers in Marine Science 44: 53.

Fujioka, R. S. "Monitoring coastal marine waters for spore-forming bacteria of faecal and soil origin to determine point from non-point source pollution." Water Science and Technology 44.7 (2001): 181-181.

Galatowitsch, Susan M., Neil O. Anderson, and Peter D. Ascher. "Invasiveness in wetland plants in temperate North America." Wetlands 19.4 (1999): 733-755.

Gassman, Philip W., and Wang Yingkuan. "IJABE SWAT Special Issue: Innovative modeling solutions for water resource problems." International Journal of Agricultural and Biological Engineering 8.3 (2015): 1-8.

Gibbs, M. S., et al. "Runoff and Salt Transport Modelling to Maximise Environmental Outcomes in the Upper South East of South Australia." 19th World IMACS

Congress and MODSIM11 International Congress on Modelling and Simulation, 2011.

Gibson, Jody R., and Raymond G. Najjar. “The Response of Chesapeake Bay Salinity to Climate-Induced Changes in Streamflow.” Limnology and Oceanography, vol. 45, no. 8, pp. 1764–72. Wiley Online Library, doi:10.4319/lo.2000.45.8.1764. Accessed 4 June 2018.

Gikas, Georgios D., et al. “Hydrodynamic and Nutrient Modeling in a Mediterranean Coastal Lagoon.” Journal of Environmental Science and Health, Part A, vol. 44, no. 13, 2009, pp. 1400–1423.

Global Water.2016. FP111-FP211 Global Water Flow Probe User’s Manual.

Gupta, Hoshin Vijai, et al. “Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration.” Journal of Hydrologic Engineering, vol. 4, no. 2, 1999, pp. 135–143.

Hanes, Roger E., et al. “Effects of Deicing Salts on Water Quality and Biota-Literature Review and Recommended Research.” NCHRP Report, no. 91, 1970.

Hauser, Edward J.P. 1972. Summary report on preliminary scientific investigation for Mentor Marsh – 1971-1972. Unpublished report. The Cleveland Museum of Natural History, Cleveland, Ohio.

Herbert, Ellen R., Paul Boon, Amy J. Burgin, Scott C. Neubauer, Rima B. Franklin, Marcelo Ardón, Kristine N. Hopfensperger, Leon P. M. Lamers, et al. “A Global Perspective on Wetland Salinization: Ecological Consequences of a Growing Threat to Freshwater Wetlands.” Ecosphere, vol. 6, no. 10, Oct. 2015, pp. 1–43.

Huckle, Jonathan M., et al. “Influence of Environmental Factors on the Growth and Interactions between Salt Marsh Plants: Effects of Salinity, Sediment and Waterlogging.” Journal of Ecology, vol. 88, no. 3, 2000, pp. 492–505.

Jain, Sanjay K., et al. “Simulation of Runoff and Sediment Yield for a Himalayan Watershed Using SWAT Model.” Journal of Water Resource and Protection, vol. 2, no. 03, 2010, p. 267.

Jones, K. 1975. The continuing story of Mentor Marsh. The Cleveland Museum of Natural History, Cleveland, Ohio.

Khalil, M. A., Fathi Amer, and M. M. Elgabaly. "A Salinity-Fertility Interaction Study on Corn and Cotton 1." Soil Science Society of America Journal 31.5 (1967): 683-686.

Krauss, Ken W., et al. “Growth and Nutrition of Baldcypress Families Planted under Varying Salinity Regimes in Louisiana, USA.” Journal of Coastal Research, vol. 16, no. 1, 2000, pp. 153–63.

Kundzewicz, ZBIGNIEW W. "Prediction in ungauged basins—a systemic perspective." Predictions in ungauged basins: PUB Kick-off. IAHS Publ 309 (2007).

Lass, C.A. 1984. Results from a three-phase research project involving Mentor Marsh and Vicinity. The Cleveland Museum Natural History, Cleveland, Ohio.

Lissner, Jørgen, and Hans-Henrik Schierup. "Effects of salinity on the growth of Phragmites australis." Aquatic botany 55.4 (1997): 247-260.

Lövei, Gábor L. “Biodiversity: Global Change through Invasion.” Nature, vol. 388, no. 6643, 1997, p. 627.

Lu, Zhong, and Oh-ig Kwoun. “Radarsat-1 and ERS InSAR Analysis over Southeastern Coastal Louisiana: Implications for Mapping Water-Level Changes beneath Swamp Forests.” IEEE Transactions on Geoscience and Remote Sensing, vol. 46, no. 8, 2008, pp. 2167–84.

Mack, Richard N., et al. “Biotic Invasions: Causes, Epidemiology, Global Consequences, and Control.” Ecological Applications, vol. 10, no. 3, 2000, pp. 689–710.

Marks, Marianne, et al. “Phragmites Australis (P. Communis): Threats, Management and Monitoring.” Natural Areas Journal, vol. 14, no. 4, 1994, pp. 285–294.

Matson, Timothy O., et al. A Survey of the Turtles of Mentor Marsh, Lake County, Ohio.

Mauchamp, André, and François Mésleard. “Salt Tolerance in Phragmites Australis Populations from Coastal Mediterranean Marshes.” Aquatic Botany, vol. 70, no. 1, May 2001, pp. 39–52.

McElroy, A. D. Loading functions for assessment of water pollution from nonpoint sources. Vol. 1. US Environmental Protection Agency, Office of Research and Development, [Office of Air, Land, and Water Use], 1976.

Meselhe, E. A., and H. M. Noshi. “Hydrodynamic and Salinity Modeling of the Calcasieu-Sabine Basin.” Bridging the Gap: Meeting the World’s Water and Environmental Resources Challenges, 2001, pp. 1–10.

Meyerson, Laura A., et al. “A Comparison of Phragmites Australis in Freshwater and Brackish Marsh Environments in North America.” Wetlands Ecology and Management, vol. 8, no. 2–3, 2000, pp. 89–103.

Michot, B. D., et al. “Hydrologic Modeling in a Marsh–Mangrove Ecotone: Predicting Wetland Surface Water and Salinity Response to Restoration in the Ten Thousand

Islands Region of Florida, USA.” Journal of Hydrologic Engineering, vol. 22, no. 1, 2015, p. D4015002.

Millero, Frank J. “History of the Equation of State of Seawater.” Oceanography, vol. 23, no. 3, 2010, pp. 18–33.

Mittelstet, Aaron R., et al. “Using SWAT to Simulate Crop Yields and Salinity Levels in the North Fork River Basin, USA.” International Journal of Agricultural and Biological Engineering, vol. 8, no. 3, 2015, p. 110.

Mohd, Ekhwan Toriman, et al. “Assessment of Water Salinity Model Using Hydrodynamic Numerical Modelling in Estuary of Selangor River, Malaysia.” Malaysian Journal of Analytical Sciences, vol. 19, no. 5, 2015, pp. 1109–1119.

Moriasi, Daniel N., et al. “Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations.” Transactions of the ASABE, vol. 50, no. 3, 2007, pp. 885–900.

Muniz, Kátia, et al. “Hydrological Impact of the Port Complex of Suape on the Ipojuca River (Pernambuco-Brazil).” Journal of Coastal Research, 2005, pp. 909–914.

Murray, Don, and Ulrich FW Ernst. An Economic Analysis of the Environmental Impact of Highway Deicing. Vol. 1, US Environmental Protection Agency, Office of Research and Development, Municipal Environmental Research Laboratory, 1976.

Neitsch, Susan L., et al. Soil and Water Assessment Tool Theoretical Documentation Version 2009. Texas Water Resources Institute, 2011.

Novotny, Eric V., et al. “Increase of Urban Lake Salinity by Road Deicing Salt.” Science of the Total Environment, vol. 406, no. 1–2, 2008, pp. 131–44.

Ohio EPA. 1980. Notes from meeting regarding salt fill: November 20, 1980. Ohio EPA, Northeast District Office, Twinsburg, Ohio.

Pezeshki, S. R., et al. “Flooding and Saltwater Intrusion: Potential Effects on Survival and Productivity of Wetland Forests along the U.S. Gulf Coast.” Forest Ecology and Management, vol. 33–34, June 1990, pp. 287–301.

Piman, T., T. Lennaerts, and P. Southalack. "Assessment of hydrological changes in the lower Mekong Basin from Basin- Wide development scenarios." Hydrological Processes 27.15 (2013): 2115-2125.

Prairie, James R., et al. “Statistical Nonparametric Model for Natural Salt Estimation.” Journal of Environmental Engineering, vol. 131, no. 1, 2005, pp. 130–138.

Poznik, Jenica. Comparison of Swamp Forest and Phragmites Australis Communities at Mentor Marsh, Mentor, Ohio. The Ohio State University, 2003.

Rafiei Emam, Ammar, et al. "Hydrological modeling and runoff mitigation in an ungauged basin of central Vietnam using SWAT model." Hydrology 4.1 (2017): 16.

Rand Development Corporation. 1970. Pollution Study of Marsh Creek and Mentor Marsh, Federal Water Quality Administration Water Pollution Control Series 11010EG009/70.

Roman, Charles T., William A. Niering, and R. Scott Warren. "Salt marsh vegetation change in response to tidal restriction." Environmental Management 8.2 (1984): 141-149.

Santhi, C., et al. “Validation of the Swat Model on a Large Rwer Basin with Point and Nonpoint Sources1.” JAWRA Journal of the American Water Resources Association, vol. 37, no. 5, Oct. 2001, pp. 1169–88.

Seliskar, Denise M., and John L. Gallagher. “Exploiting Wild Population Diversity and Somaclonal Variation in the Salt Marsh Grass Distichlis Spicata (Poaceae) for Marsh Creation and Restoration.” American Journal of Botany, vol. 87, no. 1, Jan. 2000, pp. 141–46.

Sivapalan, Murugesu. "Prediction in ungauged basins: a grand challenge for theoretical hydrology." Hydrological Processes17.15 (2003): 3163-3170.

Solinst, 2016 - 3001 Levelogger Series User Guide

Somura, Hiroaki, et al. "Impact of climate change on the Hii River basin and salinity in Lake Shinji: a case study using the SWAT model and a regression curve." Hydrological Processes: An International Journal 23.13 (2009): 1887-1900.

Thompson, D. J., and J. M. Shay. “The Effects of Fire on Phragmites Australis in the Delta Marsh, Manitoba.” Canadian Journal of Botany, vol. 63, no. 10, 1985, pp. 1864–1869.

Tomas, L. M., et al. "Salinity modelling accuracy of a coastal lagoon: a comparative river flow analysis of basin model vs. traditional approaches." Journal of Coastal Research 70.sp1 (2014): 586-591.

Van der Kamp, Garth, and Masaki Hayashi. “Groundwater-Wetland Ecosystem Interaction in the Semiarid Glaciated Plains of North America.” Hydrogeology Journal, vol. 17, no. 1, 2009, pp. 203–214.

Van Liew, M. W., et al. “Hydrologic Simulation on Agricultural Watersheds: Choosing between Two Models.” Transactions of the ASAE, vol. 46, no. 6, 2003, p. 1539.

Vasquez, Edward A., et al. "Salt tolerance and osmotic adjustment of Spartina alterniflora (Poaceae) and the invasive M haplotype of Phragmites australis (Poaceae) along a salinity gradient." American Journal of Botany 93.12 (2006): 1784-1790.

Wang, Qiwen, et al. “Modeling Salinity Dynamics in the Chesapeake Bay.” American Journal of Mathematical and Management Sciences, vol. 12, no. 2–3, 1992, pp. 227–247.

Whipple, Joshua C. Geological and Environmental Assessment of Mentor Marsh, Mentor, Ohio: A Thesis Presented to the Graduate Faculty of the University of Akron. University of Akron, Department of Geology, 1999.

Williams, W. D. “Salinisation: A Major Threat to Water Resources in the Arid and Semi-Arid Regions of the World.” Lakes & Reservoirs: Research & Management, vol. 4, no. 3–4, Sept. 1999, pp. 85–91.

Xie, Philip F. “Socio-Economic Impacts of Birdwatching along Lake Erie: A Coastal Ohio Analysis.” Bowling Green State University, Bowling Gr`een, OH, 2012.

Zedler, Joy B., and Suzanne Kercher. “Wetland Resources: Status, Trends, Ecosystem Services, and Restorability.” Annu. Rev. Environ. Resour., vol. 30, 2005, pp. 39–74.