A RETROSPECTIVE ANALYSIS OF A CONSTRUCTED STORMWATER WETLANDS

By

Stephanie Mary Molina

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DEDICATION

I dedicate this thesis to my Dad,

Mario Molina

Thank you for teaching me to never give up!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

ABS – Acoustic Backscatter Sensor

BMP – Best Management Practice

C – Concentration in ppb

CSW – Constructed Stormwater Wetlands

CSW 1.0 – CSW from 2000 – 2009

CSW 2.0 – CSW from 2010 – Present

EPA – Environmental Protection Agency

IM – Inlet Main

IN – Inlet Sedimentation Forebay

INW – Instrumentation Northwest

IQR- Inter Quartile Range

IW – Inlet West

M1 – First Meander

M2 – Second Meander

M3 – Third Meander

Opti – OptiRTC

ORB – Outlet Detention Basin

OUT – Outlet

PME – Precision Measurement Engineering

ppb – Parts per billion

SCM – Stormwater Control Measure

SWMM – Storm Water Management Model

t – Sampling time

TDS – Total Dissolved Solids

TSS – Total Suspended Solids

$\bar{t}$ – Mean retention time

Δt – Sampling interval

σ – Standard Deviation

ABSTRACT

Sustainable stormwater management is prevalent today as many seek greener solutions for runoff collection and treatment. In most cases they are implemented as means to manage rainwater before it enters sewer systems via stormwater control measures (SCM). In other cases, SCMs are implemented to regulate nutrient and metal loads transported by stormwater runoff that flow and collect in rivers and streams.

At Villanova University a Constructed Stormwater Wetlands (CSW) was designed to reduce nutrient concentration and attenuate flow entering the headwaters of Mill Creek, a tributary of Schuylkill River. For several years, studies have been conducted on the overall performance of the CSW, but there has not been enough data until now to discern performance changes over time and the parameters that influence these changes. This study focuses on analyzing the flow entering and leaving the CSW from 2012 to 2016 as well as the impacts caused by climate conditions on the overall effectiveness of flow attenuation. Initial analysis shows that rainfall patterns impact flow attenuation, as well as the substantial role of system storage and vegetation density. Additionally, Total Suspended Solids (TSS) concentrations are analyzed to determine whether it is an indicator of first flush and can be used as a decision maker in “smart” SCM systems (i.e. real time control).

CHAPTER 1 – INTRODUCTION

Sustainable stormwater management is more prevalent in the world today as many seek greener solutions for runoff collection and treatment. At Villanova University a Stormwater Control Measure (SCM) Research and Demonstration Park has been developed to further aid in the understanding of stormwater management as well as non-point pollution and its effect on these systems. This SCM Demostration Park includes bio-infiltration and bio-retention rain gardens and swales, pervious concrete/porous asphalt installations, infiltration trenches, green roofs, as well as a constructed stormwater wetlands. This study will focus on the constructed stormwater wetlands and its role on flow attenuation as well the observed changes over the past five years.

1.1 Villanova Constructed Stormwater Wetlands

The constructed stormwater wetlands (CSW) analyzed in this study is located at the northeast end of Villanova University's campus next to Villanova University's Charles Widger School of Law (Figure 1-1).

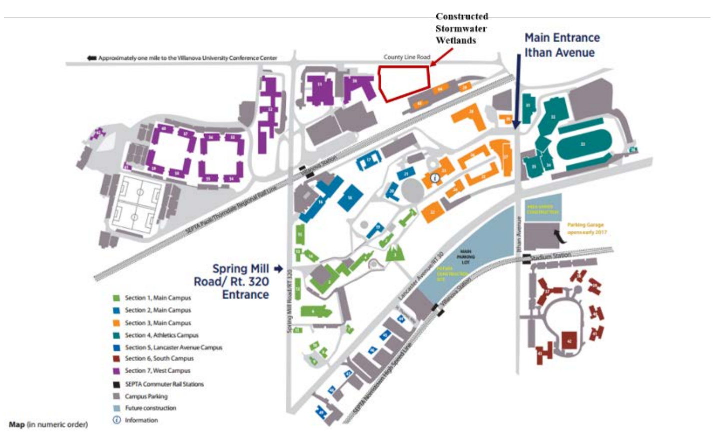

Figure 1-1: Location of CSW on Villanova University's Campus (Villanova University 2017)

This site was originally developed in the early 1980's as a stormwater detention basin with its outlet draining into the headwaters of Mill Creek. The constructed detention basin covered around one acre of land and was constructed with an underdrain to allow the basin to run dry between storm events as seen in Figure 1-2. Water entered the system via two inlet pipes located at the southwest corner of the site allowing for the collection of surface water runoff from both Villanova University's Main and West Campus (Figure 1-3). Water was allowed to exit the system via an outlet structure designed to handle different flows up to the 100 year storm event due to a combination of three separate weirs: a circular orifice, a T-notch weir, and a grate on top of the structure as seen in Figure 1-4.

Figure 1-2: 1992 Original Stormwater Detention Basin (Google Earth 2017)

Figure 1-3: Inflow Pipes

Figure 1-4: Outlet Structure

After an analysis of the site's performance, it was decided that a Constructed Stormwater Wetlands (CSW 1.0) would be suitable to retrofit the existing detention basin as a means to increase the hydraulic and water quality performance of the site. The design of CSW 1.0 incorporated a unidirectional linear channel that ran through the first half of basin which then directed the flow into a sediment forebay allowing for a longer detention time during and between storm events. The sediment forebay was a 40 by 40 feet concrete pad with a minimum 4 feet water depth that allowed sediments within the water column to settle. Flow was then directed through a series of meanders crafted using gabion baskets and earthen material to direct the flow. The overall site elevation drop from the inlet to outlet was 8.2 feet and the underdrain was removed. Both the inlet and outlet structures remained the same as seen in Figure 1-5. This expansion allowed for the treatment of a 42 acre watershed of which approximately 21 acres are collected from Villanova University's Main Campus and 21 acres are collected from Villanova University's West Campus.

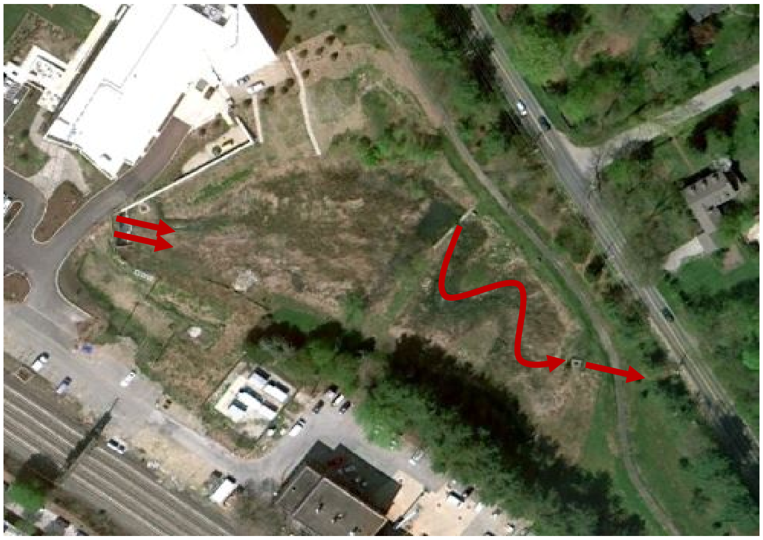

Figure 1-5: Early 2010 Constructed Stormwater Weltands 1.0 (Google Earth 2017)

The CSW 1.0 underwent several years of monitoring and analysis to measure water quantity and water quality parameters. After an analysis and a comparison of the CSW 1.0 to other constructed stormwater wetlands, it was decided that an increase in meander length would aid in the further improvement of water quality and flow rates (Jones 2009). The CSW 1.0 was then retrofitted to incorporate the entire area within the site's boundaries (0.78 acres) and modify the flow path. The new design of the CSW 2.0 includes a sediment forebay located at the inlet structure followed by a series of three meanders and a detention basin before reaching the outlet structure as seen in Figure 1-6. Additionally, adjustable sluice gates were installed at the end of each meander (Figure 1-7) to allow for different levels of pooling to aid in quantifying water quality. At the outlet structure a V-notch weir was installed in the circular orifice.

Figure 1-6: 2011 Constructed Stormwater Weltands 2.0 (Google Earth 2017)

Figure 1-7: Adjustable Sluice Gate

For the sake of this present study each section of the CSW 2.0 will be referred to as seen in Figure 1-8 where IW stands for the Inlet West inflow pipe, IM stands for the Inlet Main inflow pipe, IN for the Inlet Sedimentation Forebay, M1 for the First Meander, M2 for the Second Meander, M3 for the Third Meander, ORB for the Outlet Retention Basin, and OUT for the Outlet.

Figure 1-8: CSW 2.0 Section ID's (Google Earth 2017)

1.2 Research Plan

In this study, flow attenuation, climate and vegetation change, as well as the concentration of total suspended solids was evaluated for the CSW 2.0 from the IN of the system to the OUT to determine overall performance. This study focuses on the time period between July 2012 and December 2016 with emphasis on identifying what physical changes may be driving the observed flow changes. Additionally, a study was conducted to determine whether the first flush of pollutants can be quantified by the concentration of total suspended solids found in the system.

CHAPTER 2 – LITERATURE REVIEW

Over time, human development of the built environment has caused a serious impact in the world we live in today. One impact that has occurred is humans through urbanization have slowly changed the natural water cycle by decreasing the volume of water being infiltrated into the soil while increasing the amount of stormwater runoff (Figure 2-1). The increase in stormwater runoff results in an increase of flooding, as well an increase in the concentration of the pollutants found in rivers and streams (Faust 2014). This causes the water quality of the receiving stream to deteriorate shortening the life of the water body by causing algal blooms and eutrophication (Wadzuk et al. 2008, Al-Rubaei et al. 2016).

Figure 2-1: Increase in Stormwater Runoff with Urbanization (Faust 2014)

2.1 Stormwater Management

Sustainable stormwater management has slowly become more prevalent in the world today as many seek greener solutions for runoff collection and treatment. This can be seen on a large scale as cities begin to implement and push for greener solutions such as the City of Philadelphia with their 2035 plan to connect, thrive, and renew the city (Philadelphia City Planning Commission 2011). In most cases stormwater management is implemented as a means to manage stormwater runoff before it enters into either the stormwater or sewer systems in the form of a structural or non-structural stormwater control measures (SCM), also known as best management practices (BMP) (Martin et al. 2006). The Pennsylvania Best Management Practice (PA BMP) Manual describes a structural SCM as a stormwater management system based on a natural system that relies upon vegetation and soil mechanisms to mitigate the effects of stormwater runoff while a non-structural SCM focuses on preserving and protecting natural systems (PA BMP Manual 2006). Examples of structural SCMs include pervious pavement, infiltration trenches, rain gardens, vegetated swales, green roofs, and constructed stormwater wetlands (Figure 2-2).

Figure 2-2: Example of Structural Stormwater Control Measures

From left to right on the top row: Villanova University's Green Roof, Vegetative Swales, and Constructed Stormwater Wetlands (CSW). Bottom row: Villanova University's Bioinfiltration Traffic Island Rain Garden.

When selecting the appropriate SCM for a project one must consider the water quantity and quality control objectives which depend on effectively balancing site hydrological characteristics, hydraulic efficiency, biogeochemistry, nutrient loading, climate concerns, and public acceptance (Nietch et al. 2001, Hoyt et al. 2005). For example rain gardens are designed to reduce runoff volume and filter pollutants by encouraging infiltration through an engineered or native media layer of soil as well as encourage evapotranspiration via nutrient resistant vegetation (PA BMP Manual 2006). On the other hand, constructed stormwater wetlands are designed to attenuate peak flows and discharge volumes via the use of nutrient and flooding resistant vegetation as well as longer residence times in the system (Al-Rubaei et al 2016). Additionally, the hydraulic characterization of the site is important to consider when determining the best SCM for a project. Unfortunately, the hydraulics are often overlooked when determining SCM performance in the field (Struck et al. 2004). The nutrient concentrations and loads within stormwater runoff are cyclic due to periods of deposition followed by a first flush of pollutants after a rainfall event making SCMs extremely important to buffer the downstream environment from such a large range of pollutants (Kadlec et al. 2009).

2.2 Constructed Stormwater Wetlands

Historically, constructed wetland systems have been used all over the world to remove nutrients and pollutants from wastewater. In the 1950s a shift of this treatment technology from wastewater to stormwater was seen in Germany and slowly made its way to the western hemisphere in the 1970s (Kadlec et al. 2009). Constructed stormwater wetlands (CSWs) are designed to mimic flow control and water quality improvement functions of natural wetlands (Crowe et al. 2007) and work under the unifying principle that they are wet long enough to exclude plant species that are not resistant to saturated soil as well as changes in soil properties due to chemical, physical, and biological changes during flooding (Kadlec et al. 2009, Hammer 1992).

Properly designed, constructed, and maintained CSWs provide some of the best water quality treatment and flood control protection when compared to other SCMs (Hoyt et al. 2005). Constructer stormwater wetlands are characterized by being able to handle highly variable flow rates and variations in suspended solids and nutrients between storm events (O'Shea et al. 2004). The water quality improvement is accomplished by increasing the stormwater's residence time within the system allowing for the CSW to treat pollutants through physical, biological, and chemical interactions between plants and water flow (Wadzuk et al. 2008) making the residence time of polluted stormwater within a CSW a key factor in its treatment efficiency (Walker 1998).

The two largely studied factors that determine the length of time that the polluted stormwater spends in the CSW includes the length of the flow path as well as the storage volume within the system (Mogavero et al. 2009). Jones et al. (2009) determined that for a specific site at Villanova University, the best CSW design resulting in the lowest peak discharge rate, longest retention time, and lowest mean change in flow rate includes a continuous meander design. The mitigation of peak flows provides flood control during large events and protects stream stability during smaller events (Jones et al. 2013). A third factor that aids in increasing the retention time within a CSW is the frictional effects within the system.

To determine the retention time within a system, a form of a conservative tracer such as Rhodamine WT dye, is used. Tracer dyes have been used to aid understanding of complex systems over the past century with applications ranging from human disease vectors to environmental degradation (Arsnow et al. 2010). Similar to what is used in treatment plants, pulse tracer tests are performed in CSWs. To do so, a known mass of tracer dye is released at an upstream location of the point of interest and monitoring for the tracer chemical begins at the same time as the addition of the tracer (Teefy, 1996).

A study conducted at Prado Wetlands in Riverside County, California (Lin et al. 2003) determined that the residence time distributions predicted by the Rhodamine WT tracer was essentially equal to the residence time distribution predicted by a similar tracer Bromide. Additionally, Rhodamine WT dye showed irreversible sorption to soil suggesting losses due to biodegradation and photochemical transformation indicating that not all the dye released into the system will be recovered. Although this may present an issue, it was determined that Rhodamine WT can be used reliably as a tracer for relatively small wetlands system (less than one 1 week residence time) (Lin et al. 2003).

In open channel flow, a factor increasing the residence time within a system has proven to be the drag exerted by the channel bottom. Both lab flume experiments and field measurements were used to conclude that in CSWs the drag created by the channel bed is negligible when compared to the drag exerted by stem and litter of the vegetation found in the system (Kadlec et al. 2009). This indicates that the maturation of a CSW may have a crucial effect on not only the biological and chemical processes within the system, but also with flow attenuation (Al-Rubaei et al. 2016). Wadzuk et al. (2008) determined that constructed stormwater wetlands showed a substantial portion of the nutrients removed due to high vegetation density and high residency times of inflow in the system under baseflow conditions. Additionally, both Meriman et al. (2016) and Fassman et al. (2004) determined that the full potential of some ecosystems services of the CSW were realized immediately after construction, such as volume and TSS treatment, while others were delayed and fully developed after the first growing season indicating that vegetation growth plays an essential role in CSW performance.

In 1995, Jadhav et al. used estimated flow profiles to investigate how vegetation density, downstream boundaries, and aspect ratio affect detention time. From a one-dimensional model for unsteady, nonuniform flow through dense vegetation in a free water surface constructed wetland it was determined that that depending on the interaction between geometric and hydraulic parameters a wetlands may exhibit three separate behaviors. Of these behaviors, stem drag controls and detention time increases with vegetation density when the downstream weir is low (below 1.00 foot) and flow velocities are high.

On a similar note, Al-Rubaei et al. (2016) determined that sedimentation is likely to be enhanced due to increased vegetation growth in a matured system when compared to a newly constructed system. The presence of total suspended solids (TSS) can affect biota since they transport nutrients, detritus, and other organic matter and when found in large quantities can be detrimental to stream health (EPA 2003). This makes it essential to capture a portion of TSS within a SCM to assure the health of the receiving waters. Low water velocities, coupled with plant litter, promote settling and interception of solid materials in CSWs although hydrodynamic shear forces and/or wave and wind action may tear particles loose from the sediment bed causing re-suspension within the system. Fully vegetated systems stabilize the soil media limiting re-suspension and hence reducing the TSS exiting the system (Kadlec et al. 2009).

Constructed stormwater wetlands have been used in Canada over the past 30 years to improve stormwater quality by providing enough treatment volume in shallow pools. A similar system to the CSW 2.0 located in Hamilton, Ontario with a 56.8 acre watershed as well as three wetland cells designed for extended detention was monitored for five years in terms of water quality (Crowe et al. 2007). From the study it was determined that the facility removed TSS, TP, Cu, Zn, and E. coli on average 64%, 44%, 56%, 40%, and 68%, respectively, indicating that this configuration is adequate for the protection of aquatic life downstream (Crowe et al. 2007).

At the constructed stormwater wetlands located at Villanova University, it is expected that as the overall system matures the performance of the system, due to an increase in vegetation as well as residence time, would have substantially increased from 2012 to 2016. The use of Rhodamine WT dye will aid in determining the impact of vegetation density on the residence time in the wetlands as well as the system's performance under different inflow and outflow conditions.

CHAPTER 3 – METHODOLOGY

3.1 Introduction

The methodology section pertaining to this research focuses on all the equipment utilized for data acquisition at the CSW 2.0 as well as the standard operating procedures for water quality testing. Additionally, some data post-processing will be discussed.

3.2 Continuous Monitoring Equipment

The CSW 2.0 has been continuously monitored for analysis since installation in 2010. To have a comprehensive understanding of the mechanics of the CSW 2.0, a series of rainfall, flow, depth, temperature, dissolved oxygen, and total suspended solids readings have been recorded at different locations throughout the CSW 2.0. This section will focus on the monitoring locations as well as the instrumentation used for water quantity and water quality testing.

3.2.1 Monitoring Locations

As mentioned in section 1.1, the CSW 2.0 was designed with an inlet sedimentation forebay followed by three meanders leading to a secondary detention basin draining into the outlet structure. To create a comprehensive analysis of the CSW 2.0 continuous data has been collected at five separate locations throughout the wetlands. These locations are indicative of key areas of interest and are located at the inlet sedimentation forebay (1 and 2), the end of the first meander (4), and the outlet structure (5) as seen in Figure 3-1. Location 3 monitors inflow entering the inlet sedimentation forebay via the IM pipe.

Figure 3-1: Continuous Monitoring Locations (Google Earth 2017)

Each location is equipped with a Campbell Scientific data logger as well as monitoring equipment for different water quantity, water quality, and weather parameters including rainfall, solar radiation, relative humidity, wind speed, air temperature, flow data, level data, temperature data, dissolved oxygen, and total suspended solids. Table 3-1 describes each monitoring location and the water quantity and water quality parameters measured at each location.

Table 3-1: Monitoring Locations and Descriptions

Map Number	Location Name	Location Description	Water Quantity Parameters	Water Quality Parameters	Weather Parameters
1	SWW FLOW	Measures parameters at the IN.	Flow Meter Pressure Transducer	Dissolved Oxygen Temperature Autosampler	Rain Gauge
2	SWW ET	Measures weather parameters for an Evapotranspiration study at the IN.	-	-	Solar Radiation Relative Humidity Wind Speed Air Temperature
3	IT INLET MAIN	Measures parameters for the IM at a secondary research site.	Flow Meter	-	-
4	M1	Measures parameters at the end of M1.	Pressure Transducer	Dissolved Oxygen Temperature Autosampler	-
5	SWW OUT	Measures parameters at the OUT as well as the end of M3 and the ODB.	Flow Meter Pressure Transducer	Dissolved Oxygen Temperature Autosampler	-

3.2.2 Data Loggers

Each monitoring site is equipped with a Campbell Scientific CR1000 data logger which powers and allows for the efficient data collection of the different instrumentation used at each monitoring location. The CR1000 data logger consists of a measurement and control module and a wiring panel powered by a battery that can be charged with a solar panel or AC power. At the CSW 2.0 each data logger is powered via a PS100 rechargeable battery connected to AC power as seen in Figure 3-2. Additionally, each CR1000 allows for sensor measurement, data reduction, external device control, and data storage. At the CSW 2.0 the CR1000 located at M1 and at the OUT (SWW OUT) communicate via radio to the CR1000 located at the IN (SWW FLOW) which then communicates to a PC via an Ethernet connection.

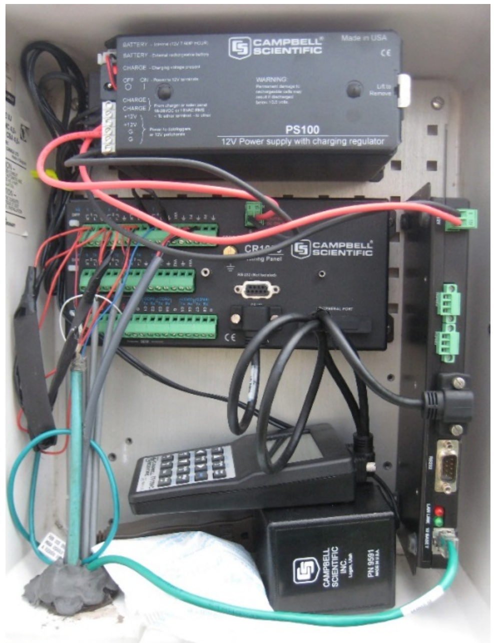

Figure 3-2: SWW FLOW Data Logger Setup

Campbell Scientific's CR1000 can be programmed to be compatible with a series of sensors by using its full programming language CRBasic via a PC through a series of software including PC400, LoggerNet, RTDAQ, PConnect, and VisualWeather. At the CSW 2.0, LoggerNet is used to communicate with each CR1000 to adapt it to the need of each individual monitoring location. Additionally each CR1000 is equipped with a CR1000KD portable keyboard and display screen for easy in field access to monitored data.

3.2.3 Weather Data

A series of weather parameters including rainfall, solar radiation, relative humidity, wind speed, and air temperature are measured at the CSW 2.0. Due to other studies taking place at the IN of CSW 2.0 rainfall is recorded by the SWW FLOW data logger while solar radiation, relative humidity, air temperature, and wind speed are recorded by the SWW ET as seen in Figure 3-3.

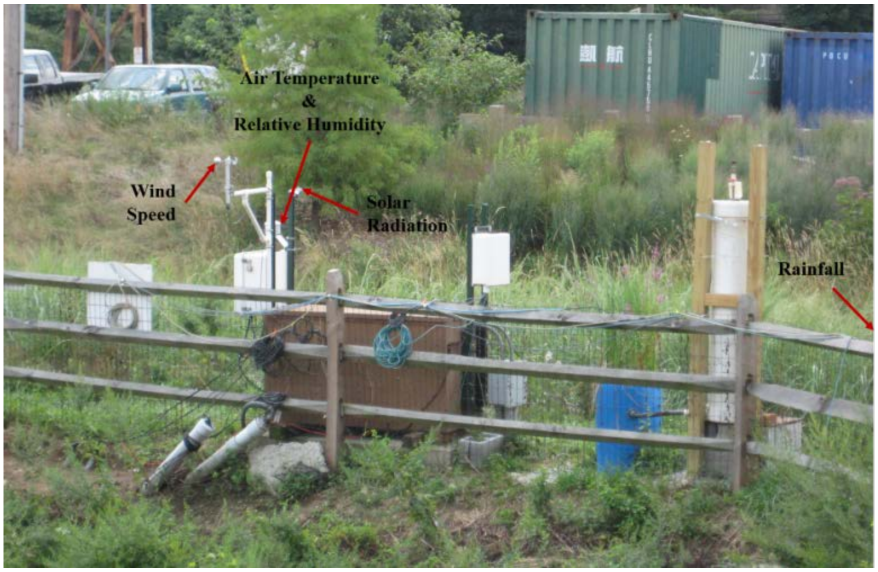

Figure 3-3: Weather Station

3.2.3.1 Rainfall

Rainfall recorded at the CSW 2.0 from 2001 to September 2014 was measured with an American Sigma 2149 Tipping Bucket Rain Gauge. The American Sigma 2149 Rain Gauge is built to National Weather Service standards to accurately measure rainfall in 0.01 inch increments and consists of an 8 inch diameter funnel that directs flow into a tipping bucket as seen in Figure 3-4. The American Sigma 2149 Rain Gauge has an accuracy of 0.5% at 0.5 in/hr and was installed on a level base near the CSW 2.0 SWW FLOW data logger.

Figure 3-4: American Sigma 2149 Tipping Bucket Rain Gauge

In September of 2014 the American Sigma 2149 Rain Gauge was replaced by a Met One 375H Heated Tipping Bucket Rain Gauge to allow for the quantification of snowfall. The Met One 375H Rain Gauge consists of an 8 inch diameter funnel that directs flow into a tipping bucket as seen in Figure 3-5. The Met One 375H Rain Gauge has an accuracy of 0.5% at 0.5" in/hr as well as 1% at 1-3 in/hr and was installed on a level base near the CSW 2.0 SWW FLOW data logger.

Figure 3-5: Met One 375H Tipping Bucket Rain Gauge (will update picture)

3.2.3.2 Solar Radiation

Solar radiation recorded at the CSW 2.0 has been measured since 2011 with a LI-COR LI200X Silicon Pyranometer (Figure 3-6). The LI200X Silicon Pyranometer has a maximum and typical absolute error in natural daylight of 5% and 3% respectively with a sensitivity of 0.2 kW $m^{-2}V^{-1}$ and was installed according to manufacturer's specifications near the CSW 2.0 SWW ET data logger.

Figure 3-6: LI200X Silicon Pyranometer

3.2.3.3 Relative Humidity and Air Temperature

Relative humidity and air temperature recorded at the CSW 2.0 has been measured since 2011 with a Vaisala HMP60 Temperature and Relative Humidity Probe (Figure 3-7). The Vaisala HMP60 Temperature and Relative Humidity Probe measures temperature via a 1000 ohm Platinum Resistance Thermometer with a measurement range of -40° to +60°C and an accuracy of +0.6°C. Additionally, the sensor measures relative humidity via an INTERCAP capacitive chip with a measurement range of 0 to 100% and a typical accuracy as seen in Table 3-2.

Figure 3-7: Vaisala HMP60 Temperature and Relative Humidity Probe with a Solar Radiation Shield

Table 3-2: Vaisala HMP60 Relative Humidity Accuracy

Temperature Range	Typical Accuracy 0% to 90% Relative Humidity	Typical Accuracy 90% to 100% Relative Humidity
-40ºC to 0 ºC	5%	7%
0ºC to 40 ºC	3%	5%
40ºC to 60 ºC	5%	7%

3.2.3.4 Wind Speed

Wind speed recorded at the CSW 2.0 has been measured since 2011 with a Met One 014A Anemometer (Figure 3-8). The Met One 014A Anemometer has a range of 0 to 45 m/s (0 to 100 mph) with an accuracy of 1.5% or 0.11 m/s (0.25 mph) and was installed according to manufacturer's specifications near the CSW 2.0 SWW ET data logger.

Figure 3-8: Met One 014A Anenometer

3.2.4 Flow Data

The CSW 2.0 consists of four inflow pipes, two monitored and two unmonitored, as well as a monitored outflow pipe (Figure 3-9) where the unmonitored inflow pipes are circled in red. Each monitored pipe is equipped with a flow meter to aid in quantifying the volume entering and exiting the system as well as the system's capacity at peak flow attenuation. Each flow meter mentioned in the following sections do not require calibration outside of the manufacturer's initial calibration.

Figure 3-9: Flow Monitoring Location (Google Earth 2017)

3.2.4.1 Inlet Main Inflow Pipe

Inflow from the watershed located on the Main Campus of Villanova University was measured from October of 2010 to March of 2012 by a Sigma 950 area velocity flow meter installed in a 106.7 cm (42 in) concrete pipe. The Sigma 950 flow meter was installed near a secondary monitoring site on main campus, IT INLET MAIN, and measures both velocity and depth to calculate the flow rate entering the system. Each velocity reading is determined via a Doppler ultrasonic sensor with an accuracy of 2% and a recommended range of -1.52 m/s to 6.1 m/s (-5 ft/s to 20 ft/s). A minimum depth of 2 cm (0.8 in) is required for accurate measurements. Due to this, a hydraulic cement dam was installed to increase depth in the area allowing for the depth reading during baseflow conditions to be between 8.64 cm to 9.65 cm (3.4 in to 3.8 in). Each depth measurement is determined via a pressure transducer with a depth range of 0 m to 3 m (0 ft to 10 ft) with a maximum allowable depth of 10.5 m (34.5 ft). The accuracy is temperature dependent as seen in Table 3-3.

Table 3-3: Accuracy of Sigma 950 Flow Meter Depth Reading

Temperature Range	Typical Accuracy
Constant Temp (± 2.5°C)	1.5%
0ºC to 30 ºC	1.7%

In March of 2012 the Sigma 950 area velocity meter was replaced by a Greyline AVFM 5.0 area velocity flow meter. The Greyline AVFM 5.0 flow meter uses a submerged ultrasonic sensor to measure both velocity and depth within the channel to calculate the flow rate entering the system. The Greyline AVFM 5.0 flow meter has a velocity range of -1.5 m/s to 6 m/s (-5 ft/s to 20 ft/s) with a flow depth range of 2.54 cm to 4.5 m (1 in to 15 ft). Each velocity reading is determined via Doppler ultrasonic sensor with an accuracy of 2% while each depth reading is determined via ultrasonic pulses with an accuracy of 0.25 %.

3.2.4.2 Inlet West Inflow Pipe

Inflow from the watershed located on the West Campus of Villanova University was measured from May of 2010 to December of 2014 by a Greyline AVFM-II area velocity flow meter installed in a 121.92 cm (48 in) concrete pipe. The Greyline AVFM-II flow meter was installed at the IN and is connected to the SWW FLOW data logger on site to effectively record and measure both velocity and depth used to calculate the flow rate entering the system. The Greyline AVFM-II flow meter has a velocity range up to 6 m/s (20 ft/s) with a flow depth range of 0 m to 5 m (0 ft to 16.4 ft). Each velocity reading is determined via Doppler ultrasonic sensor with an accuracy of 2% while each depth reading is determined via ultrasonic pulses with an accuracy of 0.25 %.

In December of 2014 the Greyline AVFM-II area velocity flow meter was replaced by a Unidata Starflow 6526H flow meter, Figure 3-10. The Unidata Starflow 6526H flow meter is profiled to reduce flow disturbance and signal electronics and is designed to be placed at the bottom of the water channel for upstream measurements. The Unidata Starflow 6526H flow meter has a bi-directional velocity range of 21 mm/s to 4.5 m/s (0.1 in/s to 14.76 ft/s) with a flow depth range of 2.54 cm to 2 m (1 in to 6.56 ft). Each velocity reading is determined via Doppler ultrasonic sensor with an accuracy of 2% while each depth reading is determined via a hydrostatic pressure sensor with an accuracy of 0.25 %.

Figure 3-10: Inlet West Unidata Starflow Flow Meter

3.2.4.3 Outlet Outflow Pipe

Outflow from the CSW 2.0 was measured from construction to February of 2013 by a Sigma 950 area velocity flow meter installed in a 91.44 cm (36 in) concrete pipe downstream of the outlet structure and is connected to the SWW OUT datalogger. Refer to section 3.2.4.1 of this report for the Sigma 950 flow meter specifications. In February of 2013 the Sigma 950 flow meter was replaced by a Greyline AVFM 5.0 area velocity flow meter, Figure 3-11. Refer to section 3.2.4.1 of this report for the Greyline AVFM 5.0 flow meter specifications.

Figure 3-11: Outflow Greyline AVFM 5.0 Flow Meter

3.2.5 Level Data

The CSW 2.0 measures water level and water pressure at three separate locations to supplement flow measurement and act as a check. Both IM as well as the OUT have been submitted to continuous level and pressure monitoring from the construction of the CSW 2.0 to the present time. In the fall of 2015 a third pressure transducer was installed at the end of M1. To ensure proper readings, each pressure transducer is calibrated every four months. It must also be noted that all pressure transducers are removed from the CSW 2.0 once temperatures reach levels below freezing and are reinstalled once temperatures remain above freezing. This measure is taken due to manufacturer's specifications of the sensor's operating temperature.

3.2.5.1 Inlet Main Inflow Pipe

Water level at the exit of the IM inflow pipe (Figure 3-12) has been recorded from 2009 to July of 2014 by an Instrumentation North West (INW) PS9800 pressure transducer connected to the SWW FLOW data logger. The INW PS9800 is a rugged and accurate pressure transducer with noise immunity designed to be submerged in liquid environments. Pressure is measured with a piezo-electric pressure element with a 0.1% accuracy and then translated to a depth reading via a linear relationship of voltage read by the meter to increasing water depth. Additionally temperature is measured with a typical accuracy of 0.3°C and an operating range of -24°C to 48°C. In July of 2014 the INW PS9800 was replaced by an INW PS9805. The INW PS9805 uses the same technology as the INW PS9800 and maintains the 0.1% accuracy.

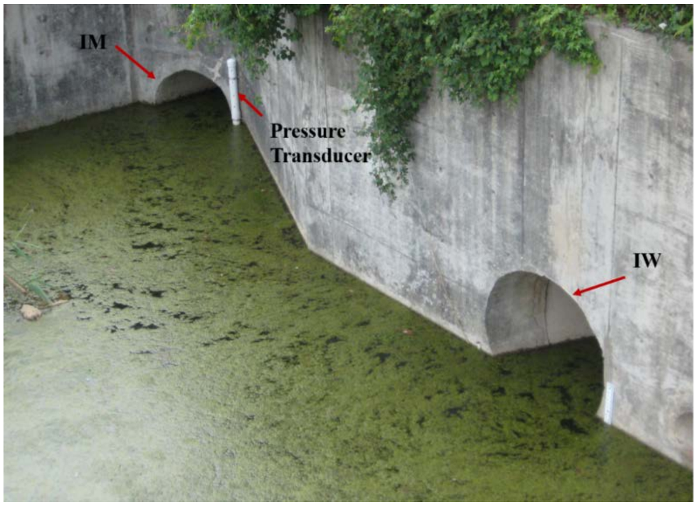

Figure 3-12: Inlet Main Pressure Transducer Location

3.2.5.2 End First Meander Sluice Gate

Water level at the sluice gate located at the end of M1 (Figure 3-13) was measured beginning in December of 2015 with a Campbell Scientific CS450 pressure transducer connected to the M1 data logger. The CS450 pressure transducer provides temperature compensated pressure measurements via a piezoresistive sensor with an accuracy of 0.1% which is then translated to a depth reading via a simple psi to feet of water conversion (1 psi = 2.31 ft of water).

Figure 3-13: End of M1 Pressure Transducer Location

3.2.5.3 Outlet Structure

Water level at the entrance of the outlet structure (Figure 3-14) has been recorded since December of 2010 by an INW PS9805 pressure transducer connected to the SWW OUT data logger. Refer to section 3.2.5.1 of this report for the PS9805 pressure transducer specifications.

Figure 3-14: Outflow Structure Pressure Transducer Location

3.2.6 Temperature Data

The CSW 2.0 has been equipped with a series of Campbell Scientific 107 temperature probes since the summer of 2014. The 107 temperature probe uses a BetaTherm 100K6A thermistor to measure temperature within a range of -35°C to 50°C with an accuracy of 0.4°C and is submersible up to 50 ft. To have an adequate understanding of the temperature flux within the CSW 2.0 and to supplement the data provided by the pressure transducers, a temperature probe was installed at the entrance of IM, the end of M1, the end of M3, and the end of the ODB.

3.2.7 Total Suspended Solids

During the summer of 2016, the CSW 2.0 was equipped with a Sequoia Scientific LISST-Acoustic Backscatter Sensor (LISST-ABS) to measure the concentration of total suspended solids (TSS) entering the system (Figure 3-15). The LISST-ABS sensor is an acoustic backscatter sensor designed to measure suspended sediment concentration at a specific point at 5 cm (1.97 inches) from the transducer within a range of 1 mg/L to 30 g/L, depending on particle size, with a resolution of 0.5%. The LISST-ABS sensor measures backscatter at approximately 5 cm (1.97 inches) from the sensor to reduce the effect of water attenuation on the readings allowing the sensor to be used in water bodies with high levels of TSS. Additionally the LISST-ABS sensor is far less sensitive to grain size changes, when compared to optical turbidity sensors, with only a 30% change in calibration when reading particles between 30 and 400 microns.

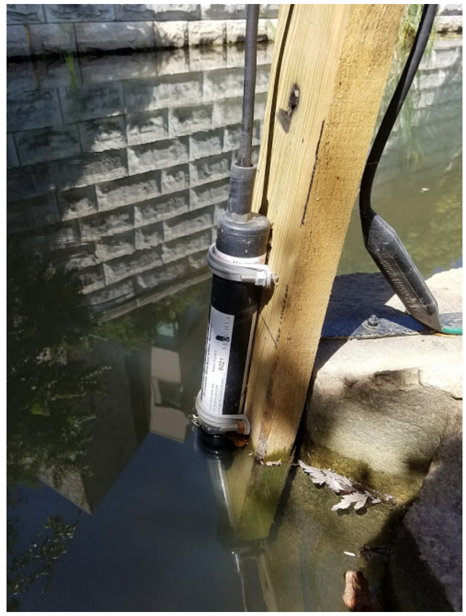

Figure 3-15: LISST-ABS TSS Sensor

3.3 Sampling and Testing Methods

The CSW 2.0 has been monitored for water quality analysis since installation in 2011 to determine the system's performance in terms of nutrient removal both during dry and wet weather. To have a comprehensive understanding of system performance, the CSW 2.0 has been tested for Nitrite (NO_2), Nitrate (NO_3), Orthophosphate (PO_4), Chlorides (Cl), Ammonia (NH_3), Total Kjeldahl Nitrogen (TKN), and Total Phosphorus (TP). This section focuses on the monitoring locations as well as the standard laboratory procedures for water quality testing.

3.3.1 Sampling Procedures

The CSW 2.0 has been tested both during dry weather and wet weather conditions at key locations to aid in determining the system's performance. From 2011 to February of 2014 all samples were collected in 350 mL glass bottles previously washed in a 10% Hydrochloric Acid

Solution and subsequently rinsed in deionized water. In February of 2014 these bottles were replaced by 600 mL polyethylene bottles to facilitate laboratory testing.

3.3.1.1 Dry Weather Sampling

At the CSW 2.0 dry weather or baseflow conditions is identified by a period of 72 hours after the last recorded rainfall or once the outflow is less than 0.10 cfs whichever occurs first. Once these conditions have been met, two separate water samples are collected as grab samples at the IN, end of M1, end of M2, end of M3, and at the OUT, Figure 3-16, and labeled as seen in Table 3-4. The samples are then immediately transported to the laboratory to be processed for water quality testing.

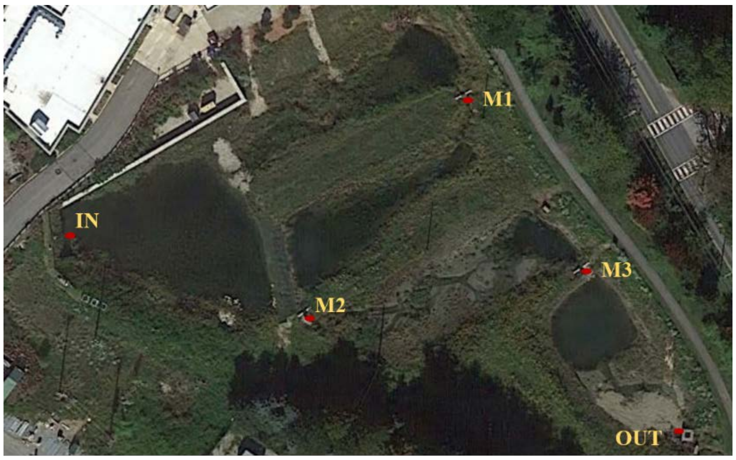

Figure 3-16: Baseflow Conditions Sampling Locations (Google Earth 2017)

Table 3-4: Baseflow Conditions Sample Names

Location	Sample Name
INLET	IN-1
	IN-2
End M1	M1-1
	M1-2
End M2	M2-1
	M2-2
End M3	M3-1
	M3-2
OUT	OUT-1
	OUT-2

3.3.1.2 Wet Weather Sampling

At the CSW 2.0 the beginning of wet weather or storm conditions is identified by a period of over 0.10 in of rainfall and ends once there has been six hour dry period after the last recorded rainfall. To account for any initial abstractions of the storm event, water quality sampling occurs on storm events greater than 0.25 in. From 2011 to August of 2014 grab samples were collected after the storm following the sampling procedures and sampling locations described in section 3.3.1.1.

In August of 2014 Sigma 900 MAX autosamplers were installed at the IN, end of M1, and at the OUT (Figure 3-17) to collect composite samples, labeled as seen in Table 3-5, during the storm event. Each autosampler holds four 600 mL bottles that are filled with three 200 mL samples triggered by a pulse emitted from the rain gauge at certain rain intervals. A 45 and 90 minute delay was chosen for the M1 and OUT, respectively, to account for the travel time of pollutant within the wetlands. Figure 3-18 highlights the different rain intervals used to trigger each sample collection.

Figure 3-17: Autosampler Sampling Locations (Google Earth 2017)

Table 3-5: Storm Event Composite Sample Names

Location	Sample Name
INLET	AS-IN1
	AS-IN2
	AS-IN3
	AS-IN4
End M1	AS-M1-1
	AS-M1-2
	AS-M1-3
	AS-M1-4
OUT	AS-OUT1
	AS-OUT2
	AS-OUT3
	AS-OUT4

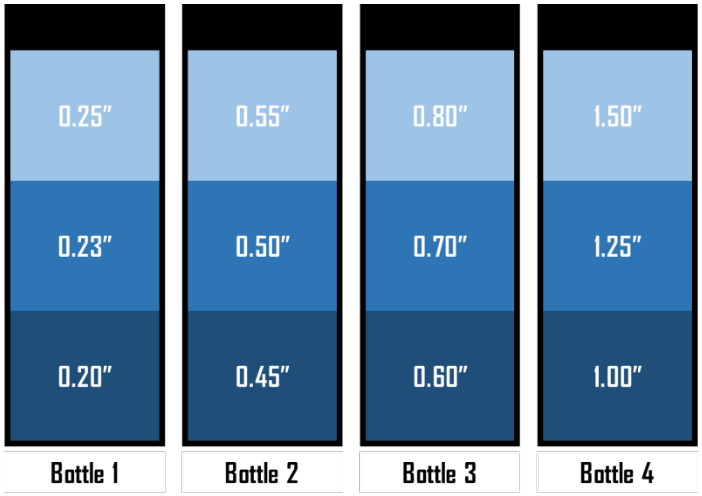

Figure 3-18: Rain Intervals for Sample Collection

After some data analysis it was determined that both the rainfall intervals at which each sample is collected as well as the time delay for sample collection at M1 and the OUT was modified to fully capture the hydrograph of an array of different storms ranging both in intensity as well as rainfall amount (7/17/2015). Due to this the rain intervals were changed as seen in Figure 3-19 and the sampling time delay of 90 min and 280 min was included for sampling at M1 and at the OUT, respectively, to account for the travel time within the system.

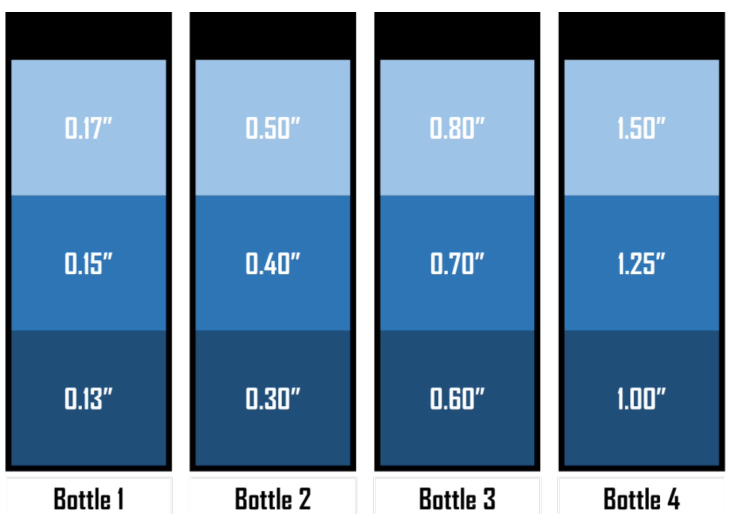

Figure 3-19: Adjusted Rain Intervals for Sample Collection

3.3.2 Standard Testing Procedures

Once the samples have been collected and taken to the laboratory for testing, a portion of each sample is set aside in a 100 mL bottle, previously washed in a 10% Nitric Acid solution and rinsed with an 18 Ω ohm milliq water, for nutrient testing. Additionally, 50 mL of each sample is preserved with 0.1 mL of Sulfuric Acid for both TKN and TKP testing. Due to the nature of this study only the standard testing procedures will be discussed for Total Suspended Solids (TSS) and Total Dissolved Solids (TDS).

3.3.2.1 Total Suspended and Dissolved Solids

Both TSS and TDS are calculated by filtering a known volume of a sample through a filter membrane with a known pore size and then drying the filtered volume in a beaker to identify the mass of particles that remains on the filter (TSS) and subsequently in the beaker (TDS). This process involves three main stages: Pre Testing Preparation, Testing, and Post Testing Analysis.

3.3.2.1.1 Pre TSS and TDS Testing Preparation

Prior to TSS and TDS testing, both filter membranes as well as 400 mL beakers must be prepared. When preparing to test TSS on samples collected at the CSW 2.0, 1.5 µm filter membranes are placed in individually labeled tins and placed in a 105°C oven for 3 to 6 hours to ensure moisture extraction. Once each tin has been removed from the oven they must be placed in a desiccator until ready to be weighed. In a similar fashion, 400 mL beakers, previously labeled and washed, in a 10% Nitric Acid solution and rinsed with an 18 Ω ohm milliq water, are placed in a 180°C oven for 24 hours. Once each beaker has been removed from the oven they must be placed in a desiccator until ready to be weighed.

Once both the filters and beakers have been removed from the oven and placed in the desiccator, individual weighing may commence. Each individual filter tin is placed on an analytical balance for at least 15 minutes and the weight is recorded to the nearest 0.0001 g, as well as the ID of the scale used. In a similar fashion each individual beaker is placed on an analytical balance for at least 30 minutes. Once weighed both filters and beaker are placed back in the desiccator until ready for testing.

3.3.2.1.2 TSS and TDS Testing

On the day of TSS and TDS testing, the appropriate number of pre-weighed filter tins and beakers are removed from the desiccators and assigned to a specific sample. Additionally the appropriate number of filter units and Erlenmeyer flasks, previously washed in a 10% Nitric Acid solution and rinsed with an 18 Ω ohm milliq water, are assembled and connected to a vacuum pump as seen in Figure 3-20.

Figure 3-20: TSS/TDS Filtering Apparatus

Using tweezers, each filter is placed on the filtering apparatus and 300 mL of the sample being tested is measured using a graduated cylinder previously washed in a 10% Nitric Acid solution and rinsed with an 18 Ω ohm milliq water. The sample is then poured into the filtering apparatus, the vacuum pump is turned on, and all floating debris such as twigs or grass are removed. Once the sample has completely filtered through, each filter is returned to its corresponding tin and placed in a 105°C oven for 3 to 6 hours. The remaining filtrate is then poured into its corresponding beaker and placed in a 180°C oven for at least 24 hours. Once dry, the filters and beakers are returned to the desiccator.

3.3.2.1.3 Post TSS and TDS Testing Analysis

Once both the filters and beakers have been removed from the oven and placed in the desiccator, individual weighing may commence. Using the same scale used when pre-weighing, each individual filter tin and beaker is weighed following the procedure described in section 3.3.2.1.1. Once the final weight has been recorded, TSS and TDS concentration can be calculated by finding the difference between pre and post weighed values, multiplying by 1000 (to convert grams to milligrams) and dividing by the sample volume used during testing.

3.4 Rhodamine Dye Tracer Tests

Two Precision Measurement Engineering (PME) Cyclops-7 Loggers were used since 2013 to measure the concentration of Rhodamine WT dye introduced into the CSW 2.0 using a fluorescent light sensor. Each sensor operates using a visible light diode to sense Rhodamine concentrations in a solution with a range of 0 to 1000 µg/L (ppb) with a minimum detection limit of 0.01 ppb. This section focuses on the PME Cyclops-7 sensor calibration as well as sensor deployment and dye release.

3.4.1 Calibration

Each PME Cyclops-7 Logger is required to be calibrated before each deployment using a two point procedure using a 0 ppb solution and a 100 ppb solution. To do so the 100 ppb standard was created from a Keystone Rhodamine WT concentrated solution of 200,000 mg/L. Once this standard has been created, the PME provided Cyclops-7 software is used to measure the sensor output in the solution as well as the sensor sensitivity to calculate the concentration read by the sensor. A separate calibration curve for each sensor was created with previously prepared 5 ppb, 10 ppb, 25 ppb, 50 ppb, and 100 ppb standards (Figure 3-21) where Sensor 21 refers to one of the sensors used and Sensor 22 refers to the second sensor used.

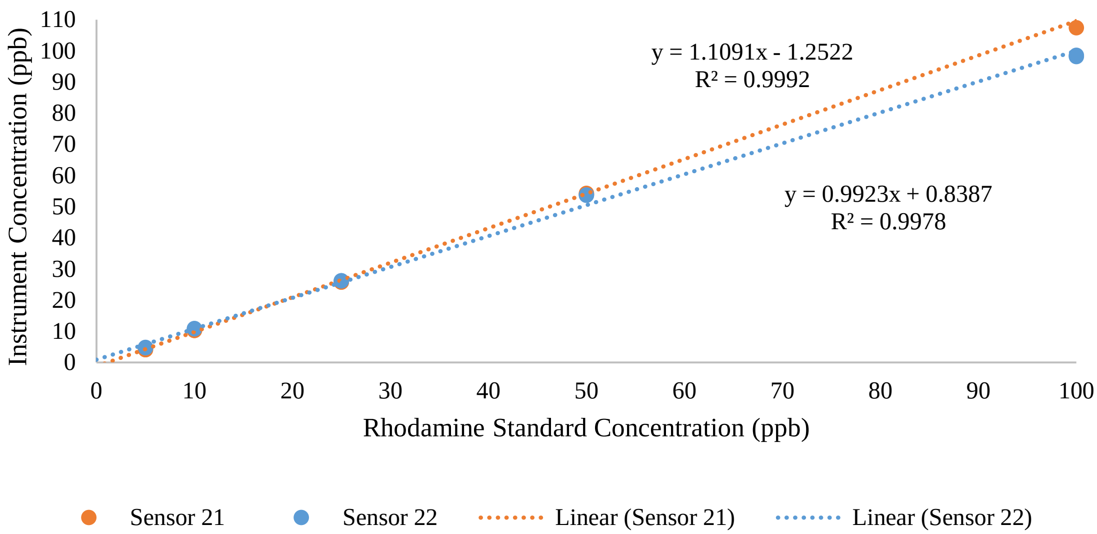

Figure 3-21: PME Cyclops-7 Calibration Curve

3.4.2 Deployment

To have a good understanding of the traveling time within the system each probe was located at strategic points in the CSW 2.0 including the south east corner of the IN, beginning of M1, the end of M1, the end of M2, and the OUT. A known volume of the Rhodamine WT dye was released at two separate locations to aid in creating a comprehensive profile of the travel time within the system, Figure 3-22. The amount of dye released into the CSW 2.0 is measured using 10 mL pipettes and the mass of the tracer input was calculated from the volume introduced into the system and the concentration of the stock solution.

Figure 3-22: Tracer Test Deployment Locations and Dye Release (Google Earth 2017)

The yellow dots represent probe deployment and red dots represent dye release.

3.4.3 Data Postprocessing

Each PME Cyclops-7 Logger stores within a SD card data files reporting the time of each sample reading as well as the battery voltage of the logger, water temperature, and rhodamine concentration. Before calculating the mean detention time the raw recorded concentration is plotted to determine whether or not the whole curve was captured by each probe. If the curve appears to be cut off then it is not taken into consideration when analyzing the mean detention time since the curve is not representative of mean detention of the whole tracer event.

Additionally, the inexplicable dips or rises in concentration were cleaned to create a smoother curve (Figure 3-23).

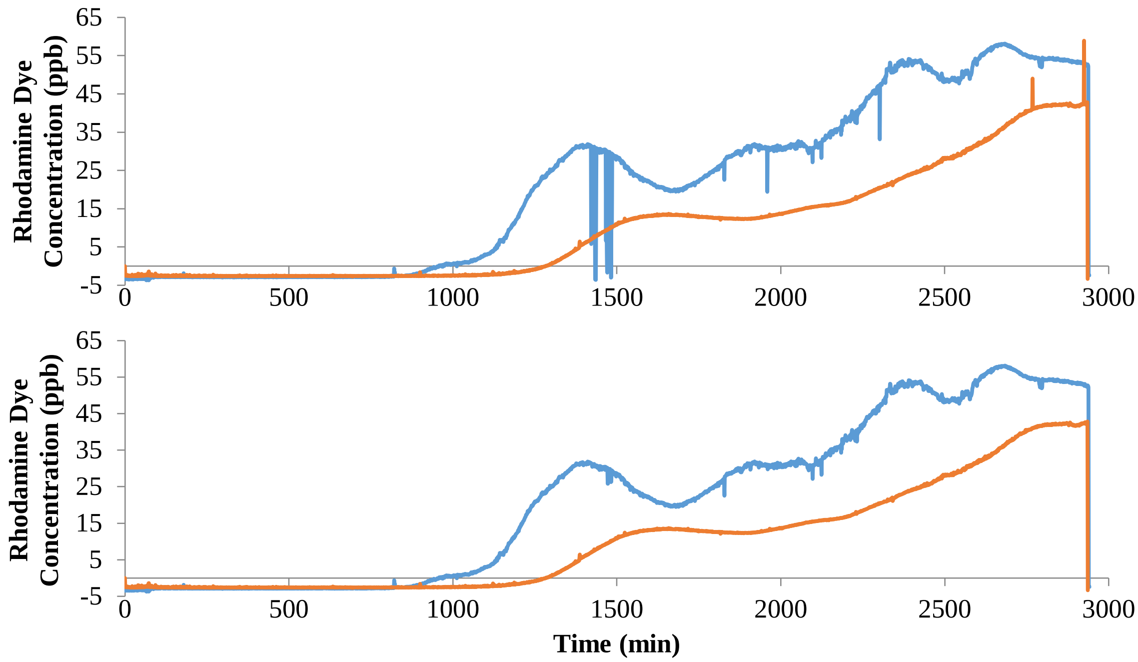

Figure 3-23: Cut-off Rhodamine Dye Concentration Curve

The top graph is an example of a cut-off curve while the bottom graph is an example of a clean graph where the blue line and orange line represents the concentration recorded at the beginning of M1 and the end of M1, respectively.

Since the rhodamine dye is released into the system at a specific point in time, it is assumed that the system will be analyzed as a pulse input dye test. The mean residence time is calculated by a ratio of the first moment under the curve and the area under the curve. Where C is the concentration read and Δt is the time sampling interval selected.

$$Mean\ detention\ time = \bar{t} = \frac{1^{st}\ moment\ of\ area\ under\ curve}{Area\ under\ the\ curve} = \frac{\sum C\Delta t * t}{\sum C\Delta t}$$

CHAPTER 4 – YEARLY FLOW, CLIMATE, AND VEGETATION CORRELATIONS

3.1 Introduction

To fully understand what is occurring at the CSW 2.0 over time, one must consider the physical changes experienced. To aid in understanding these changes, the flow entering and exiting the CSW 2.0 was analyzed from July 2012 to December 2016. Additionally, climatological parameters will be analyzed for the same time period and compared to the changes seen both in terms of the observed changes in flow and in vegetation.

3.2 Data Methodology

Data at the CSW 2.0 is averaged over a 5 minute interval and recorded on the CR1000 data logger on site. As mentioned in section 3.2.2, each CR1000 communicates to the LoggerNet software via an Ethernet connection and data is downloaded from each logger every 30 minutes. The recorded data is then uploaded monthly to a Microsoft Access database which stores and combines all the data from the different loggers and instruments to aid in data analysis. At the end of 2015, a Matlab based data interface was created by Dr. Ryan Lee to further aid in data storage and analysis. This section will focus on how different flow events are defined at the CSW 2.0 as well as the methods used to supplement missing flow data in the system.

3.2.1 Event Definition

To aid in analyzing the data collected at the CSW 2.0, three separate flow events have been defined; Storm Event, Interflow Event, and Baseflow Event. Each event is defined by a combination of rainfall recorded, elapsed time, and recorded outflow. At the CSW 2.0, a Storm

Event is defined as any period of time where the sum of rainfall is greater than 0.10 inches and there has not been a 6 hour gap between rainfall recordings. If there is a 6 hour gap since the last rainfall recording, an Interflow Event begins.

At the CSW 2.0, an Interflow Event is any period of time directly after a Storm Event where the rainfall recorded is less than 0.10 inches. Additionally, an Interflow Event ends after 72 hours from the end of the previous Storm Event or when the outflow reads below 0.10 cfs, whichever occurs first. At this moment a Baseflow Event begins.

At the CSW 2.0, a Baseflow Event is defined as any period of time directly after an Interflow Event where the rainfall recorded is less than 0.10 inches. This event ends once the rainfall recorded is greater than 0.10 inches at which point a Storm Event begins. For the sake of this study both the Interflow Events and Baseflow Events will be analyzed together since their conditions represent each other more closely than when compared to a Storm Event.

3.2.2 Data Post-Processing

The interface created by Dr. Ryan Lee aids in determining the integrity of the collected data and can be used to set upper and lower limits to each data set. From historical data at the CSW 2.0, an upper limit cap of 3.00 cfs was set at each individual inflow pipe (i.e., IM and IW) and any event with a passing integrity less than 80% is individually inspected and compared to the recorded rainfall. If the recorded rainfall as well as the supplemented data do not warrant the high flow recorded, said values are set to the upper limit.

3.2.3 Supplemented Data

As mentioned in Chapter 3, the CSW 2.0 houses a series of instruments to measure flow within the system. Occasionally, due to power loss and or instrumentation maintenance, there are periods of time with missing inflow data and/or outflow data. This section focuses on the model used to supplement missing inflow data entering the system as well as the equations developed to supplement the missing outflow data.

3.2.3.1 Unmonitored Inflow

In 2011 James Pittman IV used the United States Environmental Protection Agency's (EPA) Storm Water Management Model (SWMM) to model the CSW 2.0 to aid in understanding how the system would react in predicted storm and baseflow events (Pittman 2011). This model includes both the monitored and unmonitored inflow pipes as well as the full extent of the watershed entering the system, Figure 4-1.

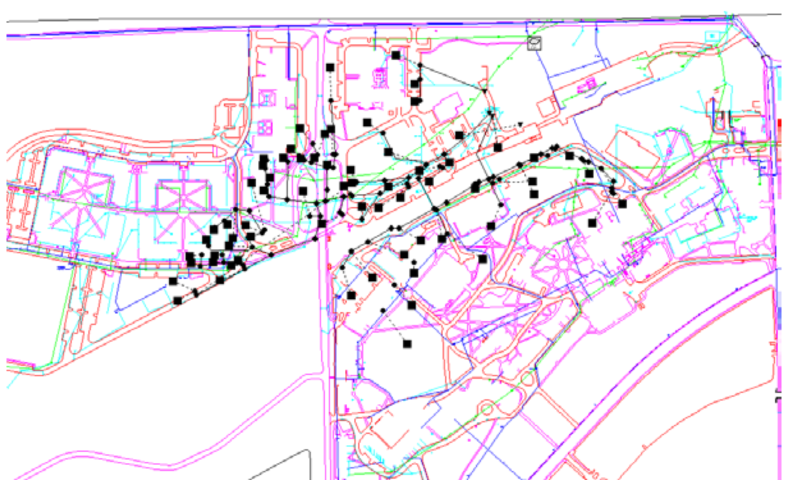

Figure 4-1: EPA SWMM Model of CSW 2.0 (Pittman 2011)

Once the model was calibrated and validated, the rainfall data collected at the CSW 2.0 was used to run the model and the inflow at each pipe (i.e., IW and IM) was determined and added to the database in Microsoft Access. This modeled data is used during time periods when there was missing flow data from the flow meters. When compared to the upper limit cap set for each inflow pipe, the supplemented data only exceeds on average by 8.3% with an average max inflow of 25.6 cfs recorded at IM and IW and an average max inflow of 16.3 cfs recorded at the two unmonitored pipes during the study period.

Additionally, the modeled flow entering the system was analyzed and it was determined that 17% of the total modeled inflow entering the CSW 2.0 is from the two unmonitored pipes. Thus, the Total Inflow entering the system consists of the sum of the inflow from the IW and IM inflow pipes as well as a 17% addition during storm events to account for the unmonitored inflow pipes.

3.2.3.2 Outlet Weir Structure

As previously mentioned in Chapter1, the CSW 2.0 is equipped with an outlet structure designed to handle different sized storm events, up to the 100 year storm, via a combination of weirs and orifices. This structure is equipped upstream of the weirs with a pressure transducer to measure depth and slightly downstream of the weirs with a flow meter to measure velocity, depth, and flow rate exiting the system (Refer to Chapter 3). This instrumentation layout allows for the creation and validation of weir equations to convert depth into flow rate for those time periods where there is missing outflow data due to power loss or instrumentation maintenance.

From the complex combination of weir and orifice flow at the outlet structure, five separate scenarios to convert the depth of the outflow to flow rate were defined (Table 4-1 and Figure 4-2). Each equation is representative of the type of weir flow experienced at each depth as well as the type of orifice flow.

Table 4-1: Outlet Structure Depth to Flow Scenarios

System Depth (in)	Scenario	Equation Type
2.85 - 16.35	1	Weir 1
16.36 - 27.3	2	Orifice 1
27.4 - 63.3	3	Orifice 1 Weir 2
63.4 - 67.3	4	Orifice 1 Weir 2 Weir 3
> 67.4	5	Orifice 1 Orifice 2

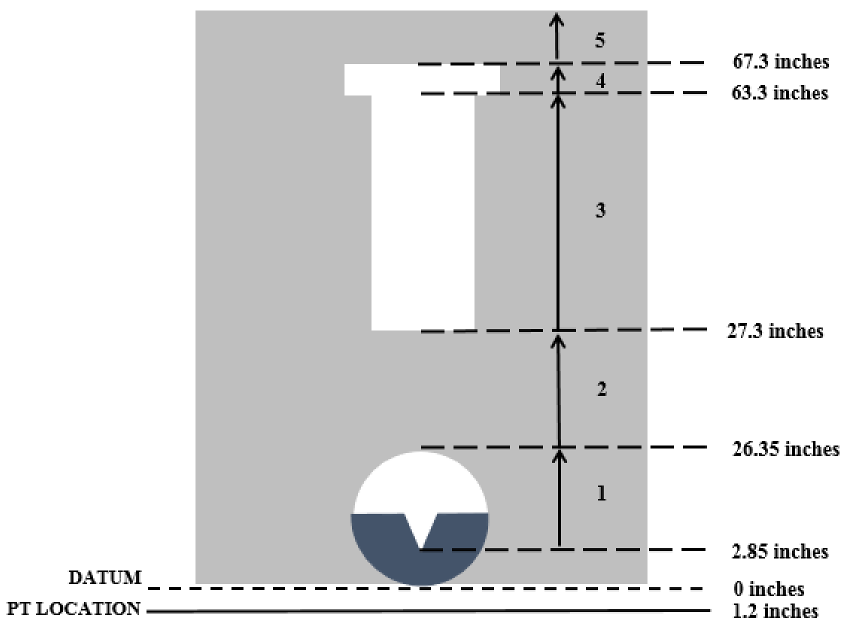

Figure 4-2: Outlet Structure Depth to Flow Scenario Visualization

From these scenarios and equations, a depth to flow curve was determined as seen in Figure 4-3 where the dotted grey lines represent the depth at which each scenario commences and the blue curve represents the calculated curve. Now that a relationship between flow and depth was created, the curve was validated using several different sized storm events during the study period (Table 4-2).

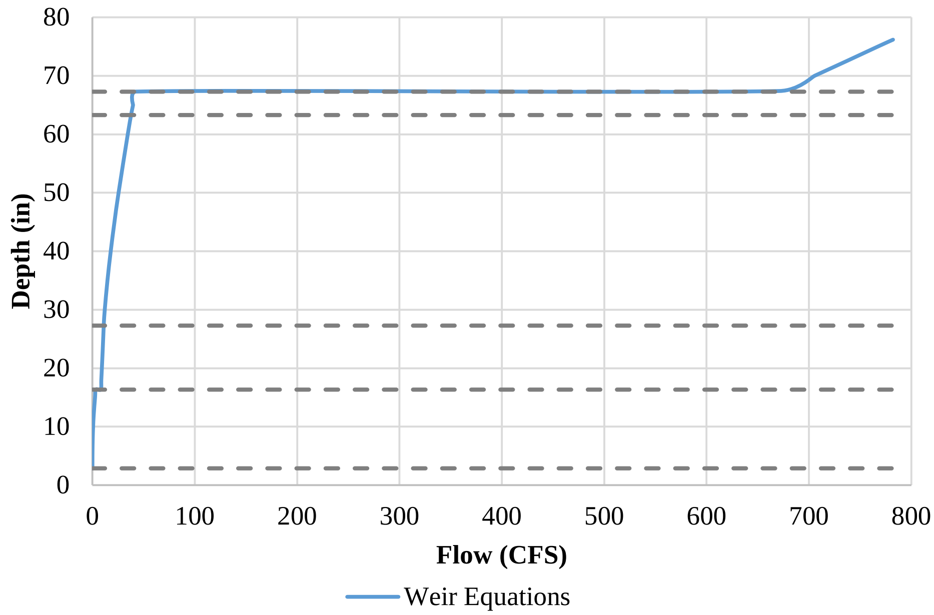

Figure 4-3: Depth to Flow Curve from Weir Equations

Table 4-2: Storm Characteristics for Depth to Flow Curve Validation

Storm Size (in)	Storm Date	Storm Duration (hrs)
0.14	4/23/2016	7.92
0.19	7/26/2014	7.08
0.19	10/30/2016	7.00
0.29	10/7/2014	8.92
0.40	10/11/2014	14.58
0.51	10/3/2014	15.67
0.75	3/18/2013	22.50
1.00	1/3/2015	28.92

The validation storm events were selected due to the availability of both level data as well and flow data from the outflow meter, as well as spanning a range of typical storm sizes. When plotted against the original depth to flow curve one can see that the measured flow to depth relationships match the measured data within ± 10% as denoted by the two red dotted lines in Figure 4-4. On the other hand once flow transitioned from the first flow scenario to the second flow scenario (weir to orifice flow), as denoted by the grey dashed line, the observed flow to depth relationship diverged from the calculated curve. This may be due to an increase in turbulence during the transition which may be affecting the flow readings downstream of the weir structure. To determine whether or not this is the case, both the velocity and depth recorded by the flow meter were analyzed for both the 10/7/2014 Storm Event and the 1/3/2015 Storm Event.

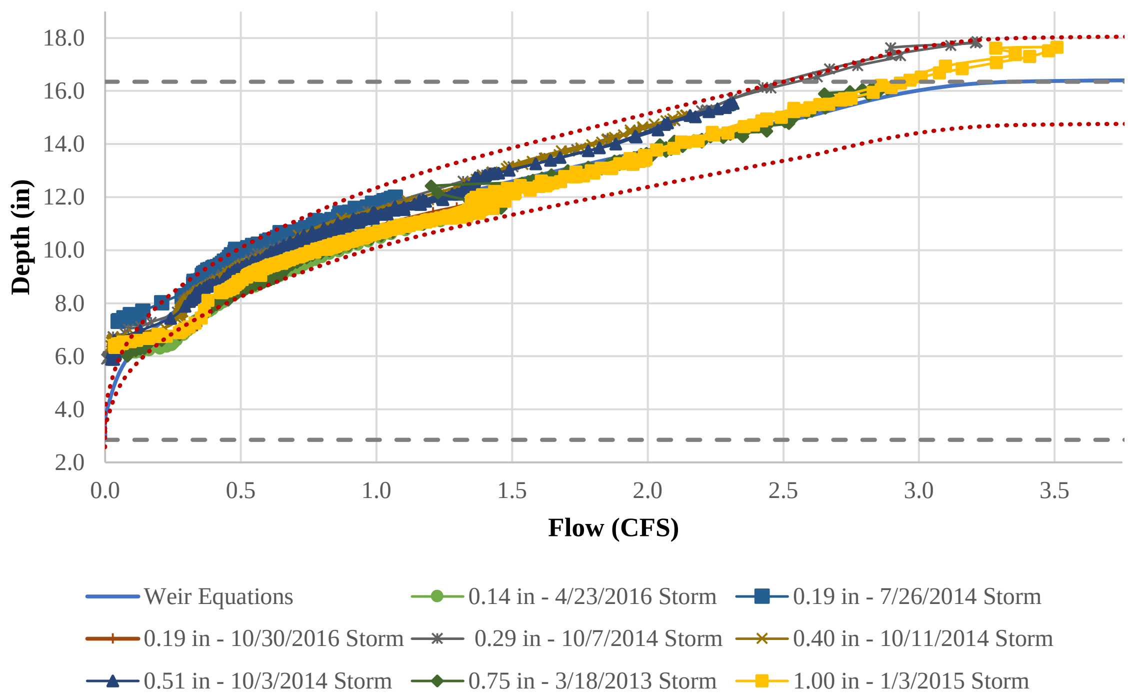

Figure 4-4: Depth to Flow Curve Validation

When looking at the relationship between the depth recorded by the pressure transducer and the depth recorded by the flow meter (Figure 4-5), one can see an almost perfect linear relationship for both the 10/7/2014 storm with an R^2 value of 0.87 and the 1/3/2017 storm with an R^2 value of 0.96. This indicates that both instruments are mirroring each other in terms of recording the changes that occur with the increase of outflow at the CSW 2.0 during a storm event. Additionally, this relationship indicates that changes in depth experienced downstream of the weir structure are not driving the previously identified difference in recorded flow versus the calculated flow curve using the weir equations.

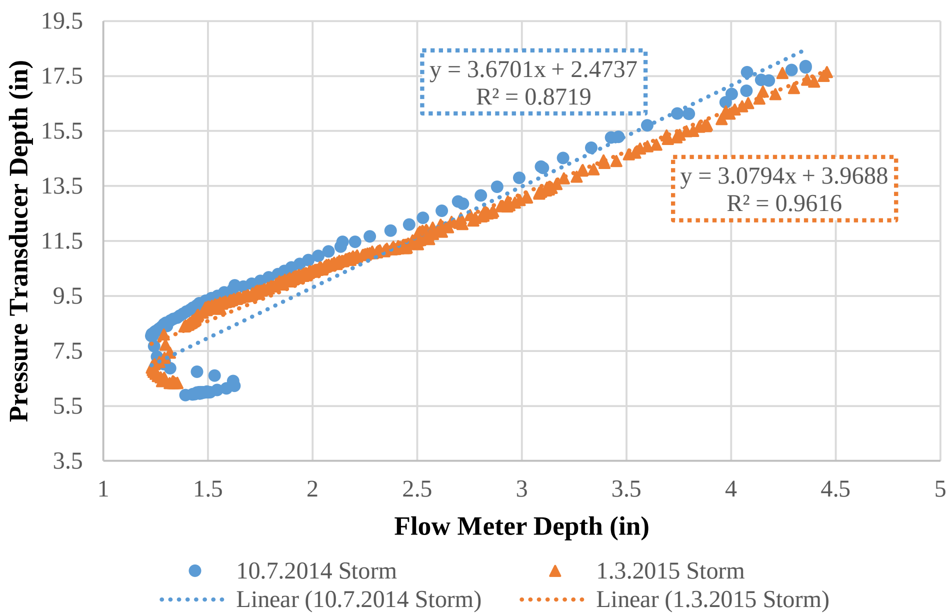

Figure 4-5: Flow Meter Depth to Pressure Transducer Depth Relationship

In addition to identifying the relationship between the depth recorded by the pressure transducer and the depth recorded by the flow meter, the relationship between the depth and the velocity recorded by the flow meter was established, Figure 4-6. From this analysis it can be seen that there is a higher variation in velocity over small increases of depth during both Storm Events.

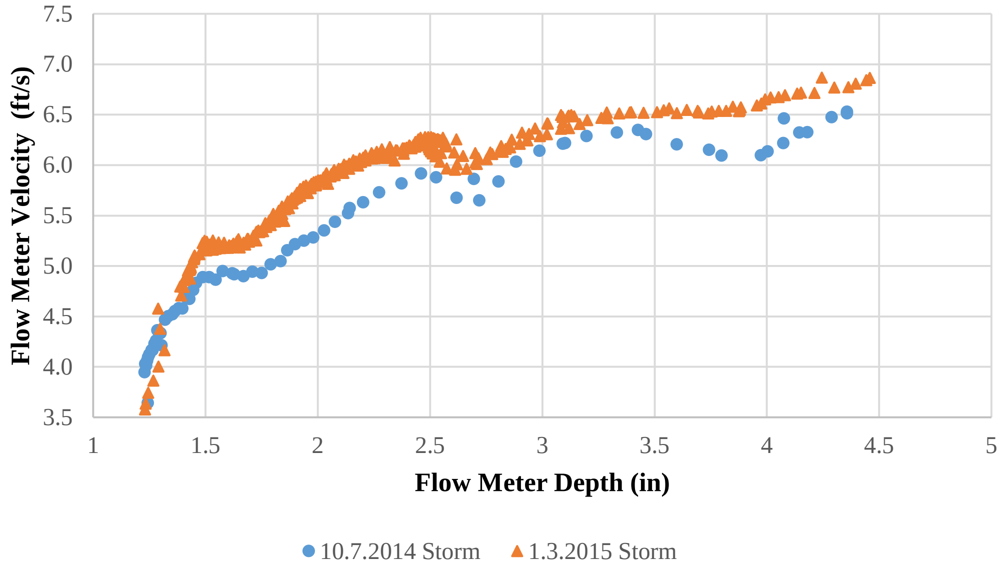

Figure 4-6: Flow Meter Depth to Velocity Relationship

To determine whether or not these observed changes are representative of an increase in turbulence, the Reynolds Number was calculated for each time step and compared to the depth recorded by the flow meter (Figure 4-7). From this analysis it can be seen that a significant increase of turbulence occurs with very little change in depth. Due to the sensitivity of the sensors on the flow meter, the significant increase in turbulence affects the measured flow from the sensor. From this it can be concluded that the divergence seen in Figure 4-4 is due to the instrumentation used and that the depth to flow curve created from the weir equations is representative of the conditions experienced at the outflow of the CSW 2.0 allowing these equations to be used to calculate outflow data when flow meter recordings are missing. Images of the outlet structure during storm events further validate the presence of turbulence (Figure 4-8).

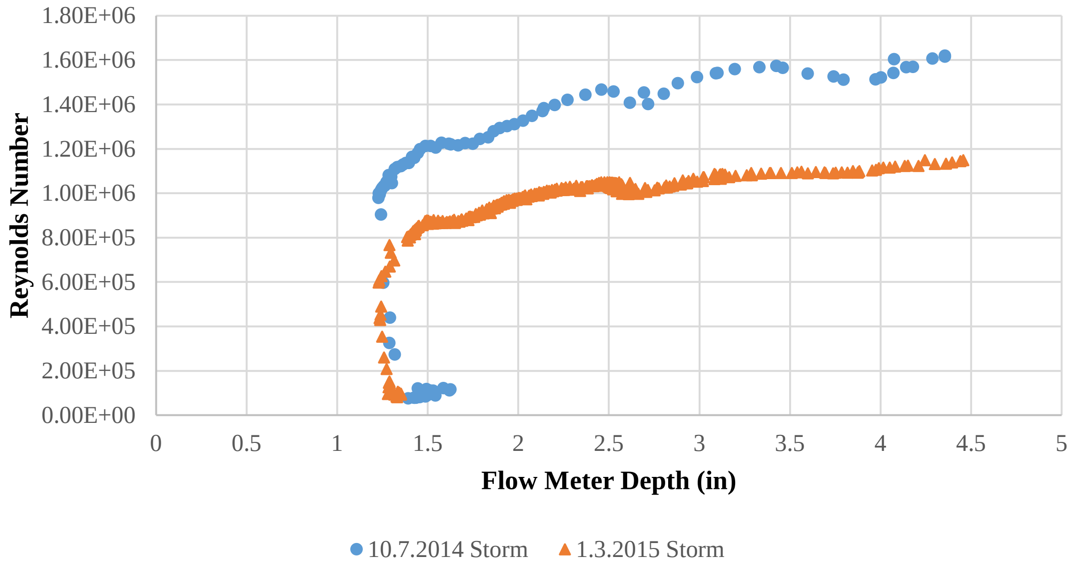

Figure 4-7: Flow Meter Depth to Reynolds Number Relationship

Figure 4-40: Outlet Structure during 9/19/2016 Storm Event

The right hand image shows the flow entering the outflow structure via a combination of orifice and weir flow while the left hand image shows the flow exiting the structure via the outflow pipe.

3.3 Yearly Flow Analysis

An important parameter to analyze when determining the performance of a hydraulic system includes the inflow and outflow entering and exiting the system. For this study, both the inflow into the CSW 2.0 and the outflow exiting the system was analyzed annually to determine changes in performance from July 2012 to December 2016 both in terms of flow rate and volume. The retention time within the system will be analyzed at separate locations via Rhodamine dye tracer tests to determine any flow pattern changes over time.

3.3.1 Inflow Analysis

3.3.1.1 Yearly Comparison

The study period began in July 2012, so unlike following years, it does not contain all annual events. The average and median values are used in comparison with other years, but this difference should be noted. When looking at the average event flow and volume entering the CSW 2.0, Table 4-3, small changes in the average inflow can be seen during the first three years of the study with an increase during the last two years of the study. This trend is also visible when analyzing the average volume entering the system with the latter two years of the study almost doubling in volume when compared to 2013 and 2014. Additionally, the amount of events (Storm, Interflow, and Baseflow) recorded each year varies with 2014 having the most events recorded, 202 events, indicating more Storm Events and subsequent Interflow and Baseflow Events. This indicates that in 2014 shorter more often storm events occurred while in 2015 there were longer periods of baseflow events.

Table 4-3: Yearly Comparison of the Average Flow and Volume entering the CSW 2.0

Year	Number Events	Average Flow (cfs)	Median Flow (cfs)	Average Volume (cf)	Median Volume (cf)
2012*	108	0.621 σ = 0.786	0.317	56594 σ = 67716	33623
2013	195	0.581 σ = 0.778	0.288	53539 σ = 101131	27462
2014	202	0.750 σ = 0.877	0.346	78941 σ = 109679	38171
2015	147	0.962 σ = 1.149	0.383	130648 σ = 237378	49863
2016	179	0.860 σ = 0.997	0.551	102246 σ = 169909	45724

*2012 was July – December; all other years are a 12 month period.

When looking at the average flow entering the system (Figure 4-9), it can be seen that as time progressed, the average distribution of the flow entering the system increased, as seen by the larger span between the upper and lower quartile. On average there was no statistical difference throughout the study period although it must be noted that a slight difference was found between the data from 2013 and 2014 (paired t-test; $p = 0.0484$) as well as between 2014 and 2015 (paired t-test; $p = 0.0471$). A significant difference was found between 2012 and 2015 (paired t-test, $p = 0.00829$) supporting the idea that as time progressed the average flow into the system changed. It must be noted that in 2015, an upstream infiltration trench, that previously diverted some impervious runoff from the CSW 2.0, was retrofitted increasing the inflow volume of the system for that year.

Additionally, the statistical outliers (defined as any value greater than 1.5 the inter quartile range (IQR) of the dataset), not depicted below, increased during 2012 to 2016 from 9, 21, 11, 79, and 16, respectively. This increase indicates that there was higher flow events recorded during 2015 when compared to any other years in this study.

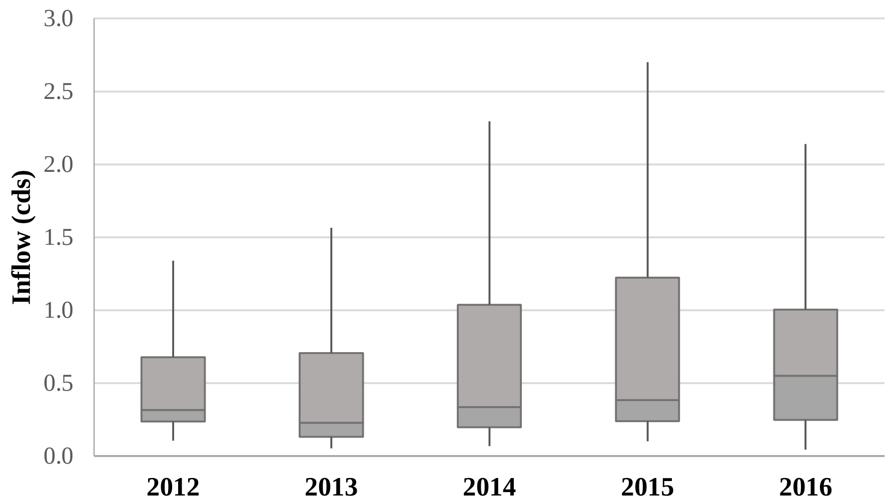

Figure 4-8: Yearly Comparison of the Flow Entering the CSW 2.0

When looking at the volume entering the system (Figure 4-10), one can see the same trends when compared to the average flow entering the CSW 2.0. On average there was no statistical difference throughout the study period although it must be noted that a slight difference was found between the data from 2013 and 2014 (paired t-test; $p = 0.0168$) as well as significant difference between 2014 and 2015 (paired t-test; $p = 0.0006$). A significant difference was found between 2012 and 2015 (paired t-test, $p = 0.00184$) indicating that the upstream infiltration trench aided in reducing the inflow volume.

Additionally, the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, increased during 2012 to 2016 from 6, 11, 11, 13, and 20, respectively. When compared to the higher number of statistical outliers found when analyzing the total average flow entering the system, the total volume entering the system shows less statistical variability and is less sensitive to larger events.

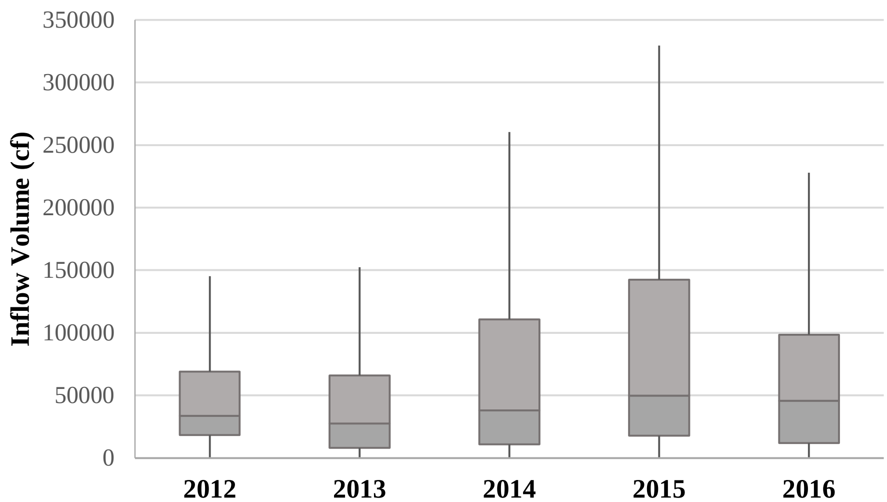

Figure 4-9: Yearly Comparison of the Volume Entering the CSW 2.0

3.3.1.2 Storm Event Comparison

In comparison, the average flow and volume entering the CSW 2.0, during storm events (Table 4-4), show little to no change in terms of the average flow entering the system during the first two years of the study period; 2012 and 2013. This does not hold true for 2014, 2015, and 2016 where an increase in average flow was recorded. This trend is also visible when analyzing the average volume entering the CSW 2.0 during the study period. Additionally, the number of storm events recorded during each year represent between 35 and 36 percent of the total events recorded for that same year. Of the 202 events in 2014, 73 events were Storm Events, the largest of any year observed.

Table 4-4: Storm Comparison of the Average Flow and Volume entering the CSW 2.0

Year	Number Events	Average Flow (cfs)	Median Flow (cfs)	Average Volume (cf)	Median Volume (cf)
2012*	38	1.290 σ = 1.027	0.908	71797 σ = 77973	46987
2013	69	1.291 σ = 0.950	0.976	77123 σ = 84365	52750
2014	73	1.478 σ = 1.068	1.27	96152 σ = 131451	59274
2015	52	1.890 σ = 1.115	1.60	127017 σ = 111799	83138
2016	64	1.620 σ = 1.279	1.24	92408 σ = 104659	54483

*2012 was July – December; all other years are a 12 month period.

When looking at the average flow entering the system during storm events (Figure 4-11), the same trend as during the yearly analysis can be identified. The data's average distribution, denoted by the span of the upper and lower quartile of each boxplot, increased from 2012 to 2015 with 2015 showing the largest distribution. In contrast to the yearly analysis, only 2014 to 2015 showed a statistical difference (paired t-test; $p = 0.0398$). A slight statistical difference was found between 2012 and 2015 (paired t-test; $p = 0.0103$) further indicating that the inflow into the system changed.

Unlike the yearly analysis, the statistical outliers (defined as any value greater than 1.5 times the IQR of the dataset), not depicted below, remained fairly constant from 2012 to 2016 with 7, 4, 5, 0, and 5 events, respectively. The decrease in outliers, when compared to the yearly analysis, is most likely due to just analyzing flows during storm conditions which would increase the means as well as reduce the IQR of the dataset.

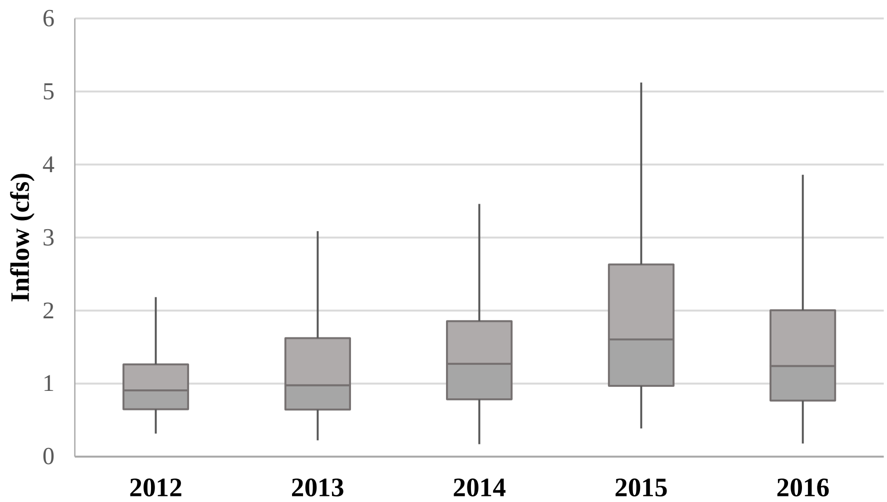

Figure 4-10: Storm Comparison of the Flow Entering the CSW 2.0

When looking at the volume entering the system during storm events (Figure 4-12), a similar trend is seen than that of the average flow entering the CSW 2.0 with no statistical difference throughout the study period. A statistical difference was found between 2012 and 2015 (paired t-test, $p = 0.0105$) indicating that 2015 resulted in higher inflow volumes. Of the total volume entering the system, the inflow volume during storm events represents on average 41% of the total inflow volume of the CSW 2.0 during a year.

Additionally from 2012 to 2013 the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, remained fairly constant from 2012 to 2016 with 3, 3, 6, 3, and 5 events, respectively. The decrease in outliers, when compared to the yearly analysis, is most likely due to just analyzing volumes during storm conditions which would increase the means as well as reduce the IQR of the dataset.

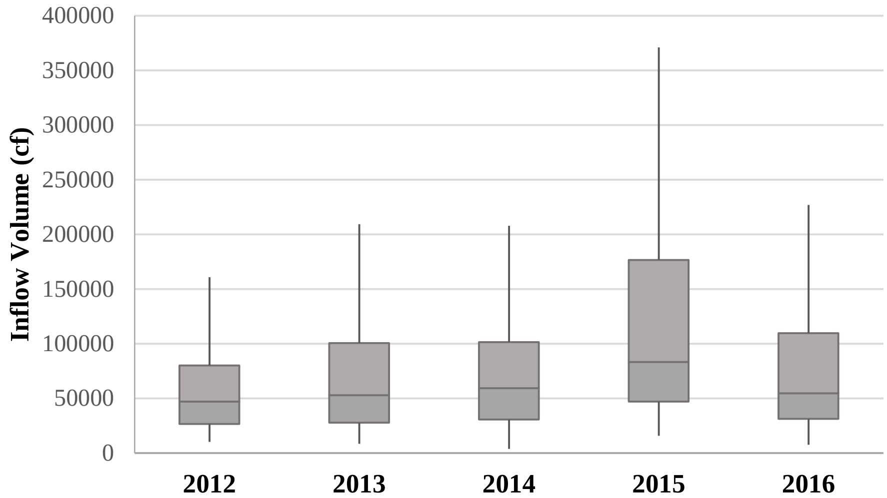

Figure 4-11: Storm Comparison of the Volume Entering the CSW 2.0

3.3.1.3 Baseflow Event Comparison

When looking at the average flow and volume entering the CSW 2.0 during baseflow events (Table 4-5), a decrease can be seen from 2012 to 2013 with an immediate increase occurring from 2013 to 2014. The lower average flow entering the system is indicative of baseflow events with shorter duration when compared to 2015 and 2016. The average baseflow duration varied from 2012 to 2016 from 54, 59, 58, 82, and 66 hours, respectively. This trend is also visible when analyzing the average volume entering the CSW 2.0. The average rainfall observed during baseflow events from 2012 to 2016 was 0.014, 0.013, 0.011, 0.023, and 0.015 inches respectively

Table 4-5: Baseflow Comparison of the Average Flow and Volume entering the CSW 2.0

Year*	Number Events	Average Flow (cfs)	Median Flow (cfs)	Average Volume (cf)	Median Volume (cf)
2012	70	0.256 σ = 0.078	0.252	48342 σ = 60450	28768
2013	126	0.193 σ = 0.136	0.158	40624 σ = 107360	13433
2014	129	0.330 σ = 0.298	0.129	69201 σ = 94370	21128
2015	95	0.453 σ = 0.799	0.254	132635 σ = 284125	27290
2016	115	0.437 σ = 0.345	0.257	107720 σ = 197368	29295

*2012 was July – December; all other years are a 12 month period.

When looking at the average flow entering the system during baseflow events, (Figure 4-13), a different trend can be identified with 2016 showing the largest distribution in the data with the largest IQR (1.47 cfs). Significantly statistical differences was seen from 2012 to 2013 (paired t-test; p = 0.0005) and from 2013 to 2014 (paired t-test; $p = 1.22*10^{-5}$) indicating that 2013 observed abnormal baseflow conditions when compared to the rest of the study period. A significant difference was found from 2012 to 2016 (paired t-test; $p = 2.33*10^{-5}$). It must be noted that construction for the new Southeastern Pennsylvania Transportation Authority's (SEPTA) train station began late 2016 that may have resulted in higher baseflow volumes entering the CSW 2.0.

Unlike the storm event analysis, from 2012 to 2013 the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, remained less constant from 2012 to 2016 with 1, 9, 19, 9, and 0 events, respectively, when compared to the number of outliers seen during storm events. The increase in outliers in 2014 may be a result of the transition from a Greyline AVFM II flow meter to a Unidata Starflow flow meter.

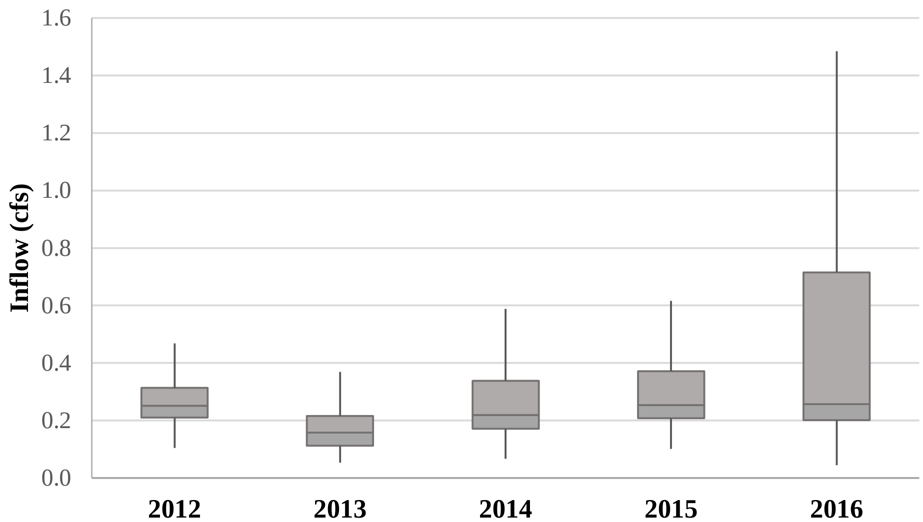

Figure 4-12: Baseflow Comparison of the Flow Entering the CSW 2.0

When looking at the volume entering the system during baseflow events (Figure 4-14), the same trend can be seen as when analyzing the average flow entering the system with the exception that the volume entering the CSW 2.0 shows a higher range of the observed values. A slight statistical difference was observed from 2013 to 2014 (paired t-test; $p = 0.0247$) and from 2014 to 2015 (paired t-test; $p = 0.0188$). The volume increase seen in 2014, paired with the total amount of storm events in the year, indicates that the delay from the rainfall event to runoff was large enough to impact the volume during the interflow/baseflow event immediately following the rainfall event. The volume observed during baseflow events represents on average 59% of the total inflow volume of the CSW 2.0. From 2012 to 2013, the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, increased from 2012 to 2016 from 3, 6, 3, 13, and 16 events.

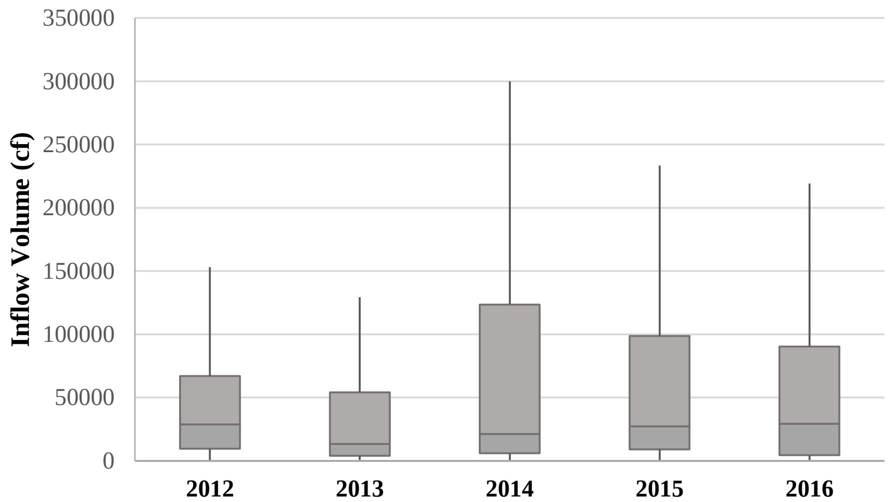

Figure 4-13: Baseflow Comparison of the Volume Entering the CSW 2.0

3.3.2 Outflow Analysis

3.3.2.1 Yearly Comparison

When looking at the average flow and volume leaving the CSW 2.0 (Table 4-6), the average outflow from the system shows a decrease from 2012 to 2016 with an average flow rate decreasing from 0.612 to 0.374 cfs. The decrease in outflow indicates an increase in storage within the CSW 2.0 over time. Additionally, the amount of outflow events match the amount of inflow events for the yearly analysis with the exception of 2016 due to periods of time where there was missing both level and flow data at the outlet structure.

Table 4-6: Yearly Comparison of the Average Flow and Volume Leaving the CSW 2.0

Year	Number Events	Average Flow (cfs)	Median Flow (cfs)	Average Volume (cf)	Median Volume (cf)
2012*	108	0.612 σ = 0.946	0.189	50552 σ = 94002	21005
2013	195	0.419 σ = 0.666	0.224	31622 σ = 42905	18388
2014	202	0.476 σ = 0.419	0.317	43783 σ = 50727	27015
2015	147	0.430 σ = 0.385	0.270	43691 σ = 51270	26127
2016	120	0.374 σ = 0.334	0.244	40944 σ = 42275	27380

*2012 was July – December; all other years are a 12 month period.

When looking at the average flow leaving the system (Figure 4-15), it can be seen that as time progressed the range of the average flow exiting the system decreased over time while the median remained fairly constant. No statistical difference was found during the study period and the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, remained fairly constant from 2012 to 2016 with 7, 8, 6, 2, and 3 events, respectively. Additionally, the percentage of inflow leaving the CSW 2.0 decreased from 2012 to 2016 with 98%, 72%, 63%, 45%, and 37%, respectively. The change in the percentage of inflow leaving the CSW 2.0 indicates that over time the system matured increasing both the available storage as well as the resistance due to vegetation.

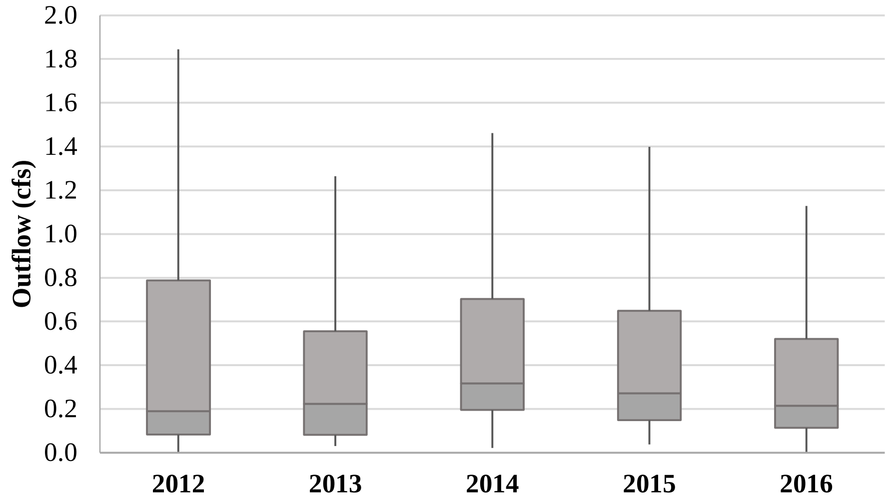

Figure 4-14: Yearly Comparison of the Flow Leaving the CSW 2.0

When looking at the yearly volume exiting the CSW 2.0 (Figure 4-16), a similar trend can be seen as that of the outflow of the system with the range of observed data decreasing over time as well as a fairly constant median. A slight statistical difference was found from 2012 to 2013 (paired t-test; $p = 0.049$) and a slightly larger statistical difference was found from 2013 to 2014 (paired t-test; $p = 0.0104$) indicating that 2013 was an abnormal year when in comparison to the rest of the study period. Additionally the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, fluctuated from 2012 to 2016 from 4, 9, 11, 4, and 6 events, respectively. The percentage of average inflow volume leaving the CSW 2.0 decreased from 2012 to 2016 with 89%, 59%, 55%, 33%, and 40%, respectively further indicating that the maturation of the system is important.

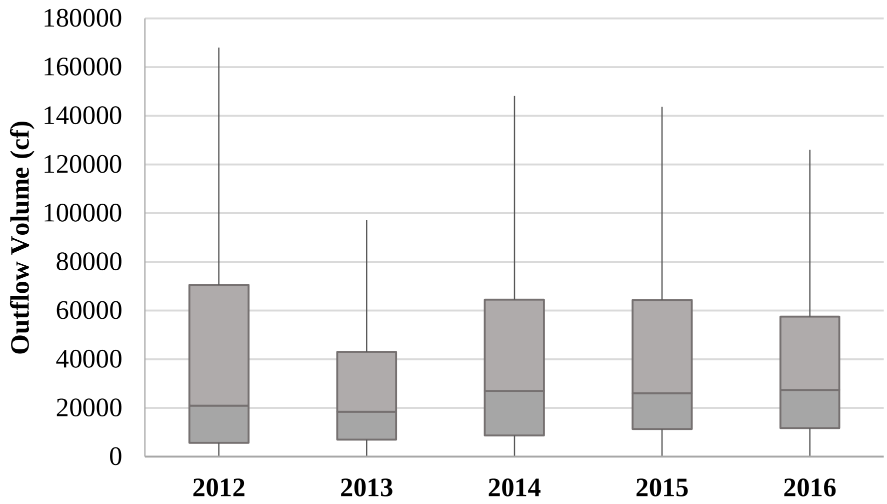

Figure 4-15: Yearly Comparison of the Volume Leaving the CSW 2.0

3.3.2.2 Storm Event Comparison

When looking at the average flow and velocity exiting the CSW 2.0 (Table 4-7), the average outflow from the system shows a decrease from 2012 to 2016 with the outflow remaining almost constant from 2013 to 2015. Similarly to the average outflow of the system, the average volume exiting the system decreases from 2012 to 2016. Additionally, the amount of outflow events match the amount of inflow events during storm events with the exception of 2016 due to periods of time where there was missing both level and flow data at the outlet structure. The recorded storm events represent 35 to 36 percent of the total yearly events recorded.

Table 4-7: Storm Comparison of the Average Flow and Volume Leaving the CSW 2.0

Year	Number Events	Average Flow (cfs)	Median Flow (cfs)	Average Volume (cf)	Median Volume (cf)
2012*	38	1.206 σ = 1.340	0.825	77906 σ = 143802	41335
2013	69	0.814 σ = 0.948	0.687	44766 σ = 48894	35154
2014	73	0.876 σ = 0.410	0.843	51679 σ = 48187	35686
2015	52	0.850 σ = 0.341	0.866	56730 σ = 41781	44752
2016	43	0.687 σ = 0.318	0.645	41562 σ = 37105	28071

*2012 was July – December; all other years are a 12 month period.

When looking at the average flow exiting the system during storm events (Figure 4-17), it can be seen that the range of recorded values increased when compared to the yearly analysis. The median of the data remained fairly constant between 0.5 and 1.0 cfs throughout the study period while the distribution of the data decreased from 2012 to 2013 and remained fairly constant until 2016. On average no statistical differences were apparent throughout the study period with the exception of 2015 to 2016 (paired t-test; $p = 0.0176$). Although 2015 showed the largest distribution of inflow into the system, the outflow during that same period remained similar than the outflow of the previous year (paired t-test; $p = 0.355$). From 2012 to 2013, the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, remained fairly constant from 2012 to 2016 with 3, 2, 4, 0, and 0 events, respectively.

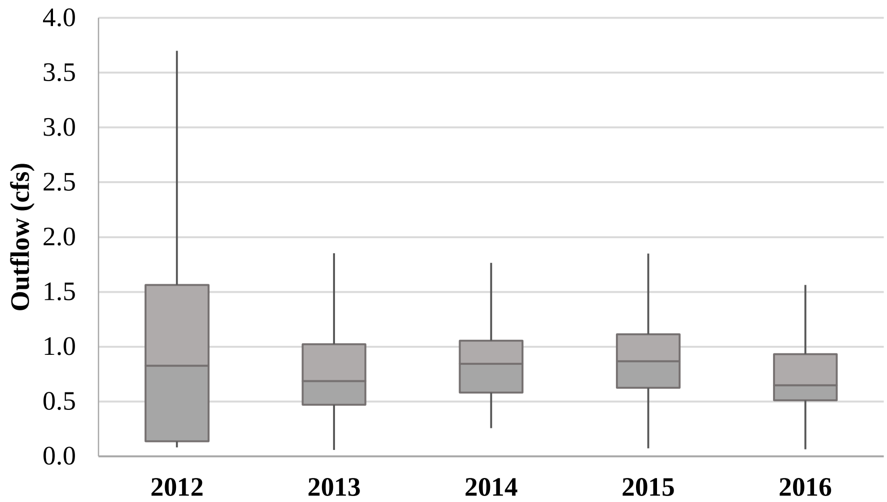

Figure 4-16: Storm Comparison of the Flow Leaving the CSW 2.0

When looking at the volume exiting the CSW 2.0 during storm events (Figure 4-18), a different trend, when compared to the flow exiting the system can be identified. Both 2012 and 2015 show a larger distribution of data when compared to the rest of the years in the study period. The distribution of data in 2012 is expected due to the system recently being installed while the distribution of data in 2015 can be attributed to the increase in inflow observed in section 4.3.1.2. No statistical difference was found during the study period. Additionally, from 2012 to 2016 the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, increased from 2, 4, 8, 1, to 4 events. The outflow volume during storm events represents on average 45% of the yearly outflow recorded at the CSW 2.0.

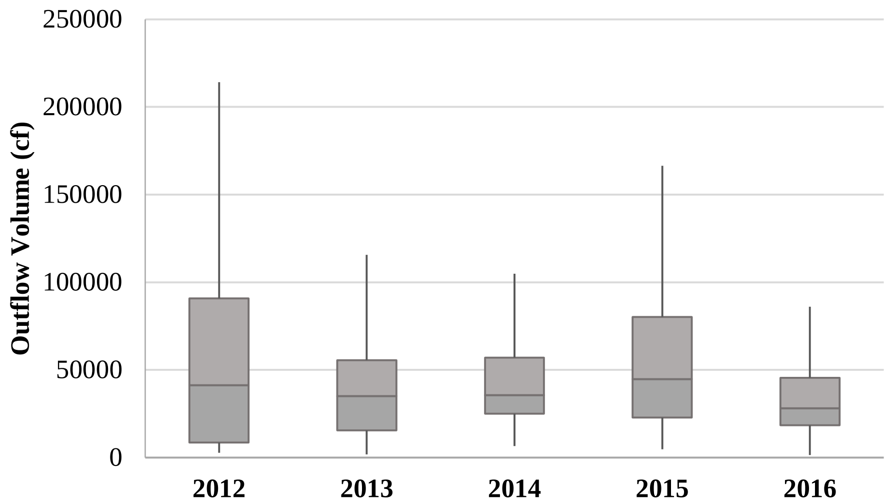

Figure 4-17: Storm Comparison of the Volume Leaving the CSW 2.0

3.3.2.3 Baseflow Event Comparison

When looking at the average flow and volume exiting the CSW 2.0 during baseflow events (Table 4-8), no significant change can be seen. The average outflow from the system remains fairly constant throughout the whole study period. Similarly the average volume leaving the CSW 2.0 remains fairly constant from 2012 to 2015 and then proceeds to increase slightly more than the average volume from 2015 to 2016. The amount of outflow events match the amount of inflow events recorded during baseflow with the exception of 2016 due to periods of time where there was missing both level and flow data at the outlet structure.

Table 4-8: Baseflow Comparison of the Average Flow and Volume Leaving the CSW 2.0

Year	Number Events	Average Flow (cfs)	Median Flow (cfs)	Average Volume (cf)	Median Volume (cf)
2012*	70	0.289 σ = 0.353	0.118	35703 σ = 44478	14846
2013	126	0.203 σ = 0.260	0.129	24424 σ = 37536	12745
2014	129	0.249 σ = 0.419	0.224	39314 σ = 51759	12457
2015	95	0.198 σ = 0.122	0.195	36554 σ = 54681	18732
2016	77	0.199 σ = 0.181	0.199	40599 σ = 45135	22807

*2012 was July – December; all other years are a 12 month period.

When looking at the average outflow of the system during baseflow events (Figure 4-19), it can be seen that 2012 remains as the year with the highest outflow distribution followed by 2014. The distribution of data in 2012 is indicative of a fairly young system that is not equipped to absorb the flow rates properly while the distribution of data in 2014, paired with the total amount of storm events in the year, indicates that the delay from the rainfall event to runoff was large enough to impact the interflow/baseflow event immediately following the rainfall event. On average no statistical difference was found during the study period except from 2014 to 2015 (paired t-test; $p = 0.0149$). Additionally, from 2012 to 2013 the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, remained fairly constant from 2012 to 2016 with 1, 5, 5, 1, and 2 events, respectively.

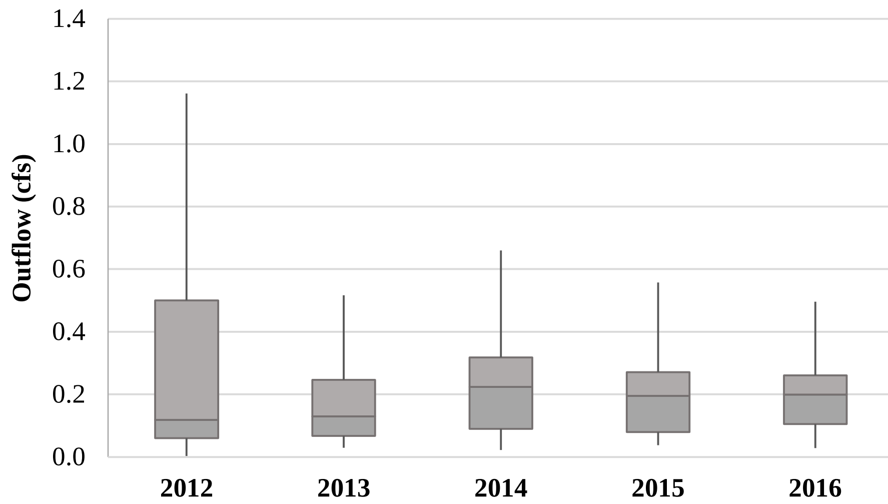

Figure 4-18: Baseflow Comparison of the Flow Leaving the CSW 2.0

A similar trend can be identified when looking at the volume exiting the system during baseflow events (Figure 4-20) with the exception that 2016 demonstrates an increase in data distribution. A significant statistical difference was found between 2013 and 2014 (paired t-test; $p = 0.00899$) indicating that the increase in storm events during 2014 largely impacted the system. The increase in data distribution for 2016 is unexpected, in comparison to the inflow trends during baseflow events, although may be attributed to both the construction of the new SEPTA train station as well as some changes on site discussed further on in this study. From 2012 to 2013 the statistical outliers (defined as any value greater than 1.5 the IQR of the dataset), not depicted below, increased from 2012 to 2016 with 4, 5, 8, 6, and 2 events, respectively.

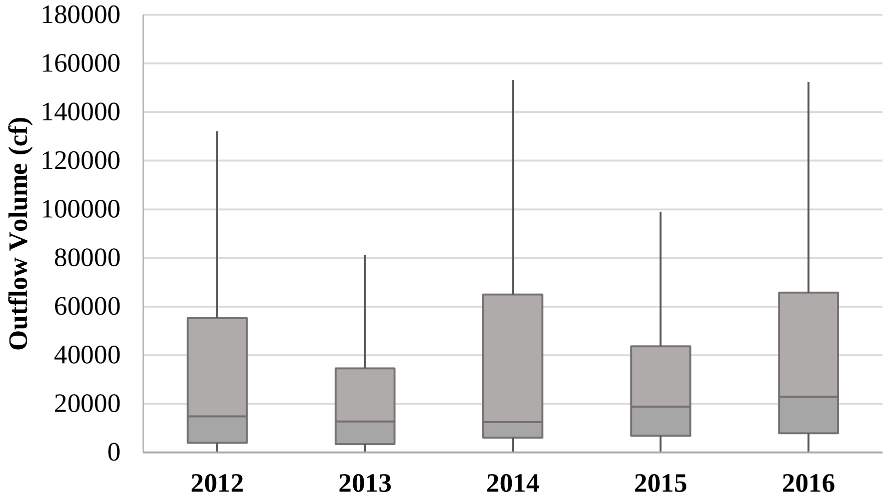

Figure 4-19: Baseflow Comparison of the Volume Leaving the CSW 2.0

3.3.3 CSW 2.0 Performance

The performance of the CSW 2.0 was quantified by determining the percentage of inflow retained in the system. For this particular analysis the flow entering the system is compared to the flow exiting the system to determine the percent of attenuation achieved within the CSW 2.0. During the yearly analysis (Table 4-9), 2014 showed the highest peak flow attenuation (50%) and 2015 showed the highest average volume attenuation (29%) when compared to the other years of this study. On the other end of the spectrum, 2013 showed the least peak flow (14%) and average volume (-11%) attenuation. The low peak flow attenuation indicates that there was less resistance to flow within the system, which may have been because the CSW 2.0 was not fully established with vegetation. The large standards of deviation indicate that the outflow of the system was greater than the inflow 36, 30, 32, 22, and 18 % of the time from 2012 to 2016, respectively.

Table 4-9: Yearly Analysis of the CSW 2.0 Performance

Year	Number Inflow Events	Number Outflow Events	Peak Flow Attenuation	Average Volume Attenuation
2012	108	108	18 % σ = 123 %	-5 % σ = 117 %
2013	195	195	14 % σ = 168	-11 % σ = 157 %
2014	202	202	50 % σ = 81%	4 % σ = 93 %
2015	147	147	48 % σ = 49 %	29 % σ = 54 %
2016	179	120	19 % σ = 86%	23 % σ = 63 %

Similarly during storm events (Table 4-10), 2014 as well as 2012 showed the highest peak flow attenuation (65% and 67% respectively) and 2015 showed the highest volume attenuation (44%). The year 2013 continued to show the least peak flow attenuation (59%) and 2012 showed the least average volume attenuation (6%) when compared to the rest of the years in this study. Although 2012 showed the highest peak flow attenuation within the CSW 2.0 during the whole study period, the system was not able to retain the volume resulting in the low percentage of volume attenuation. This is a result of the system still being in the process of establishing its vegetation. The large standards of deviation indicate that the outflow of the system was greater than the inflow 45, 7, 18, 8, and 13 % of the time from 2012 to 2016, respectively.

Table 4-10: Storm Event Analysis of the CSW 2.0 Performance

Year	Number Inflow Events	Number Outflow Events	Peak Flow Attenuation	Average Volume Attenuation
2012	70	70	67 % σ = 35 %	6 % σ = 66 %
2013	126	126	59 % σ = 94 %	14 % σ = 150 %
2014	129	129	63 % σ = 18 %	18 % σ = 73 %
2015	95	95	65 % σ = 27 %	44 % σ = 73 %
2016	115	77	61 % σ = 28 %	31 % σ = 39 %

Lastly, during baseflow events (Table 4-11), 2014 showed the highest peak flow attenuation (42%) while 2015 showed the highest average volume attenuation (21%) when compared to the rest of the years of this study. The year 2013 showed negative peak flow attenuation (-27%) indicating that during the first years of the study, the average outflow rate exceeded the average inflow rate into the system. Additionally, 2013 also showed the least amount of average volume attenuation (-27%) when compared to the rest of the years in this study. The large standards of deviation indicate that the outflow of the system was greater than the inflow 0, 42, 41, 32, and 21 % of the time from 2012 to 2016, respectively.

Table 4-11: Baseflow Event Analysis of the CSW 2.0 Performance

Year	Number Inflow Events	Number Outflow Events	Average Flow Attenuation	Average Volume Attenuation
2012	38	38	-9 % σ = 144 %	-14 % σ = 138 %
2013	69	69	-11 % σ = 195 %	-27 % σ = 161 %
2014	73	73	42 % σ = 97 %	-4 % σ = 102 %
2015	52	52	39 % σ = 55 %	21 % σ = 62 %
2016	64	43	-5 % σ = 98 %	18 % σ = 73 %

3.3.4 Retention Time

An additional parameter to consider when understanding the flow dynamics within the CSW 2.0 is the retention time within the system itself. As specified in Chapter 3, the retention time within the system was determined at different locations of interest within the CSW 2.0 over a total of 26 different events. From these 26 events, ten events resulted in acceptable data for storm events out of which there were observed errors in two events. The data collected at the location where the errors were observed were not considered in this analysis and are highlighted in red in Table 4-12. Additionally, eight events resulted in acceptable data for baseflow events out of which there were observed errors in three events. Due to these errors, the data collected at these locations were not considered in this analysis and are highlighted in red in Table 4-13.

Table 4-12: Tracer Test Summary during Storm Events

Date	Event Type	Probe 1 Location	Probe 2 Location	Mass Injected (mL)
4/7/2014	Storm	Start M1	End M1	25
4/25/2014	Storm	End M1	OUT	25
6/19/2014	Storm	End M1	OUT	40
8/1/2014	Storm	Start M1	End M1	39
9/13/2014	Storm	End M1	OUT	100
10/22/2014	Storm	End M1	OUT	105
12/6/2014	Storm	End M1	OUT	100
10/27/2016	Storm	Start M1	OUT	100
1/27/2017	Storm	Start M1	OUT	100
4/3/2017	Storm	Start M1	End M1	100

Table 4-13: Tracer Test Summary during Baseflow Events

Date	Event Type	Probe 1 Location	Probe 2 Location	Mass Injected (mL)
8/8/2014	Baseflow	End M1	OUT	65
8/28/2014	Baseflow	End M1	OUT	52
11/11/2014	Baseflow	End M1	OUT	100
3/18/2015	Baseflow	Start M1	OUT	102
8/27/2015	Baseflow	Corner IN	Start M1	100
9/17/2015	Baseflow	Corner IN	Start M1	100
2/15/2017	Baseflow	Start M1	OUT	100
3/25/2017	Baseflow	Start M1	End M1	100

3.3.4.1 Storm Event Retention Times

An average retention time of 25 hours (1533 min) was determined from the IN to the start of M1 (Figure 3-16) during 4 separate tracer tests events. When looking at the dye concentration curve for each event, no substantial similarities can be seen (Figure 4-21). The difference in the shape of each tracer event may be accounted for when looking at the differences between each individual rainfall event, Table 4-14. Additionally, due to the small sample size no yearly comparisons can be made in terms of the retention time within the IN of the CSW 2.0.

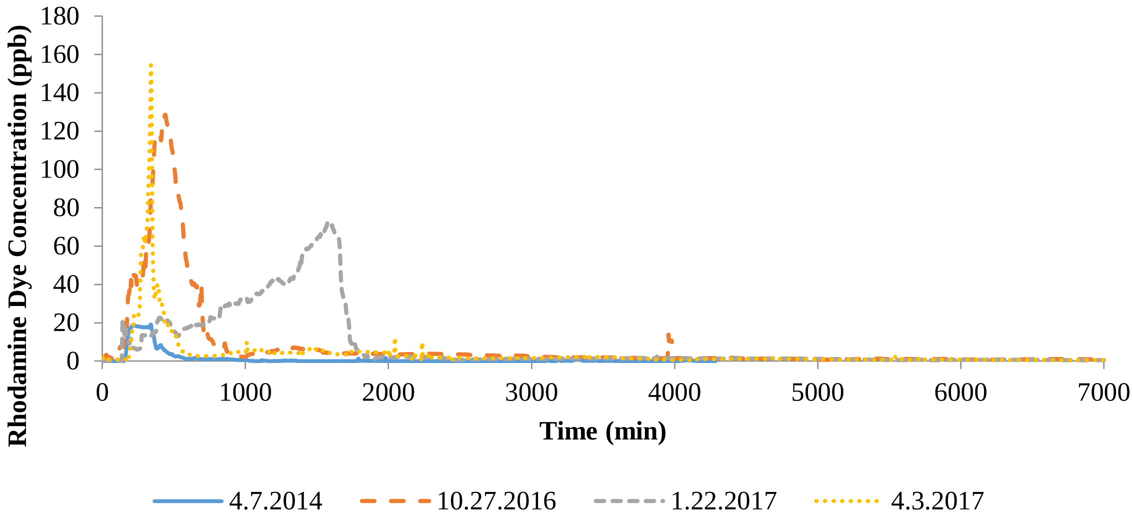

Figure 4-20: Start of M1 Storm Event Tracer Curves

Table 4-14: Start of M1 Storm Event Tracer Test Results

Date	Dye Released (mL)	Mean Residence Time (hr)	Rain (in)	Intensity (in/hr)	Average Outflow (cfs)
4/7/2014	28	8.40	0.36	0.02	0.54
10/27/2016	100	21.57	0.74	0.04	0.79
1/22/2017	100	32.32	0.80	0.01	0.23
4/3/2017	100	36.64	0.38 + 0.75	0.016 + 0.053	0.29

An average retention time of 26 hours (1560 min) was determined from the IN to the end of M1 (Figure 3-16) during eight separate tracer tests events. When looking at the dye concentration curve for each event, no substantial differences can be seen (Figure 4-22). Unlike the tracer test curves seen at the start of M1, a similarity in the shape of each tracer event can be seen with a sharp rise of dye concentration followed by an almost as rapidly decreasing recession limb. The subtle differences in each curve may be accounted for when looking at the differences between each individual rainfall event (Table 4-15).

For example a 0.37 inch storm event on 9/13/2014 had a mean residence time of 67 hours (4506 min) while a 0.38 inch storm event on 10/22/2014 had a mean residence time of 32 hours (1937 min). The difference in mean residence time between these two similar rain events lies in the shape of the curve with the 9/13/2014 peaking between 60 and 80 ppb as well as a gradual recession limb while the 10/22/2014 storm event peaked between 80 and 100 ppb with a much steeper recession limb. Attention must be brought to the 6/19/2014 and 4/3/2017 tracer test event where two separate back to back rainfall events were recorded and the rainfall as well as intensity of each storm was reported separately. Additionally, the 4/3/2017 tracer test event showed a secondary peak that indicates Rhodamine dye entrapment within the meander that was not released until the next rainfall event.

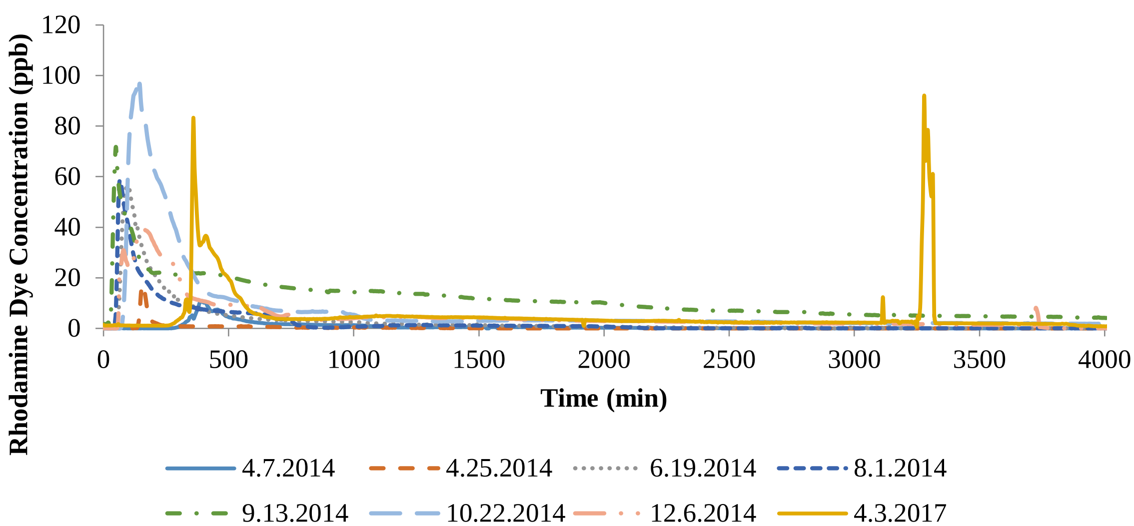

Figure 4-21: End of M1 Storm Tracer Test Curves

Table 4-15: End of M1 Tracer Test Results

Date	Dye Released (mL)	Mean Residence Time (hr)	Rain (in)	Intensity (in/hr)	Average Outflow (cfs)
4/7/2014	28	13.57	0.36	0.02	0.54
4/25/2014	25	6.78	0.43	0.03	0.42
6/19/2014	40	7.70	0.14 + 0.17	0.0195 + 0.0208	0.25
8/1/2014	39	10.89	0.48	0.05	0.20
9/13/2014	100	67.43	0.37	0.03	0.08
10/22/2014	105	32.28	0.38	0.02	0.09
12/6/2014	100	18.27	0.64	0.04	0.29
4/3/2017	100	51.12	0.38 + 0.75	0.016 + 0.053	0.29

An average retention time of 50 hours (2663 min) was determined from the IN to the OUT (Figure 3-16) during six separate tracer tests events. When looking at the dye concentration curve for each event, no substantial similarities can be seen (Figure 4-23). The difference in the shape of each tracer event may be accounted for when looking at the differences between each individual rainfall event (Table 4-16). An increase of the retention time within the CSW 2.0, when comparing the tracer test on 10/22/2014 to the tracer test on 10/27/2016, indicate an increase of resistance to flow within the system seeing that both events resulted in a similar retention time when the storm event on 10/27/2016 was almost double the volume and intensity of the storm event on 10/22/2014.

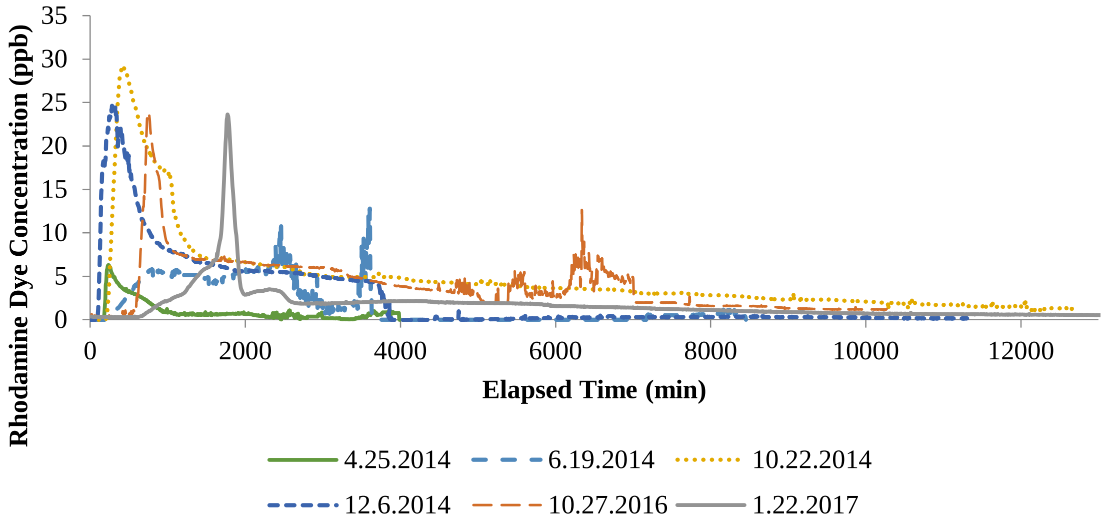

Figure 4-22: Outlet Storm Event Tracer Curves

Table 4-16: Outlet Storm Event Tracer Test Results

Date	Dye Released (mL)	Mean Residence Time (hr)	Rain (in)	Intensity (in/hr)	Average Outflow (cfs)
4/25/2014	25	20.22	0.43	0.03	0.42
6/19/2014	40	36.45	0.14 + 0.17	0.0195 + 0.0208	0.25
10/22/2014	105	65.22	0.38	0.02	0.09
12/6/2014	100	30.41	0.64	0.04	0.29
10/27/2016	100	63.38	0.74	0.04	0.79
1/22/2017	100	83.87	0.80	0.01	0.30

3.3.4.2 Baseflow Event Retention Times

An average retention time of 39 hours (2683 min) was determined from the IN to the start of M1 (Figure 3-16) during five separate tracer tests events. Unlike the tracer test curves seen during storm events, a similarity in the shape of each tracer event can be seen with a resemblance to a normally distributed bell curve (Figure 4-24). For example the 3/18/2015 baseflow event shows a faster rising limb when compared to a baseflow event with a similar mean residence time, 9/17/2015. This steeper rising limb indicates a higher average outflow during the 3/18/2015 event (0.33 cfs) when compared to the average outflow during the 9/17/2015 event (0.05 cfs). The subtle differences in the shape of each tracer event may be accounted for when looking at the differences in the outflow of each event, (Table 4-17).

An increase of the retention time within the CSW 2.0, when comparing the tracer test on 3/18/2015 to the tracer test on 3/25/2017, indicate an increase of resistance to flow within the system seeing that the retention time increased by 26%. Although the tracer test performed on 3/25/2017 falls outside of the time period of the flow analysis study, the results give an indication that the retention time within the system has increased over time.

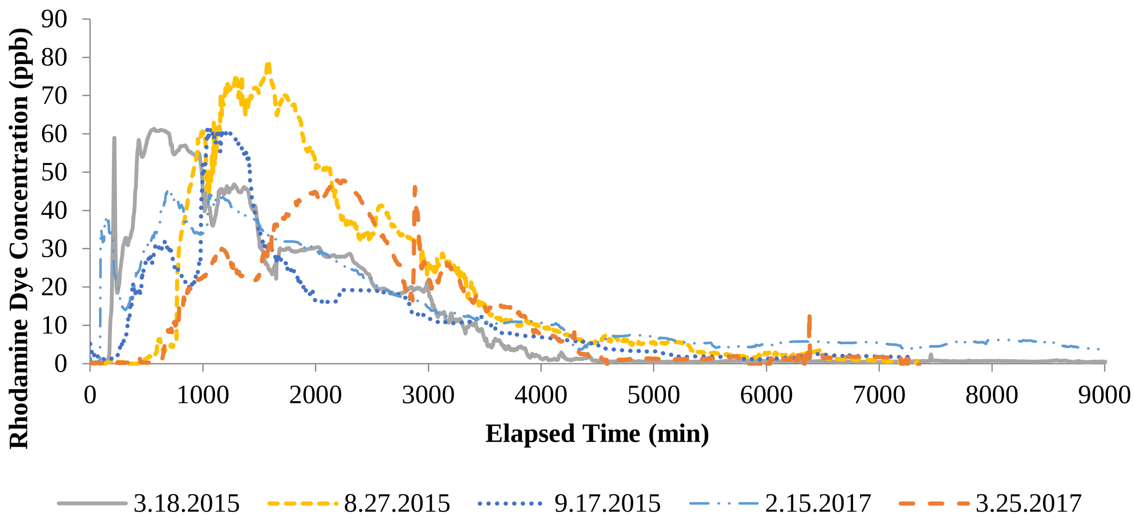

Figure 4-23: Start of M1 Baseflow Event Tracer Test Curves

Table 4-17: Start of M1 Baseflow Event Tracer Test Results

Date	Dye Released (mL)	Mean Residence Time (hr)	Average Outflow (cfs)
3/18/2015	102	29.45	0.33
8/27/2015	100	22.83	0.06
9/17/2015	100	29.78	0.05
2/15/2017	100	72.74	0.22
3/25/2017	100	40.04	0.28

An average retention time of 58 hours (3860 min) was determined from the IN to the end of M1 (Figure 3-16) during four separate tracer tests events. Similarly to the tracer test curves seen at the start of M1 during baseflow events, a similarity in the shape of each tracer event can be seen with a resemblance to a skewed normally distributed bell curve (Figure 4-25). For example the 8/28/2014 baseflow event shows a slight delay in the rising limb when compared to a baseflow event with a similar mean residence time, 8/8/2014. This delay indicates a lower average outflow during the 8/28/2014 event (0.11 cfs) when compared to the average outflow during the 8/8/2014 event (0.22 cfs). On the other hand both events peak between 25 and 30 ppb and have a similar recession limbs. The subtle differences in the shape of each tracer event may be accounted for when looking at the differences in the outflow of each event (Table 4-18).

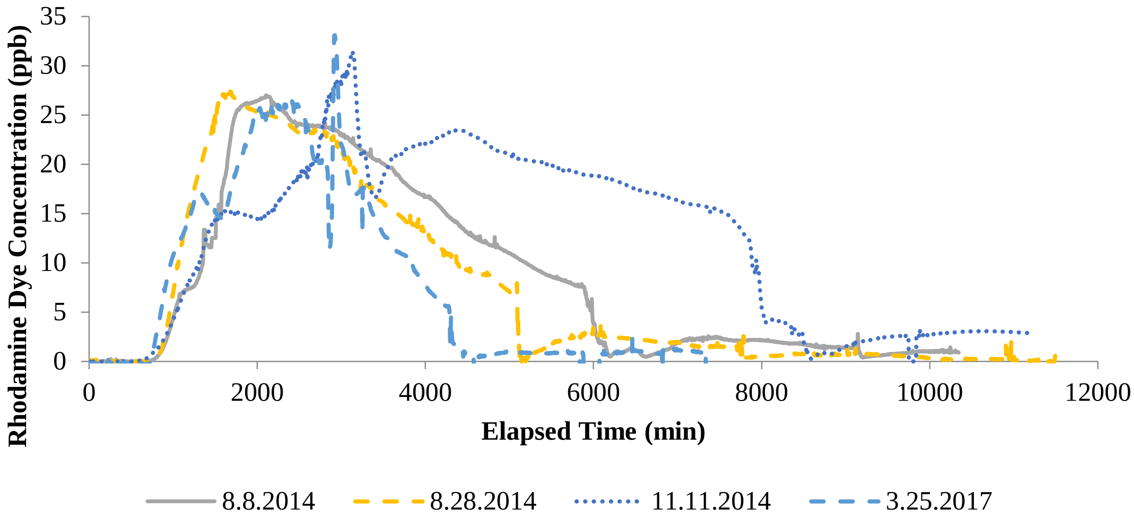

Figure 4-24: End of M1 Baseflow Event Tracer Test Curves

Table 4-18: End of M1 Baseflow Event Tracer Test Results

Date	Dye Released (mL)	Mean Residence Time (hr)	Average Outflow (cfs)
8/8/2014	65	57.38	0.22
8/28/2014	52	51.35	0.11
11/11/2014	100	79.79	0.17
3/25/2017	100	42.98	0.28

An average retention time of 98 hours (5884 min) was determined from the IN to the OUT (Figure 3-16) during four separate tracer tests events. Similarly to the tracer test curves seen during the storm event tracer test, no similarity in the shape of each tracer event can be seen (Figure 4-26). For example the 8/8/2014 baseflow event shows a slower rising limb when compared to a baseflow event, 3/18/2015. This delay indicates a lower average outflow during the 8/8/2014 event (0.22 cfs) when compared to the average outflow during the 3/18/2015 event

(0.33 cfs). Additionally, the 3/18/2015 baseflow event shows a much smoother curve when compared to the 8/8/2014 baseflow event. The differences in the shape of each tracer event may be accounted for when looking at the differences in the outflow of each event (Table 4-19).

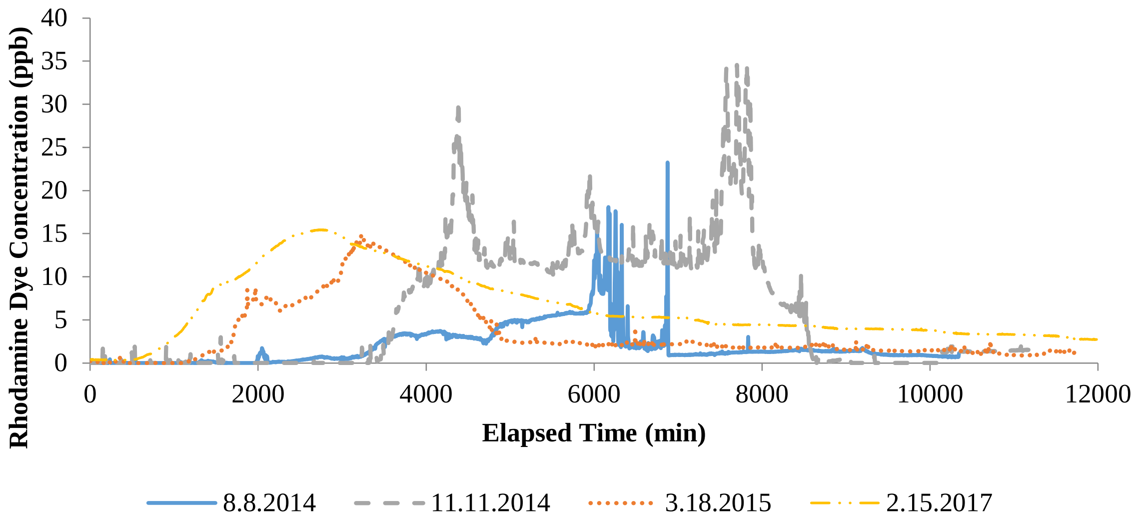

Figure 4-25: Outlet Baseflow Event Tracer Test Curves

Table 4-19: Outlet Baseflow Event Tracer Test Result

Date	Dye Released (mL)	Mean Residence Time (hr)	Average Outflow (cfs)
8/8/2014	65	96.98	0.22
11/11/2014	100	103.42	0.17
3/18/2015	102	77.17	0.33
2/15/2017	100	114.67	0.22

3.4 Yearly Climate Analysis

Now that there is a general understanding of the observed hydraulic changes at the CSW 2.0, during the study period of July 2012 to December 2016, the climate parameters that could possibly be driving these changes must also be analyzed. As mentioned in Chapter 3, the CSW 2.0 is equipped with a weather station which allows for the continual monitoring of Rainfall, Solar Radiation, Humidity, Air Temperature, and Wind Speed. This section of the study will focus on the analysis of Rainfall and Air Temperature at the CSW 2.0 from January of 2012 to December of 2016.

3.4.1 Rainfall Analysis

When looking at the total rainfall and the average rainfall volume at the CSW 2.0 (Table 4-20), it can be seen that the first three years of this study were at or above the yearly average rainfall volume for Pennsylvania of 44 inches per year. On the other hand, the latter two years of the study are below average and present slight drought conditions. The first three years of this study also experienced rainfall events greater than 4.00 inches (including Superstorm Sandy in October 2012) while the latter two years of the study had no recorded rainfall event greater than 2.5 inches. Additionally, the average duration of each rainfall event remained fairly consistent throughout the study while the maximum duration varied throughout the study with the shortest duration corresponding to 2013, the year with the highest recorded volume (Table 4-20). No statistical difference was found between throughout the study period.

Table 4-20: Yearly Rainfall Summary

Year	Number Rainfall Events	Total Volume (in)	Average Event Volume (in)	Max Event Volume (in)	Average Duration (hrs)	Max Duration (hrs)
2012*	66	41.92	0.64	4.22	14	51
2013	69	52.40	0.76	4.41	15	37
2014	73	47.24	0.65	5.02	16	51
2015	52	38.26	0.74	2.37	18	59
2016	64	36.20	0.57	2.39	15	45

*Unlike the flow analysis, 2012 is a 12 month period.

When looking at the distribution of the rainfall events recorded at the CSW 2.0 (Figure 4-27), no major differences can be seen in the range of the data recorded. The year 2012 was characterized with a median event volume of 0.36 inches of rainfall and five statistical outliers (defined as any value greater than 1.5 the IQR of the dataset); four outliers between 1.82 and 2.83 inches of rainfall and one outlier with a rainfall volume greater than 2.83 inches. The year 2013 was characterized with a median event of 0.50 inches of rainfall and six statistical outliers; three outliers between 1.82 and 2.76 inches of rainfall and one outlier with a rainfall volume greater than 2.76 inches. The year 2014 was characterized with a median event of 0.40 inches of rainfall and four statistical outliers; all with a rainfall volume greater than 2.32 inches. The year 2015 was characterized with a median event of 0.65 inches of rainfall and four statistical outliers; all between 1.82 and 2.84 inches of rainfall. Finally the year 2016 was characterized with a median event of 0.39 inches of rainfall and two statistical outliers; all between 1.74 and 2.67 inches of rainfall. The substantial increase in large rainfall events in 2014 resulted in an increase of the CSW 2.0's performance in terms of peak flow attenuation for both storm and baseflow events. This indicates that the performance of the system is largely based on the available water.

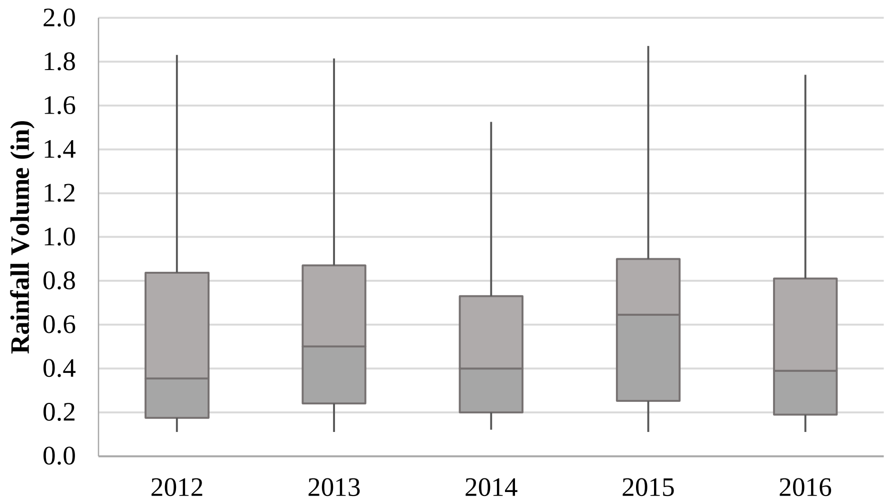

Figure 4-26: Yearly Rainfall Distribution

3.4.2 Temperature Analysis

When looking at the average yearly air temperature at the CSW 2.0 (Table 4-21), a significant difference in the data was seen from 2015 to 2016 (paired t-test; $p = 0.000752$) indicating that 2016 observed abnormal temperatures when compared to the rest of the study period. From 2012 to 2015 the average air temperature at the CSW 2.0 remained fairly constant between 11 and 12 °C (50 and 54 °F). This holds true for the distribution of the yearly temperature data (Figure 4-28). This indicates that the air temperature experienced at the CSW 2.0 does not directly affect the performance of the system over time.

Table 4-21: Yearly Temperature Summary

Year	Number Days	Average Temperature (°C)	Average Temperature (°F)
2012*	316	11.58	53.89
2013	365	11.96	54.60
2014	365	11.24	53.24
2015	365	12.54	55.70
2016	366	15.13	60.60

*Unlike the flow analysis, 2012 is a 12 month period.

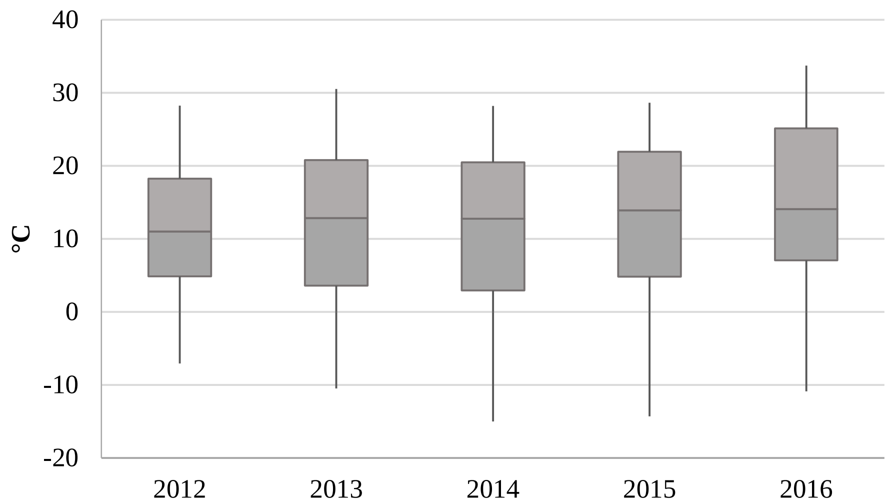

Figure 4-27: Yearly Temperature Distribution

3.5 Yearly Vegetation Analysis

In addition to understanding both the hydraulic and climatologic changes that have occurred at the CSW 2.0 during the study period of July 2012 to December 2016 one must consider any natural and or human driven vegetation changes that have occurred. This section of the study will focus on a yearly analysis of any observed changes in vegetation at the CSW 2.0 as well as the maintenance plan set into motion to aid in improving the amount of native species found.

3.5.1 Yearly Observed Data

The CSW 2.0 has slowly matured and the vegetation has become more established since its construction in 2010. In 2011 the CSW 2.0 still showed little to no signs of vegetation with the majority of the system acting as an unobstructed open channel system (Figure 4-29). Additionally, the system was relatively shallow as water was still accumulating in the system. The top two images as well as the bottom left image was taken of the CSW 2.0 during May of 2011 (5/18, 5/25, and 5/25, respectively) while the bottom right image was taken during June of that same year (6/6).

Figure 4-28: 2011 Vegetation Establishment

In 2012 the CSW 2.0 showed signs of an increase of vegetation throughout the meanders as well as surrounding the inlet (Figure 4-30). Although the system showed signs of a vegetation increase, unobstructed open channel flow was still observed in the system and erosion occurred due to the rainfall events experienced and the relatively unestablished system. The top two images were taken of the CSW 2.0 during July of 2012 (7/30) while the bottom left image was taken during a 2.5 inch storm event in August (8/9) of that same year. The bottom right image was taken in September of 2012 (9/18).

Figure 4-29: 2012 Vegetation Establishment

In 2013 the CSW 2.0 showed a substantial increase in vegetation both in terms of native wetland species and more invasive species such as cattails and phragmites (Figure 4-31). At this point the system had increased the stored water and due to the visible plant establishment, tracer tests began. The top two images were taken of the CSW 2.0 during February (2/18) and March (3/25) of 2013, respectively, while the bottom two images were taken during November (11/7) of that same year.

Figure 4-30: 2013 Vegetation Establishment

In 2014 the CSW 2.0 did not show a substantial increase in vegetation when compared to 2013 (Figure 4-32). During this year, the berms between each meander were mowed and algae grew during the warmer months. The top two images were taken of the CSW 2.0 during February (2/14) and April (4/25) of 2014, respectively, while the bottom two images were taken during May (5/16) and July (6/30), respectively, of that same year.

Figure 4-31: 2014 Vegetation Establishment

In 2015 the CSW 2.0 showed an increase in vegetation with higher densities than in previous years (Figure 4-33). Additionally, the system had accumulated enough organic matter in its basins as well as its meanders to create a foot deep layer in certain areas of the CSW 2.0, which potentially could impede flow, but also compromise storage volume. The increase of vegetation observed from the previous year indicates that the amount of resistance within the system has increased allowing for a higher performance when compared to the previous years resulting in the year with the highest volume attenuation during both storm and baseflow events as discussed in section 4.3.3. The top two images were taken of the CSW 2.0 during June (6/2) and August (8/27) of 2015, respectively, while the bottom two images were taken during October (10/22) and December (12/7), respectively, of that same year.

Figure 4-32: 2015 Vegetation Establishment

During 2015 year, a plan was set in motion to reduce and/or remove the invasive plant species, such as cattails and phragmites, within the CSW 2.0 and replace them with more native species. The plan will take place over a series of years and initially consisted of two separate spraying events of the phragmites and cattails during the fall of 2015 followed by the mowing of the dead plant material as well as the dormant sections of the CSW 2.0 during the winter of 2016. Additionally, seed was laid for native warm season grasses towards the end of the winter. At this point a regimen of spraying weeds and laying seeds would take place over a series of years until the native species are established.

In 2016 the CSW 2.0 still showed a slight decrease in density in vegetation due to the removal of both the cattails and phragmites (Figure 4-34). This decrease of vegetation from the previous year indicates that the amount of resistance within the system decreased as well allowing for a lower performance (18% and 31% average volume attenuation during baseflow and storm events, respectively) when compared to 2015 (21% and 44% average volume attenuation during baseflow and storm events, respectively). The erosion along the berm between the sediment forebay and the end of M2 as well as the end of M3 warranted reconstruction and a contractor was hired to rebuild and strengthen said areas. Unfortunately, before vegetation was established on the berm, a large storm caused additional erosion. The top two images were taken of the CSW 2.0 during January (1/28) and May (5/22) of 2016, respectively, while the bottom two images were taken during October (10/7 and 10/27 from left to right) of that same year.

Figure 4-33: 2016 Vegetation Establishment

CHAPTER 5 – TOTAL SUSPENDED SOLIDS CORRELATIONS

5.1 Introduction

During the summer of 2016 the CSW 2.0 was equipped with a Sequoia LISST-ABS Total Suspended Solids (TSS) sensor to continuously monitor and determine whether or not the concentration of TSS entering the system can be used as a decision maker during real time control. This chapter will focus on the trends observed from the uncalibrated sensor data from September of 2016 to December of 2016.

5.2 LISST-ABS Data Output

The Sequoia LISST-ABS sensor is equipped with different types of data connections; SDI-12, RS232, and analog output. When connected to the OptiRTC (Opti) data logger panel, the analog output was selected. This output converts a digital un-calibrated concentration value to a voltage output which is recorded and can be converted back to an un-calibrated concentration. A higher voltage output is associated with an increase in TSS concentration.

5.3 LISST-ABS Probe Calibration

To accurately measure the concentration within the CSW 2.0, the LISST-ABS sensor must be calibrated with onsite sediment samples. This can be accomplished by using the software provided by Sequoia Scientific to calculate a calibration factor based off of the soil sample at hand. At the CSW 2.0 the LISST-ABS sensor is part of an ongoing research program with Opti, a company based in the Northeast that focuses on the integration of onsite sensor and weather forecast information into control logic to improve the performance of engineered environmental systems. Due to the nature of Opti's operating system, a calibration curve must be provided relating the voltage output of the LISST-ABS sensor to a TSS concentration.

Before attempting to calibrate the LISST-ABS sensor, it was determined that a grain distribution analysis as well as a soil wash should be performed to determine whether or not the particles found at the CSW 2.0 fall within the particle range mentioned when discussing the sensitivity of the probe's calibration. Said analysis was performed in compliance with ASTM method D422 with soil samples taken next to where the LISST-ABS sensor was installed. From the soil wash preformed, on a portion of the collected soil sample, it was determined that a Hydrometer Analysis was not necessary since only 1.76% of the sample passed the #200 sieve. From the ASTM Sieve Analysis it was determined that the soil particles most likely to be held in suspension do indeed fall within the sensor's range.

After contacting Sequoia Scientific, it was determined that the best way to calibrate the TSS concentration measured by the LISST-ABS sensor was to apply a corrected calibration post laboratory testing. This was achieved by daily collecting multiple water samples near the installed sensor at a specific time and using standard laboratory procedures, discussed in section 3.3.2.1 of this report, testing for the TSS concentration of each sample. This value was then compared to the output voltage of the LISST-ABS sensor as well as the un-calibrated probe concentration. After several weeks of testing and data analysis it was determined that there was no direct correlation between laboratory tested TSS concentration and the voltage output produced by the LISST-ABS sensor as seen in Figure 5-1 where the blue dots represent the measured data and the red line represents the line of best fit. Due to this, it was determined that a secondary method for calibration should be explored.

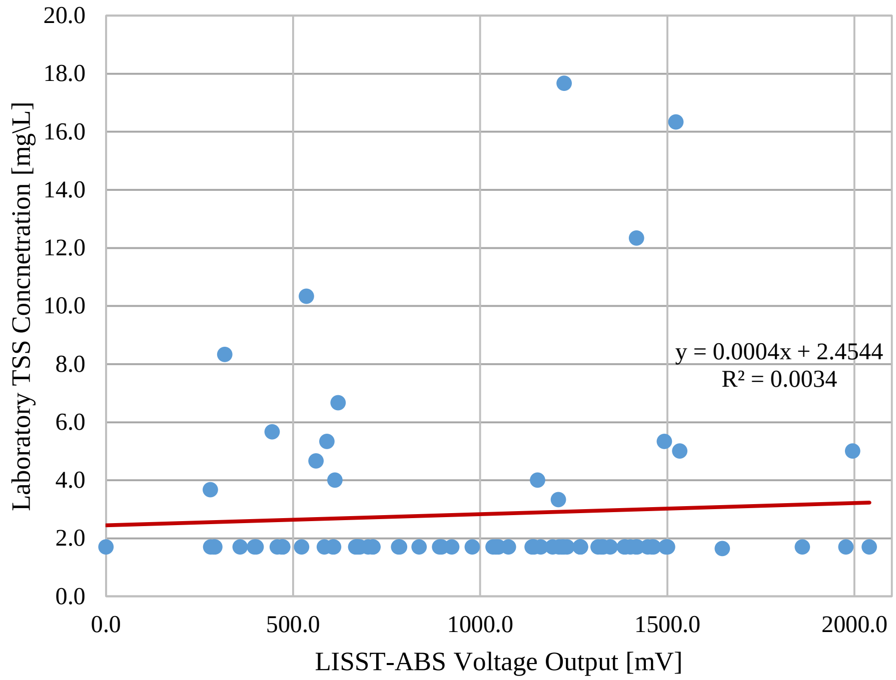

Figure 5-67: Correlation between Laboratory Tested TSS and LISST-ABS Output Voltage

After some thought, it was determined that an effective way to create a calibration curve relating TSS concentrations to the LISST-ABS voltage output was to create standard samples with a known TSS concentration and using them to measure a voltage reading from the LISST-ABS sensor. This was accomplished by collecting several soil samples, as described earlier in this section, and classifying them according to grain size using the procedures described in the ASTM method D422. Once the soil was separated into the different grain sizes, the portion of soil that passed the No. 200 (0.075 mm) sieve was used to create standard solutions with concentrations of 0 mg/L, 3 mg/L, 5 mg/L, 10 mg/L, 15 mg/L, 20 mg/L, 25 mg/L, 50 mg/L, 100 mg/L, 200 mg/L, 500 mg/L, and 1000 mg/L, Figure 5-2. To confirm the accuracy of the TSS concentrations of each standard, TSS laboratory testing was performed, Figure 5-3. From Figure 5-4 it was determined that the soil sample used to create these standards could have a high percentage of dissolved solids which were filtered through during the laboratory procedure. Additionally, since a hydrometer test was not performed on the soil samples taken, there is no knowledge of what percentage of the soil used is smaller than the pore size of the filters used. Due to this, this method was repeated using the soil captured on the No. 200 sieve and additional testing of Total Dissolved Solids was added following the procedures described in section 3.3.2.1 of this report.

Figure 5-68: TSS Standards (increasing concentration from left to right)

Figure 5-69: TSS Filters after testing (increasing infiltration from left to right)

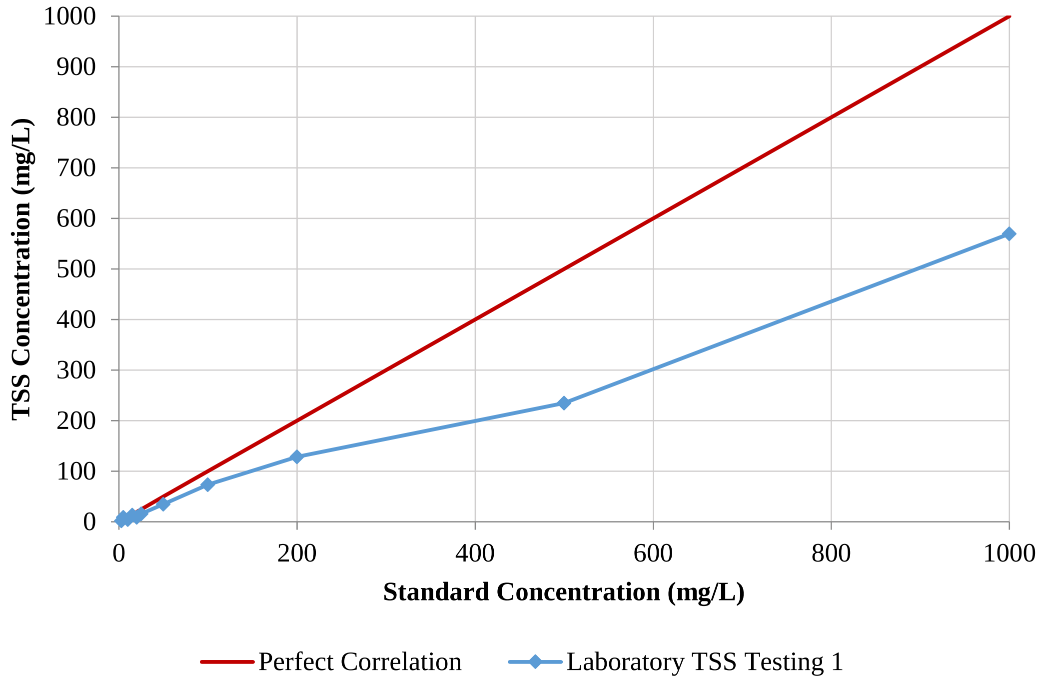

Figure 5-70: Correlation between Pan Standard TSS Concentration and Laboratory tested TSS Concentration

The red line represents a perfect relationship between the standard concentration and the laboratory concentration while the blue line represents the results of laboratory testing.

The portion of soil that remained on the No. 200 (0.075 mm) sieve was used to create standard solutions with concentrations of 0 mg/L, 3 mg/L, 5 mg/L, 10 mg/L, 15 mg/L, 20 mg/L, 25 mg/L, 50 mg/L, 100 mg/L, 200 mg/L, 500 mg/L, and 1000 mg/L. To confirm the accuracy of the TSS concentrations of each standard, TSS laboratory testing was performed. Figure 5-5 indicates that the standards made from the soil that remained on the No. 200 sieve were not representative of the theoretical concentration. The TDS of each sample was measured to be on average 7.4 mg/L (σ = 10.34 mg/L) which is extremely low compared to the average historical TDS data from the CSW 2.0 (636.02 mg/L; σ = 635.75 mg/L). Although the TDS indicated that dissolved solids is not a major component of the soil sample remaining on the No. 200 sieve it was determined that the new standards we adequate for this study and the first set of standards made was revisited.

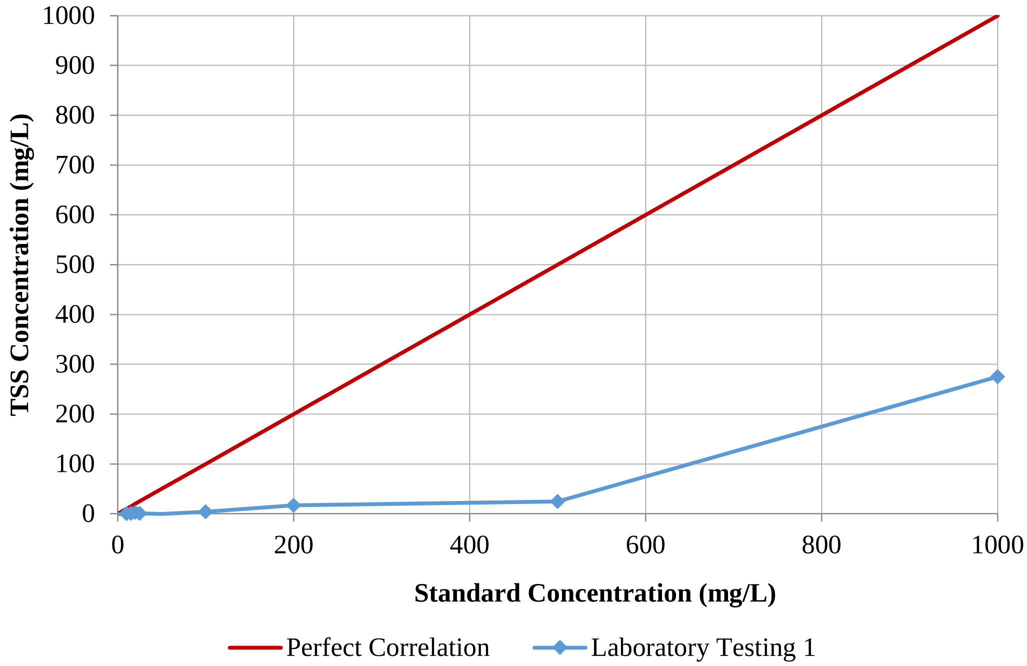

Figure 5-71: Correlation between No. 200 Standard TSS Concentration and Laboratory tested TSS Concentration

The red line represents a perfect relationship between the theoretical standard concentration and the laboratory concentration while the blue line represents the results of laboratory testing.

To validate the use of the initial standards made, TSS was tested a second time within the laboratory (Figure 5-6). This round of laboratory tested resulted in the laboratory tested concentrations to be on average within 10% of the theoretical concentration. Although these were favorable results, one of the concerns that arose when testing the standards made included the uncertainty of what percentage of the sample was composed of TDS since TDS was not originally tested. In 2016, Erica Forgione determined a specific correlation between the TDS observed at the CSW 2.0 at Villanova University to the observed conductivity. This correlation allowed for the quantification of TDS in the standards resulting in an average TDS concentration of 3.04 mg/L (σ = 4.44 mg/L) which is once again insignificant when compared to the historical average TDS observed at the CSW 2.0 (636.02 mg/L; σ = 635.75 mg/L).

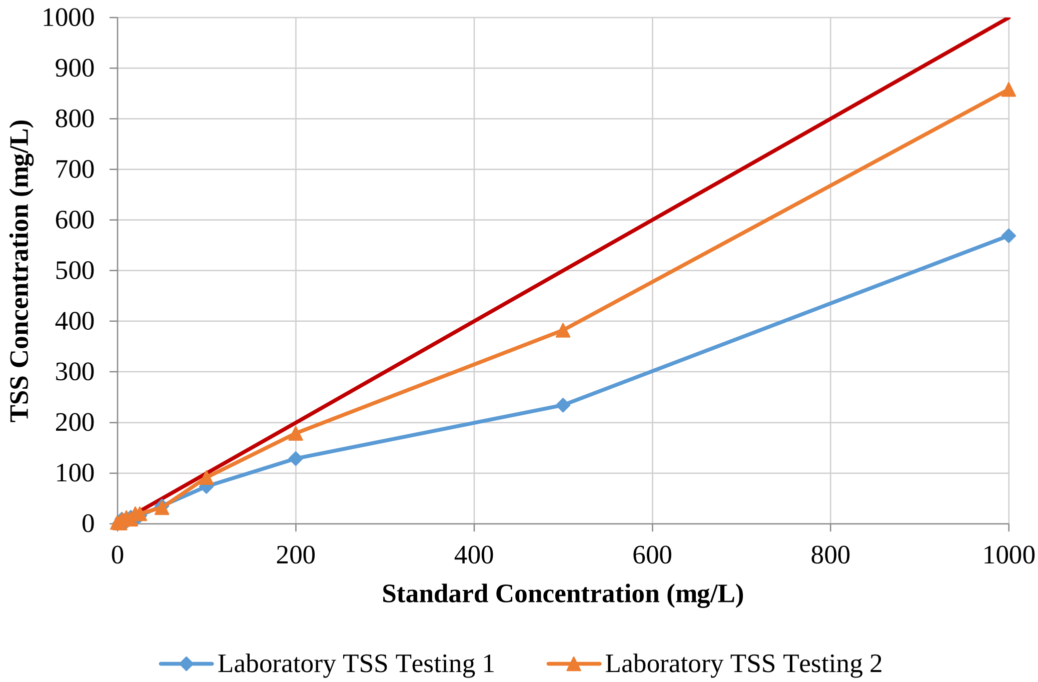

Figure 5-72: Correlation between Pan Standard TSS Concentration and Laboratory tested TSS Concentration

The red line represents a perfect relationship between the standard concentration and the laboratory concentration, the blue line represents the results of the first round of laboratory testing, and the orange line represents the results of the second round of laboratory testing.

Seeing as Opti needs a relationship between a TSS concentration and mV output from the LISST-ABS standard to collect data from the sensor, a mV reading of each standard was collected. To do so the LISST-ABS sensor was connected to the power source provided by Opti and allowed to record 20 minutes of mV readings without being in any liquid solution. This determined that the average mV reading of the sensor when not in solution is 4351 mV (σ = 85 mV). To measure the mV of each standard, the LISST-ABS sensor was submerged in the solution for five minutes and the mV was recorded. A five minute time period was selected to match the sample period of the other sensors located at the CSW 2.0. To assure that each standard was completely mixed, a stir bar and a stirring plate was used. The mV of each standard was read two separate times allowing for a five minute resting time in between sampling. The LISST-ABS sensor was removed from the solution during this resting period.

Once the data was downloaded from Opti's data logging cloud, it was observed that during several mV calculations, the LISST-ABS sensor recorded values indicative that the sensor was not always submerged during the five minute testing period. From observations during testing, these values may be attributed to a vortex forming within the sample due to the stir bar. These values where removed from the data set for this analysis. The mV recorded for each standard showed some variation between the two separate reading periods (Figure 5-7). Additionally, it was expected that as the concentration of the standard increased, the mV reading from the sensor would increase as well; a trend that was not observed in the recorded data.

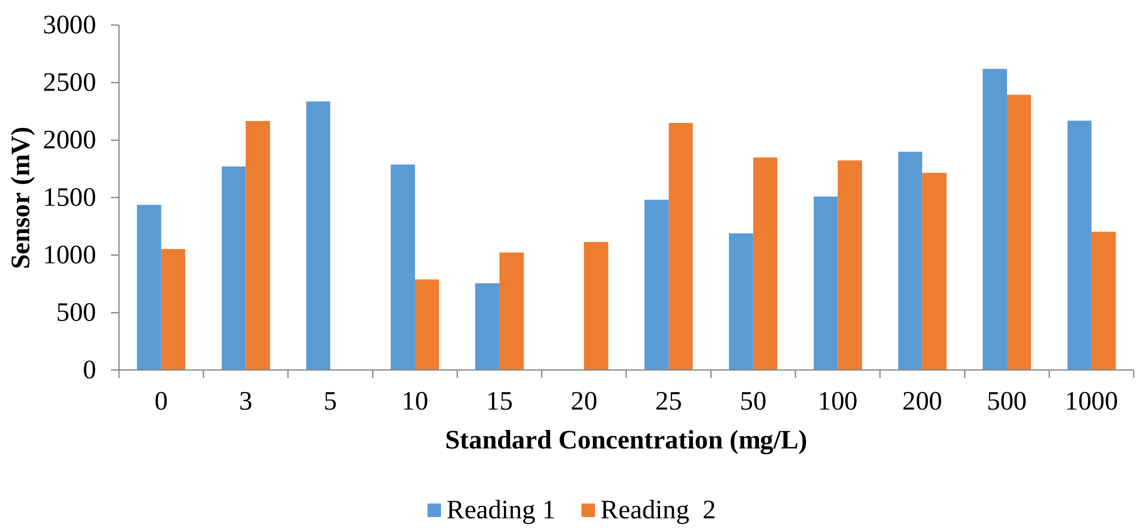

Figure 5-73: LISST-ABS mV Readings for each Standard

The equations provided by Sequoia for converting mV into concentration for the LISST-ABS sensor was used to further determine if the mV recorded is representative of the concentration of each standard (Table 5-1). Once again the calculated concentrations failed to represent the concentration of each standard.

Table 5-22: LISST-ABS Calculated TSS Concentration from mV

Standard Concentration (mg/L)	Reading 1 Calculated Concentration (mg/L)	Reading 2 Calculated Concentration (mg/L)
0	23	8
3	446	1061
5	12622	NA
10	4362	0
15	0	2
20	NA	6
25	145	225
50	2	312
100	44	97
200	504	192
500	6666	735
1000	729	53

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In one final attempt to create a calibration curve for the LISST-ABS sensor, Sequoia's provided software was used to determine a calibration constant. Once the software was installed on the computer, the LISST-ABS sensor was connected to the computer and submerged into the 100 mg/L standard. The concentration of the standard was indicated within the software and the sensor proceeded to record 100 readings of the solution's concentration to determine the calibration constant. This procedure was repeated four separate time resulting in an average calibration constant of 1.33 (σ = 0.11). The calibration constant was applied to the calculated concentrations (Table 5-1) and resulted in similar values (Table 5-2). This indicates that the

LISST-ABS sensor cannot be easily calibrated to the observed sediment within the CSW 2.0 and that the observed levels of TSS within the system may be too low with a historical average of 16.73 mg/L (σ = 45.64 mg/L).

Table 5-23: LISST-ABS Calibrated TSS Concentrations

Standard Concentration (mg/L)	Reading 1 Calibrated Concentration (mg/L)	Reading 2 Calibrated Concentration (mg/L)
0	26	6
3	198	1131
5	6726	NA
10	5812	0
15	0	3
20	NA	5
25	193	120
50	1	416
100	39	129
200	537	256
500	8881	979
1000	972	23

5.4 LISST-ABS Un-calibrated Data Analysis

Seeing as a calibration curve representative of the sediment within the CSW 2.0 was not calculated, the raw mV output of the sensor was analyzed to determine a threshold from which to make decisions for real time control. This section of the study will focus on the LISST-ABS mV output both during storm and baseflow events.

5.4.1 LISST-ABS Un-calibrated Storm Event Analysis

During the study period of September 2016 to December of 2016, the LISST-ABS sensor recorded data during several different sized storm events. It is expected that an increase in the mV reading of the sensor will occur after rainfall has been recorded and at the same time as an increase in sediment-laden inflow into the system. This relationship would indicate that the inflow into the system is increasing the concentration of TSS. Twelve storms were observed and this expected performance was only observed 25% of the time. Three of the 12 storm events recorded (Table 5-3) showed the LISST-ABS sensor responding as expected with relation to the rainfall recorded as well as the total inflow (highlighted in green). Four of the 12 storm events were tested in the laboratory out of which two events correspond to events where the sensor responded as expected, 9/19/2016 and 11/30/2016.

Table 5-24: Storm Events Recorded by the LISST-ABS Sensor

Storm Date	Storm Size (in)	Storm Duration (hrs)	Storm Intensity (in/hr)
9/19/2016	2.28	14.33	0.16
9/29/2016	1.54	37.42	0.04
10/9/2016	0.49	13.17	0.04
10/21/2016	0.35	21.25	0.02
10/27/2016	0.55	15.58	0.04
10/30/2016	0.19	7.00	0.03
11/9/2016	0.54	18.50	0.03
11/29/2016	1.21	19.67	0.06
11/30/2016	1.26	24.17	0.05
12/5/2016	0.15	11.75	0.01
12/6/2016	0.88	21.08	0.04
12/12/2016	0.36	13.50	0.03

The LISST-ABS sensor's response during the storm event on 9/19/2016 (Figure 5-8), shows an initial peak after 1.42 inches of rainfall (denoted by a peak in the precipitation) followed closely by a secondary peak at 1.61 inches of rainfall as well as a tertiary peak at 2.11 inches of rainfall. This is mirrored as well by the total inflow into the system, which for the sake of clarity in this figure has been multiplied by a factor of 10. The response (i.e., sharp increase in mV reading) of the LISST-ABS sensor, in conjunction with the peak in total inflow, indicates that the stormwater runoff entering the system contains elevated concentrations of TSS. From laboratory testing it was determined that the average TSS concentration during this storm event was 23.4 mg/L (σ = 21.2 mg/L) with a maximum TSS concentration of 42.3 mg/L.

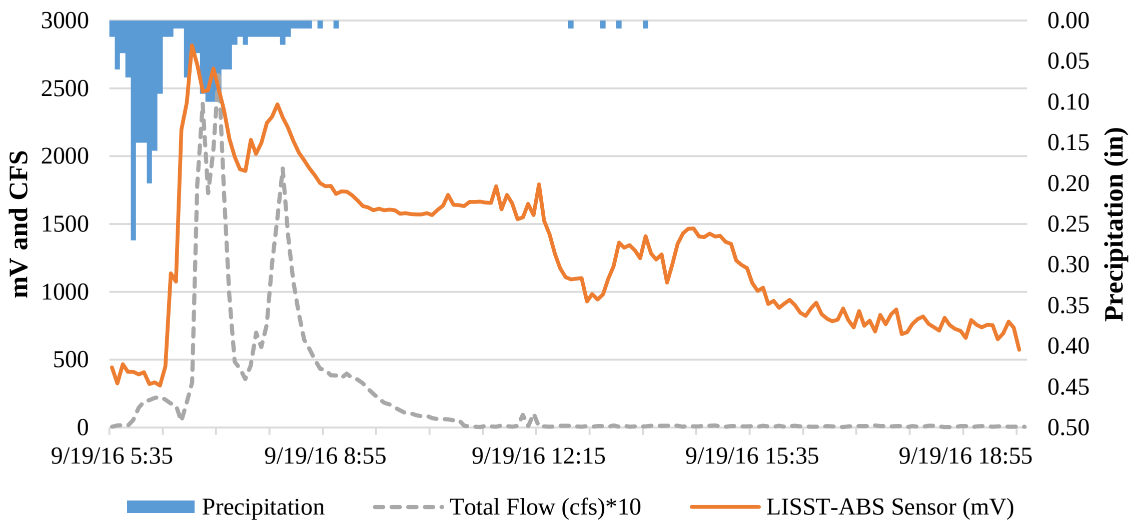

Figure 5-74: LISST-ABS 9/19/2016 Storm Event Response

Similar observations of the LISST-ABS sensor's response during the storm event on 10/30/2016 (Figure 5-9) and 11/30/2016 (Figure 5-10) show a peak of rainfall followed by a peak in total inflow and TSS as represented by the LISST-ABS sensor.

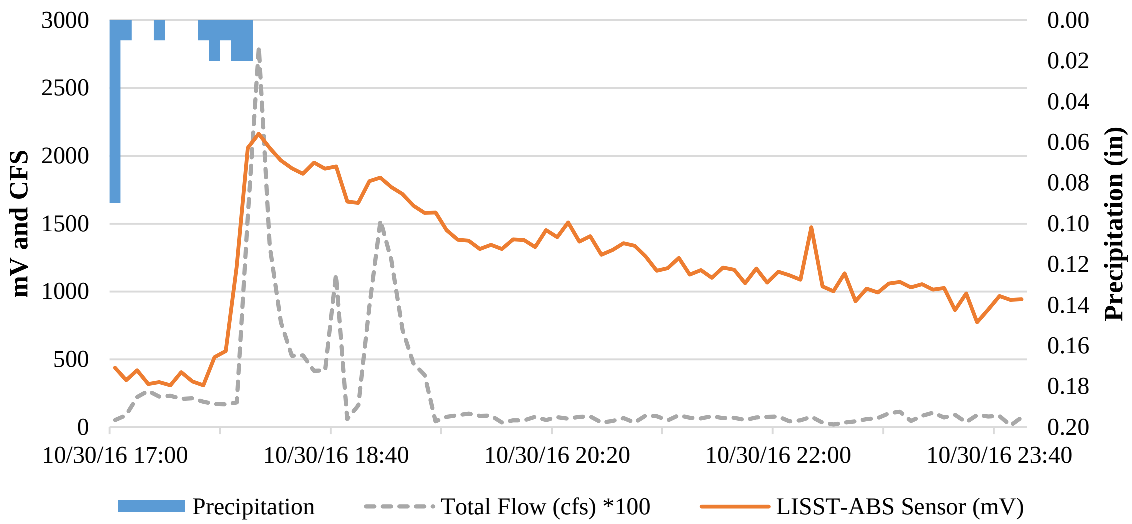

Figure 5-75: LISST-ABS 10/30/2016 Storm Event Response

There is a qualitative observation that the storm intensity and volume are correlated to TSS concentration (Table 5-3), such that a storm with higher intensity and volume may have a greater capability of transporting solids when compared to a storm with a lower intensity and volume. The 9/19 event was the largest and most intense and had the greatest mV reading (max 2815 mV), while the 10/30/2016 and 11/30/2016 events had a max peak mV of 2162 mV and 2340 mV, respectively. The 10/30 and 11/30 events have similar intensities, although appear to be different enough for this correlation between intensity and mV to be observed. It appears that intensity is correlated to higher TSS concentrations in the CSW 2.0. From laboratory testing it was determined that the average TSS concentration during the 11/30 storm event was 9.6 mg/L (σ = 4.6 mg/L) with a maximum TSS concentration of 16 mg/L. Looking at the difference in peak mV read from the sensor, the lower TSS concentration recorded during the 11/30 storm event when compared to the 9/19 storm event indicate that small changes in mV represent larger changes in the observed TSS concentration.

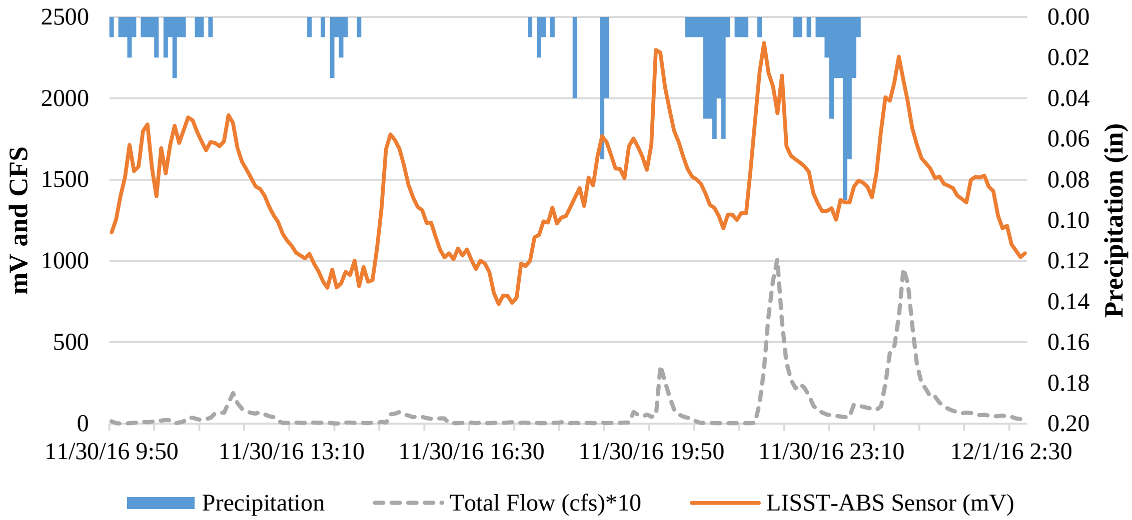

Figure 5-76: LISST-ABS 11/30/2016 Storm Event Response

Contrary to what was observed during the 9/19/2016, 10/30/2016, and the 11/30/2016 storm events, the nine other storms did not show the same close relationship between precipitation, LISST-ABS sensor readings, and total inflow. For example, the 11/9/2016 storm event (Figure 5-11) shows a similar relationship between precipitation and the LISST-ABS sensor with the sensor peaking after a peak in rainfall. The total inflow of the system peaks much later in the storm event. This same offset between peak inflow and peak mV readings is also seen during the storm event on 9/29/2016 (Figure 5-12) with the LISST-ABS sensor reacting after precipitation has been recorded and the total inflow of the system peaks sporadically throughout the storm event almost always after the LISST-ABS sensor has shown an increase in mV. This indicates that the LISST-ABS sensor is much more sensitive to change than the flow meters. Additionally, the lack of a peak in the total inflow when the LISST-ABS sensor first peaks indicates that TSS may not necessarily be introduced into the system but rather just re-suspended within the CSW 2.0.

While some storms showed a correlation among precipitation, mV and inflow, others did not. However, max mV readings were similar (in the range of 1800 to 2800 mV) in all cases. As the sensor under this condition is not calibrated, it is unclear if the same TSS concentration was actually recorded. Because of the inconsistency in the observed mV reading of each storm event, the impact of the preceding baseflow conditions were also analyzed.

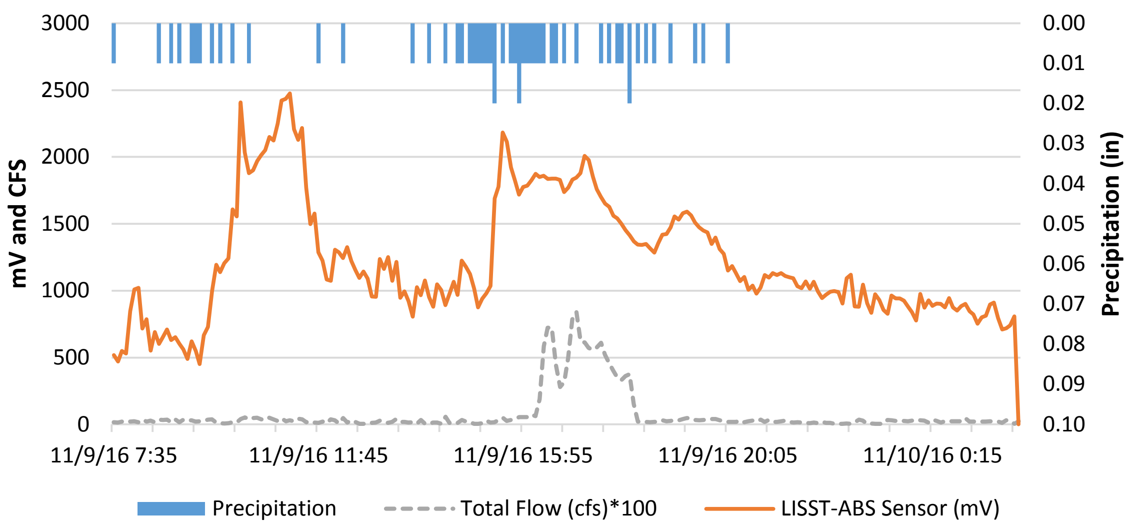

Figure 5-77: LISST-ABS 11/9/2016 Storm Event Response

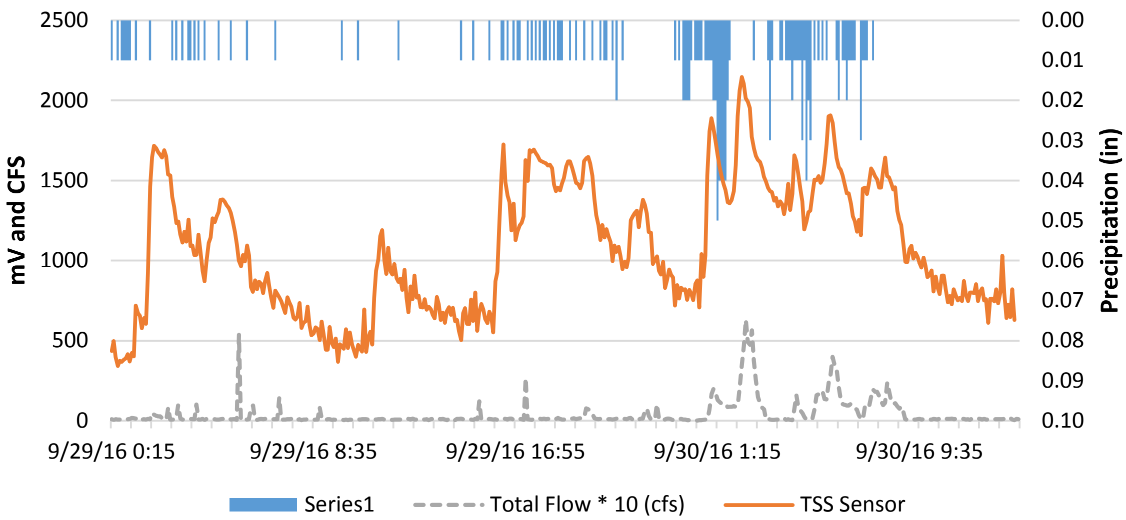

Figure 5-78: LISST-ABS 9/29/2016 Storm Event Response

5.4.2 LISST-ABS Un-calibrated Baseflow Event Analysis

During the study period of September 2016 to December of 2016, the LISST-ABS sensor recorded data during several different duration baseflow events. For this study a handful of baseflow events were selected and analyzed (Table 5-4) and it is expected that the readings from the LISST-ABS sensor will remain fairly constant when compared to the storm events.

Table 5-25: Baseflow Events Recorded by the LISST-ABS Sensor

Baseflow Start Date	Baseflow End Date	Baseflow Duration (hrs)	Average LISST-ABS Reading (mV)	Standard Deviation LISST-ABS Reading (mV)
9/1/2016	9/19/2016	421.75	507	214
10/28/2016	10/30/2016	61.17	709	367
10/31/2016	11/9/2016	223.58	584	177
12/5/2016	12/6/2016	86.83	682	216
12/7/2016	12/12/2016	109.66	914	378

When looking at a baseflow event beginning on 9/1/2016 and ending before the beginning of the 9/19/2016 storm event (Figure 5-13), one can see that the mV recorded by the LISST-ABS sensor ranges between 260 and 1500 mV with the exception of the peak on 9/4/2016 of 3507 mV. This peak is likely due to human or animal disturbance of the settled material in the CSW 2.0. The inflow peak observed during the 10/31 baseflow event is indicative of discharge into the system not related to a rainfall event. Additionally, the average mV reading within the CSW 2.0 during this time period was 507 mV with a standard deviation of 214 mV. Similarly, the baseflow event beginning on 10/31/2016 and ending before the beginning of the 11/9/2016 storm event (Figure 5-14), had a LISST-ABS sensor range of 270 and 1500 mV and an average mV reading of 584 mV with a standard deviation of 177 mV. This range is true for all baseflow examples.

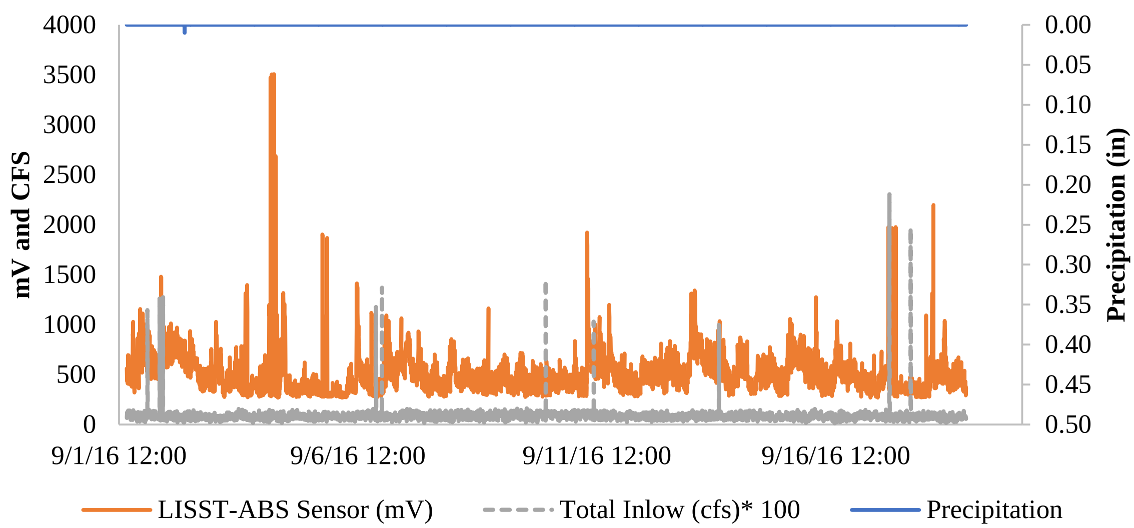

Figure 5-79: LISST-ABS 9/1/2016 Baseflow Event Response

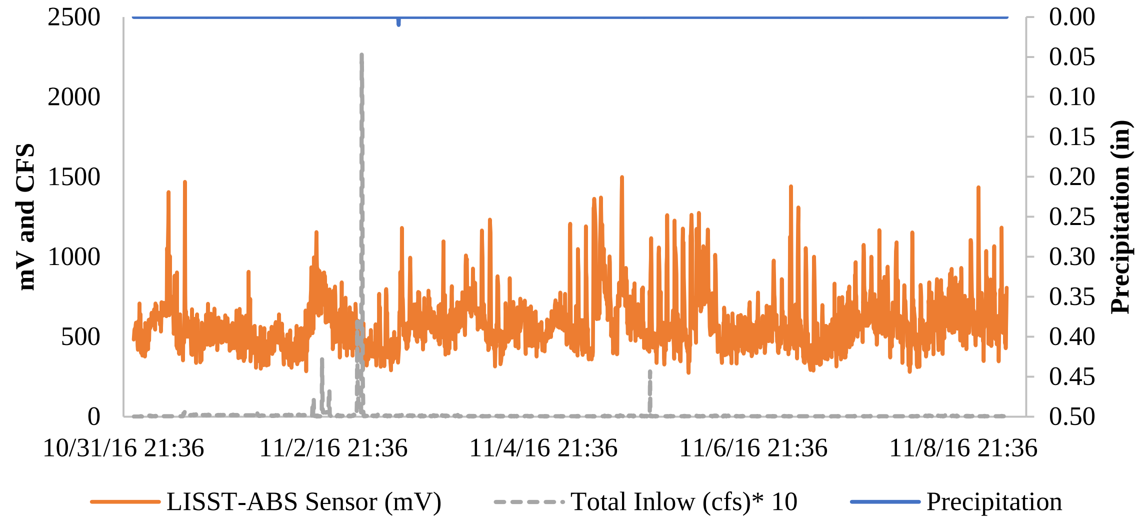

Figure 5-80: LISST-ABS 10/31/2016 Baseflow Event Response

CHAPTER 6 – CONCLUSIONS

6.1 CSW 2.0's Performance

During the study period of June 2012 to December 2016, the annual precipitation observed in 2012 of 41.92 inches was on par with the expected annual precipitation of 44 inches for the state of Pennsylvania. The annual precipitation then increased in 2013 to 52.40 inches followed by 2014 with a total precipitation volume of 47.24 inches including the largest number of recorded storm and baseflow events, 202, as well as two rainfall events greater than 4.0 inches. 2015 and 2016 followed with a total precipitation volume of 38.26 inches and 36.20 inches respectively indicating slight drought conditions in the area.

Although 2015 accounted for the least amount of recorded storm and baseflow events, 147, during the study period, significant differences were found in the both the average yearly inflow as well as average yearly volume when compared to 2012 (paired t-test; $p = 0.00829$, 0.00184, respectively). A significant difference was also found in the average yearly inflow volume when compared to 2014 (paired t-test; $p = 0.0006$). This indicates that although 2014 experienced larger storm events, changes in the watershed, in the form of an upstream infiltration trench being retrofitted, resulted in higher runoff volumes for 2015. The increase in runoff volume during 2015 was further highlighted when statistical differences in the average storm inflow were found from 2014 to 2015 (paired t-test; $p = 0.0398$) as well as in the average storm inflow and volume from 2012 to 2015 (paired t-test; $p = 0.0103$, 0.0105, respectively). Significant statistical differences were found in the average baseflow inflow between 2012 and 2013 (paired t-test; $p = 0.0005$) as well as between 2013 and 2014 (paired t-test; $p = 1.22*10^{-5}$)

indicating that although 2013 recorded the largest volume of precipitation, the runoff inflow into the CSW 2.0 was captured during the individual storm events and did not carry over to the baseflow events.

No statistical differences were found in the average yearly outflow of the CSW 2.0 during the study period and the average inflow exiting the system decreased from 98% to 37% from 2012 to 2016 indicating that the system became better equipped to handle flow. No statistical difference in the average storm outflow was found between 2014 and 2015 (paired t-test; $p = 0.355$) indicating that although 2015 resulted in higher inflow into the CSW 2.0 than 2014, the performance of the system was not compromised and attenuation was achieved. A statistical difference was found in the average outflow between 2015 and 2016 (paired t-test; $p = 0.0176$) indicating that a change within the system has impaired the system's ability to handle inflow.

The CSW 2.0 showed the highest yearly peak flow attenuation (50%) in 2014 followed by 2015 with the highest yearly average volume attenuation (29%). 2013 resulted in both the lowest yearly peak flow attenuation (14%) as well as the lowest yearly average volume attenuation (-11%) indicating that the outflow of the system was greater than the inflow. This is a result of the CSW 2.0 not having sufficient vegetation to increase the drag within the system. Both 2012 and 2014 resulted in the highest storm peak flow attenuation (67% and 65%, respectively) while 2015 resulted in the highest storm average volume attenuation (44%). 2013 resulted in the lowest storm peak flow attenuation (59%) while 2012 resulted in the lowest storm average volume attenuation (6%). These values, although smaller than the other percent attenuations during this study, indicates that the CSW 2.0 is attenuating both peak flow and average volume during storm events throughout the entire study period. 2014 and 2015 resulted in the highest baseflow peak flow and average volume attenuation (42% and 21%, respectively) while 2013 showed both the lowest peak flow and average volume attenuation (-11% and -27%, respectively).

The increase in vegetation, from 2011 to 2015, indicates that the volume attenuation observed in 2015 is a factor of the increased density of the macrophytes within the system and that the removal of cattails and phragmites result in larger distributions of outflow data. Similarly, the mean residence time within the CSW 2.0, during storm events, increased from 2014 to 2017: 9 and 37 hours, respectively, to the beginning of M1, 7 and 52 hours, respectively, to the end of M1, and 36 to 84 hours, respectively, to OUT. The mean residence time within the CSW 2.0, during baseflow events, increased from 2014 to 2017: 22 and 72 hours, respectively, to the beginning of M1, and 97 to 115 hours, respectively, to OUT. A slight decrease in residence time from 2014 to 2017 was seen at the end of M1 with a mean residence time of 51 and 43 hours, respectively.

The observations made above indicate that the two factors that play the most influential role when determining the performance of a system includes both the available inflow as well as the vegetation density. The distribution of the first can determine the available water storage within the system while the second determines the mean residence time. An increase in both the stored volume as well as the mean residence time allows for a better removal of nutrients and pollutants via physical, chemical, and biological processes.

A study of the CSW 2.0 from 2016 to the present date should be conducted to determine the impact of the removal of macrophytes from the CSW 2.0 and if this form of maintenance is detrimental to the performance of the system. Additionally, a study of the water quality of the system from July 2012 to December 2016 would further determine the importance of vegetation and hydraulic residence time in stormwater management within a constructed stormwater wetlands.

6.2 Sequoia LISST-ABS TSS Sensor

Several attempts were made to create a LISST-ABS calibration curve representative of the soil found at the CSW 2.0 but none resulted in adequate curves. Standards with known concentrations were made from soil collected on site and the concentrations were validated in the laboratory. The sensor's mV was recorded in each standard resulting in data that does not result in the expected trend; as the TSS concentration increases and increase in the mV is recorded. This, combined with the efforts to calibrate the mV results of each standard with the equations provided by Sequioa as well as the calibration constant calculated using their software, indicates that the LISST-ABS is too sensitive for the concentration of TSS observed at the CSW 2.0 (on average 16.73 mg/ L).

An analysis of the LISST-ABS sensor's response to storm events indicates that that the intensity of the storm event results in higher TSS correlations. Additionally, the analyzed storm events showed a maximum mV peak ranging between 1800 and 2800 mV although not all events showed the desired correlation between precipitation, flow, and TSS. The response of the LISST-ABS sensor during baseflow events was also analyzed to determine a mV baseline when zero to no TSS is expected. It was determined that during baseflow conditions the LISST-ABS sensor read between 270 and 1500 mV. Although these values are much lower than the peaks observed during storm events, large variability in the data exists indicating that the sensor is highly sensitive. Thus this sensor should be used in an environment with higher TSS levels.

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APPENDIX

A.1 Tracer Test Standards Dilutions

Rhodamine dye is a 20% solution (200,000 mg/L)

Need the following dilutions:

ppb	5	10	25	50	100	400	40000
mg/L	0.005	0.01	0.025	0.05	0.1	0.4	40

The following equations were used to calculate the volume of dye needed (x) to mix a solution with the desired concentration.

Stock Solutions

2,000 mg/L (2,000,000 ppb)

$$\left(2{,}000\frac{mg}{L}\right)(1000\ mL) = \left(200{,}000\frac{mg}{L}\right)(x\ mL)$$

$$10\ mL = x$$

100 mg/L (100,000 ppb)

$$\left(100\frac{mg}{L}\right)(100\ mL) = \left(2{,}000\frac{mg}{L}\right)(x\ mL)$$

$$5\ mL = x$$

10 mg/L (10 ppb)

$$\left(10\frac{mg}{L}\right)(100\ mL) = \left(100\frac{mg}{L}\right)(x\ mL)$$

$$10\ mL = x$$

Standard Solutions

From 2,000 mg/L

<u>40 mg/L (40,000 ppb)</u>

$$\left(400\frac{mg}{L}\right)(900\ mL) = \left(2{,}000\frac{mg}{L}\right)(x\ mL)$$

$$18\ mL = x$$

From 100 mg/L

<u>0.4 mg/L (400 ppb)</u>

$$\left(0.4\frac{mg}{L}\right)(900\ mL) = \left(100\frac{mg}{L}\right)(x\ mL)$$

$$3.6\ mL = x$$

<u>0.1 mg/L (100 ppb)</u>

$$\left(0.1\frac{mg}{L}\right)(900\ mL) = \left(100\frac{mg}{L}\right)(x\ mL)$$

$$0.9\ mL = x$$

<u>0.05 mg/L (50 ppb)</u>

$$\left(0.05\frac{mg}{L}\right)(900\ mL) = \left(100\frac{mg}{L}\right)(x\ mL)$$

$$0.45\ mL = x$$

From 10 mg/L

<u>0.025 mg/L (25 ppb)</u>

$$\left(0.025\ \frac{mg}{L}\right)(900\ mL) = \left(10\frac{mg}{L}\right)(x\ mL)$$

$$2.25\ mL = x$$

<u>0.01 mg/L (10 ppb)</u>

$$\left(0.01\ \frac{mg}{L}\right)(450\ mL) = \left(10\frac{mg}{L}\right)(x\ mL)$$

$$0.45\ mL = x$$

From 0.05 mg/L

<u>0.005 mg/L (5 ppb)</u>

$$\left(0.005\frac{mg}{L}\right)(450\ mL) = \left(0.05\frac{mg}{L}\right)(x\ mL)$$

$$45\ mL = x$$

A.2 Event Definition Code

```
% t is the time in excel datetime format
% X is the [CSW_OUT_Q, RAINIntegral]
Qout = X(:,1);
R = X(:,2);

Rnum = 100000000;
Inum = 200000000;
Bnum = 300000000;

N=length(t);
Timestamps = datetime(t, 'ConvertFrom','Excel');
DayID= yyyymmdd(Timestamps);
ID=R*0;

cutoff = 0.1; %inches
interTimeLimit = 3; %days
interQoutLimit = 0.1; % cfs
numQoutAverage = 12; % number of previous points to average

inInterEvent = 0;
inBaseEvent = 0;
currentID = 0;
interStartTime=0;

if R(1)>=cutoff,
    inRainEvent=1;
    currentID = DayID(1)+Rnum;
    ID(1)=currentID;
else
    inRainEvent=0;
    ID(1)=0;
end

for i=2:N,
    if inRainEvent,
        if R(i)<cutoff,
            %End rainfall, start interflow
            inRainEvent = 0;
            inInterEvent = 1;
            inBaseEvent = 0;
            interStartTime = t(i);
            currentID = DayID(i)+Inum;
            ID(i)=currentID;
        else
            ID(i)=currentID;
        end
    else
        if R(i)>=cutoff,
            % Whenever R exceeds cutoff, start a new Rain event
            inRainEvent = 1;
            inInterEvent = 0;
            inBaseEvent = 0;
```

```
            currentID = DayID(i)+Rnum;
            ID(i)=currentID;
            % Also, since R is now >= 0.1, work backwards to include the
            % previous rainfall in this event.
            j=i-1;
            while j>0 && R(j)>0,
                ID(j)=currentID;
                j=j-1;
            end
        elseif inInterEvent,
            n1 = max(i-numQoutAverage, 1);
            if (t(i)-interStartTime)>=interTimeLimit || mean(Qout(n1:i),
'omitnan')<interQoutLimit,
                % does there need to be an additional rain check?
                % Pass into Baseflow
                inRainEvent = 0;
                inInterEvent = 0;
                inBaseEvent = 1;
                currentID = DayID(i)+Bnum;
                ID(i)=currentID;
            else
                ID(i)=currentID;
            end
        elseif inBaseEvent,
            ID(i)=currentID;
        else
            %Shouldn't end up here, except maybe before first Rain event
            inRainEvent = 0;
            inInterEvent = 0;
            inBaseEvent = 0;
            ID(i)=0;
        end
    end
end

Y=ID;
```

A.3 Outlet Weir Structure Equations and Correlations

Weir Equation 1

$Q = C(H_1)^{5/2}$

$C = 2.49$

Orifice Equation 1

$Q = CA(2gH_2)^{1/2}$

C =	0.591	in m
A =	0.9044	ft^2
g =	32.2	ft/s^2
C =	1.07	in ft

Weir Equation 2

$Q = C_e L_e (H_e)^{3/2}$

$L_e = (L/12) + k_L$

$H_e = H_3 + 0.0001$

L =	15	inches
b =	96	inches
L/b =	0.2	
k_L =	0.0025	
P =	42.84	inches
L_e =	1.2525	

C_e

H_e / P	C (in m)	C (in ft)
0 - 0.4	1.735	3.145
0.41 - 0.8	1.730	3.1356
0.81 - 1.2	1.725	3.127
1.21 - 1.6	1.200	2.1753
1.61 - 2.0	1.150	2.0844
2.01 - 2.4	1.100	1.994

Weir Equation 3

$Q = C_e L_e (H_e)^{3/2}$

$L_e = (L/12) + k_L$

$H_e = H_4 + 0.0001$

L =	7	inches
b =	96	inches
L/b =	0.1	
k_L =	0.0025	
P =	78.84	inches

C_e

H_e / P	C (in m)	C (in ft)
0 - 0.4	1.735	3.145
0.41 - 0.8	1.730	3.1356
0.81 - 1.2	1.725	3.127
1.21 - 1.6	1.200	2.1753
1.61 - 2.0	1.150	2.0844
2.01 - 2.4	1.100	1.994

Orifice Equation 2

$Q = CA(2gH_5)^{1/2}$

C =	0.603	in m
A =	52.3	ft^2
g =	32.2	ft/s^2
C =	1.093	in ft

Variable	Calculation
H_1	(PT - 2.85)/12
H_2	(PT - 3.03)/12
H_3	(PT - 27.3)/12
H_4	(PT - 63.3)/12
H_5	(PT - 43.07)/12

Figure CCCC-1: Equations used at the Outlet Structure

Table Z-1: Rainfall Events Used to Validate Weir Equation Curve

StartTime	**EndTime**	**Duration**	**RAIN**
date/Time	*date/Time*	*hours*	*in*
12/11/12 4:40	12/11/12 12:00	7.42	0.12
6/11/14 23:00	6/12/14 6:45	7.83	0.12
7/13/14 22:20	7/14/14 6:05	7.83	0.14
4/23/16 8:00	4/23/16 15:50	7.92	0.14
7/26/14 8:05	7/26/14 15:05	7.08	0.19
10/30/16 17:00	10/30/16 23:55	7.00	0.19
10/7/14 20:50	10/8/14 5:40	8.92	0.29
4/26/16 15:15	4/26/16 23:35	8.42	0.29
5/28/13 8:35	5/29/13 1:00	16.50	0.37
9/13/14 12:30	9/14/14 2:35	14.17	0.37
10/11/14 3:30	10/11/14 18:00	14.58	0.40
10/19/12 0:30	10/19/12 15:50	15.42	0.40
10/3/14 23:10	10/4/14 14:45	15.67	0.51
5/31/15 23:15	6/1/15 11:40	12.50	0.51
11/24/14 0:55	11/24/14 11:30	10.67	0.63
2/25/17 16:45	2/26/17 0:35	7.92	0.63
3/18/13 17:10	3/19/13 15:35	22.50	0.75
1/3/15 11:35	1/4/15 16:25	28.92	0.98
8/12/14 6:20	8/13/14 7:50	25.58	1.00
10/15/14 11:00	10/16/14 9:20	22.42	1.01
7/27/14 21:15	7/28/14 10:10	13.00	1.24
8/1/13 5:35	8/1/13 18:55	13.42	1.26
1/18/15 8:10	1/19/15 0:10	16.08	1.49
6/10/13 5:35	6/11/13 5:30	24.00	2.70
6/6/13 18:35	6/8/16 6:10	35.67	4.41

In Figure A1 – Figure A15 the grey lines represent the beginning of each flow scenario while the blue line is the curve created from the weir equations for each scenario.

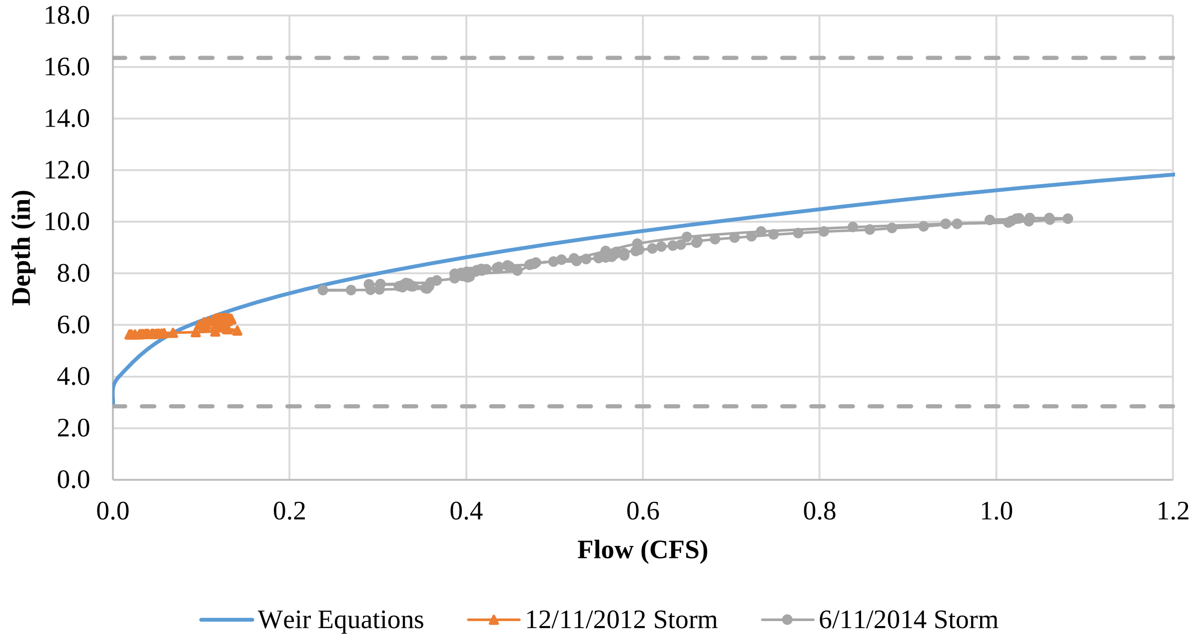

Figure A-2: 0.12" Storm Event Weir Equation Curve Validation

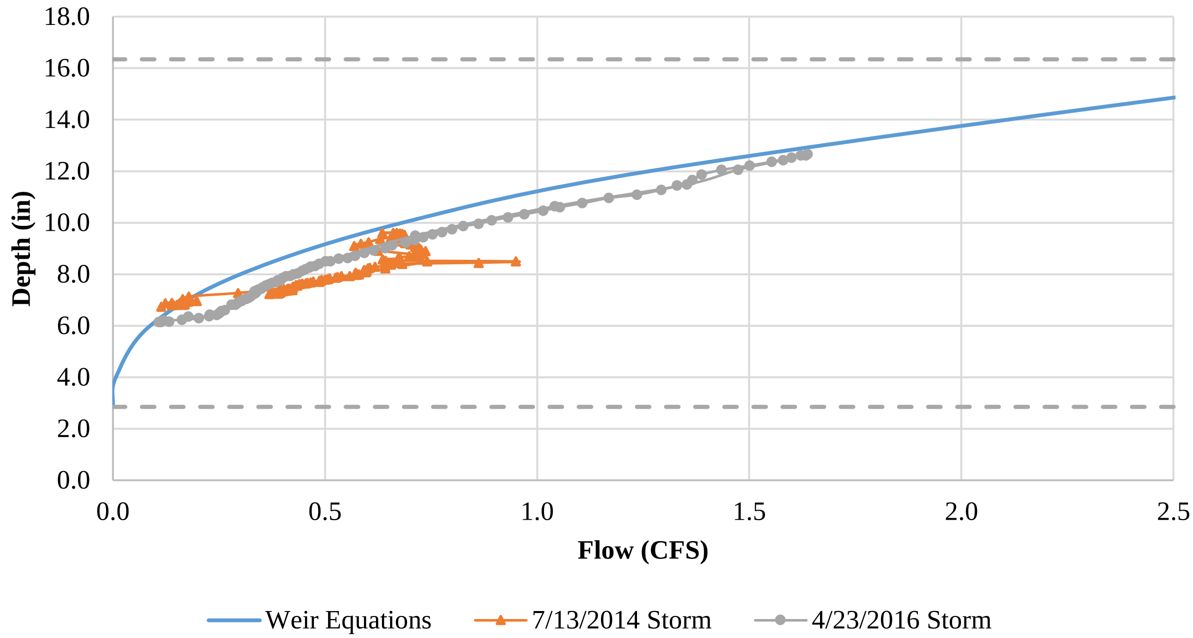

Figure A-3: 0.14" Storm Event Weir Equation Curve Validation

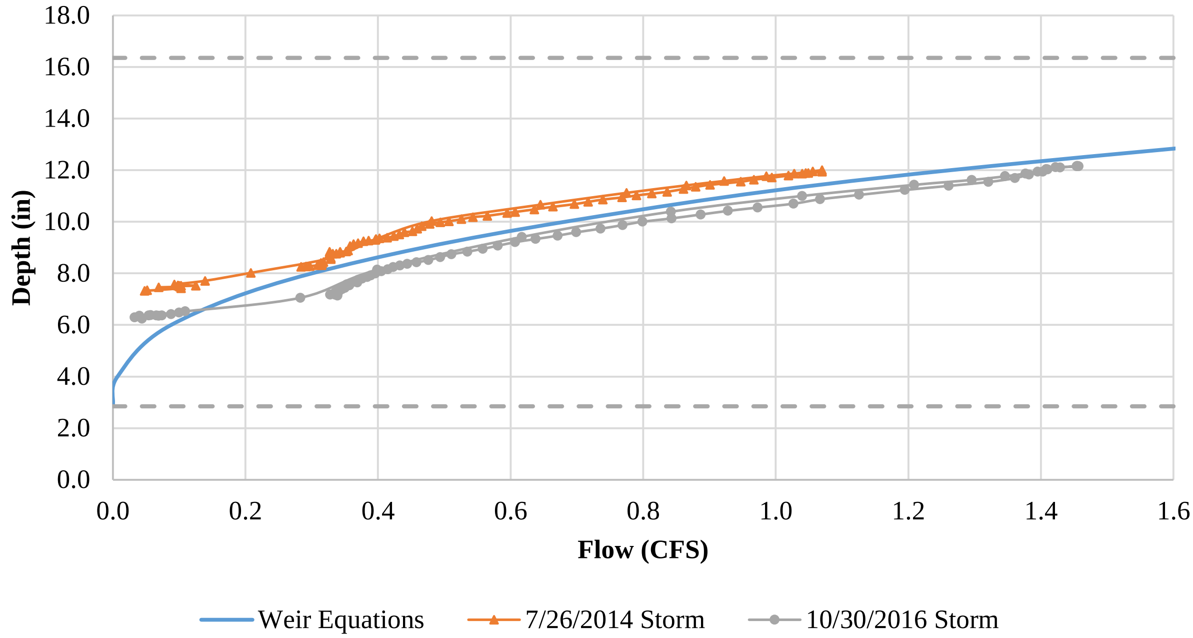

Figure A-4: 0.19" Storm Event Weir Equation Curve Validation

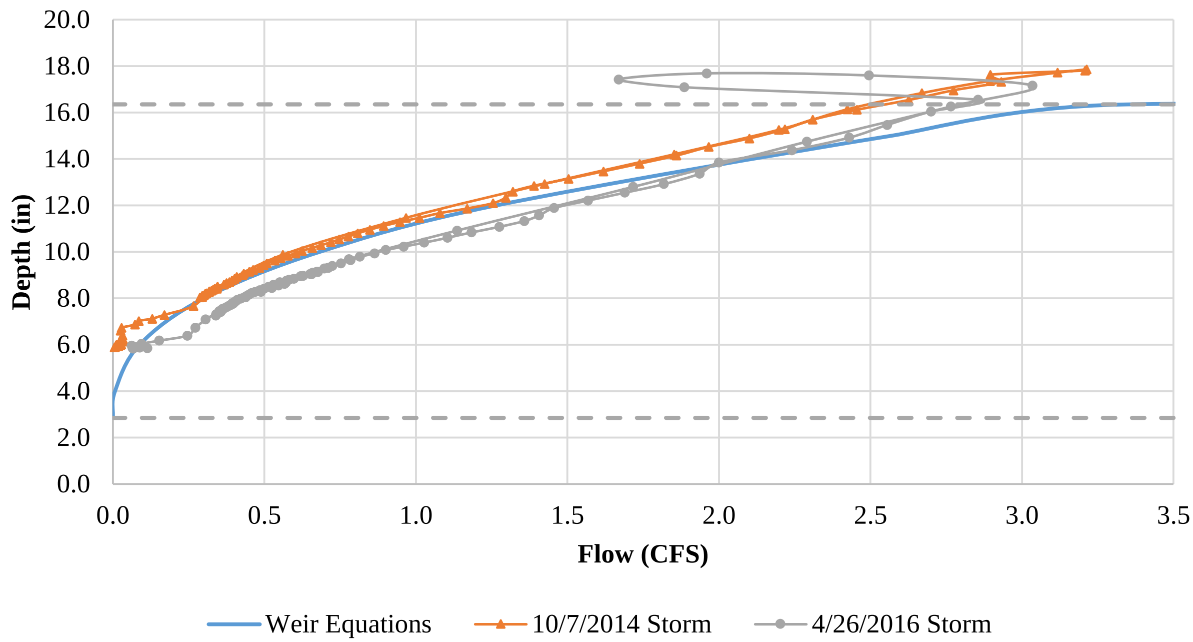

Figure A-5: 0.29" Storm Event Weir Equation Curve Validation

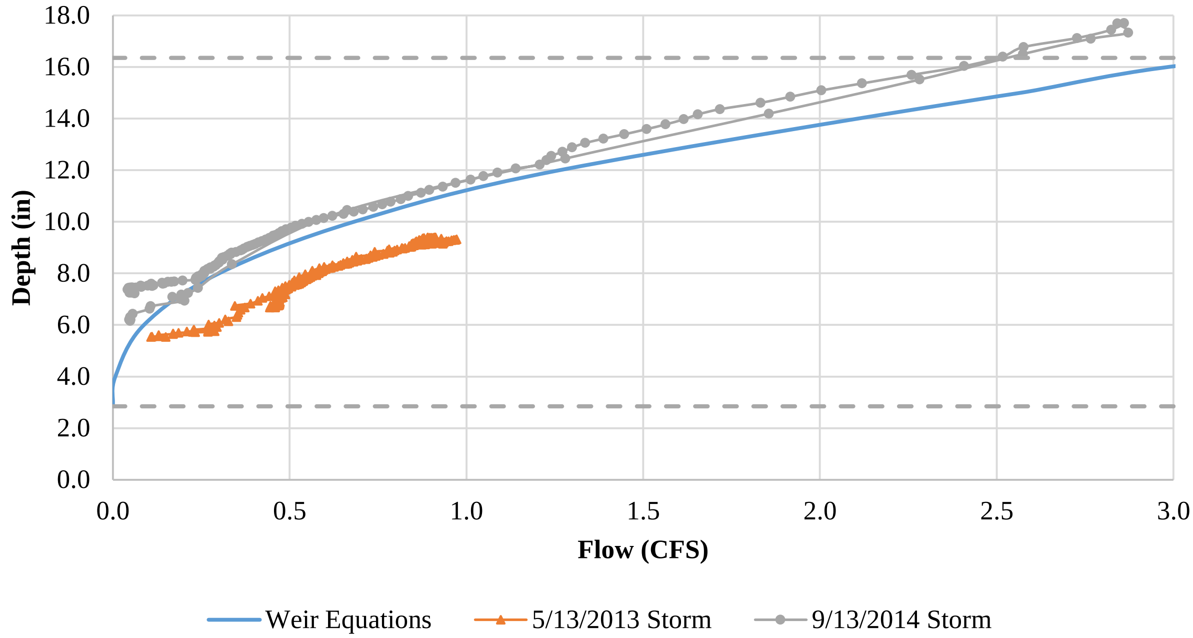

Figure A-6: 0.37" Storm Event Weir Equation Curve Validation

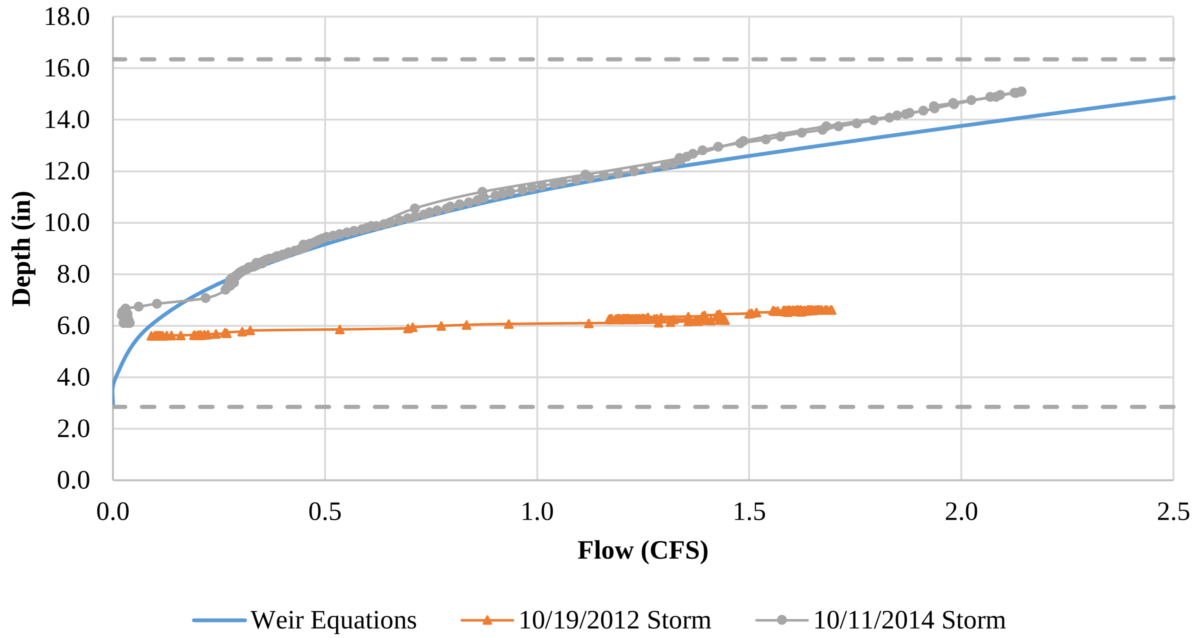

Figure A-7: 0.40" Storm Event Weir Equation Curve Validation

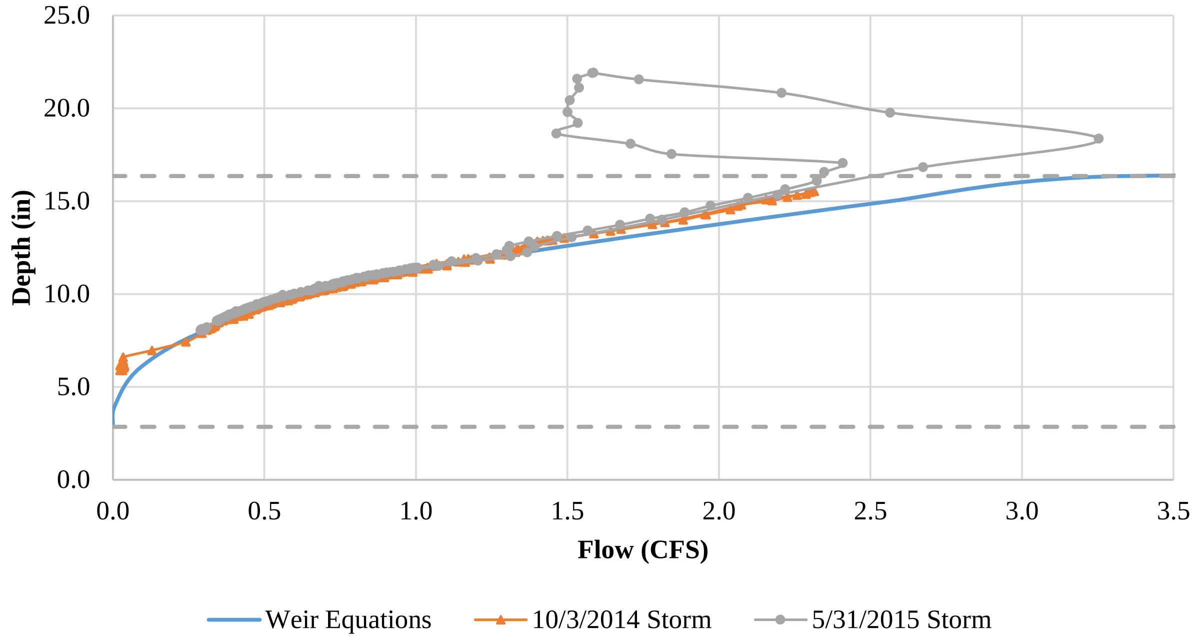

Figure A-8: 0.51" Storm Event Weir Equation Curve Validation

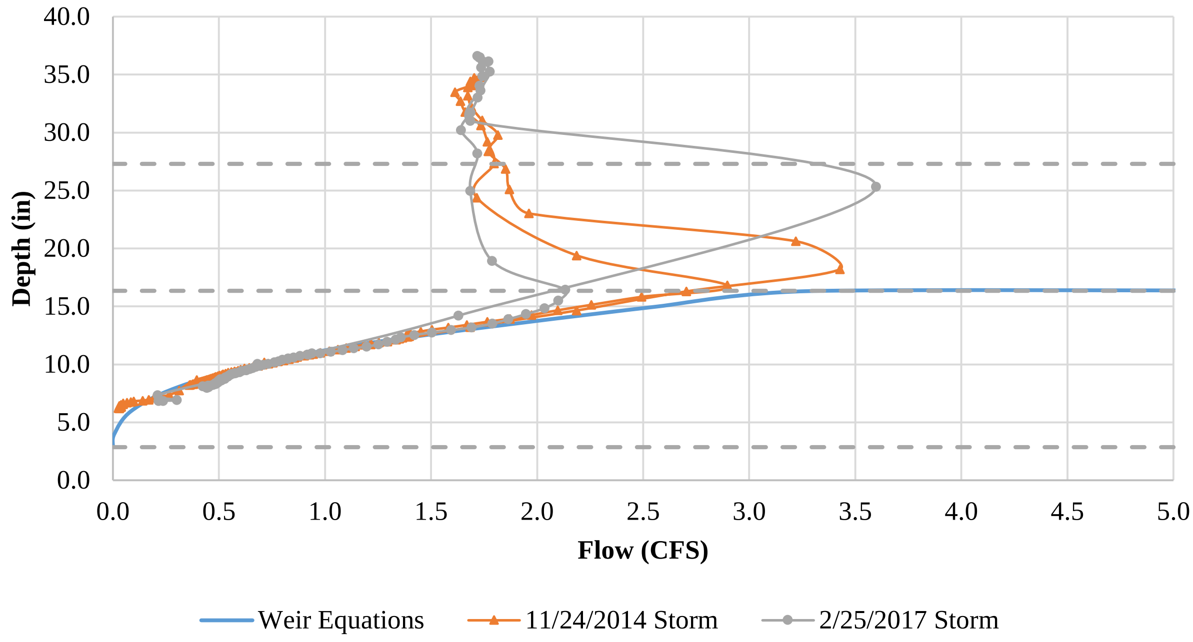

Figure A-9: 0.63" Storm Event Weir Equation Curve Validation

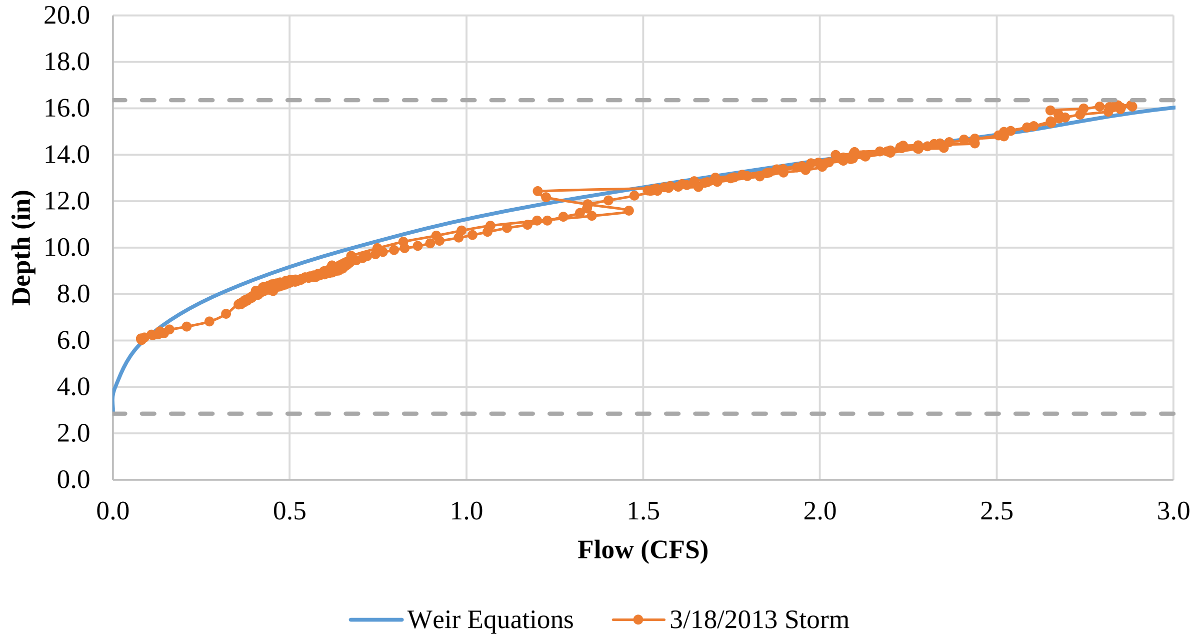

Figure A-10: 0.75" Storm Event Weir Equation Curve Validation

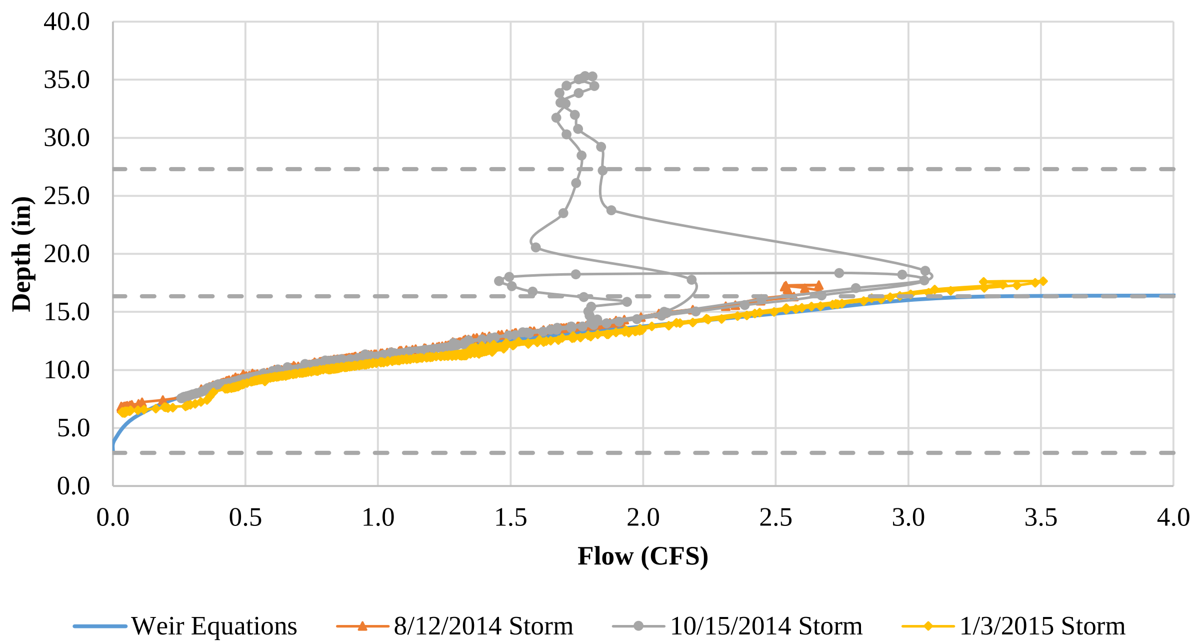

Figure A-11: 1.00" Storm Event Weir Equation Curve Validation

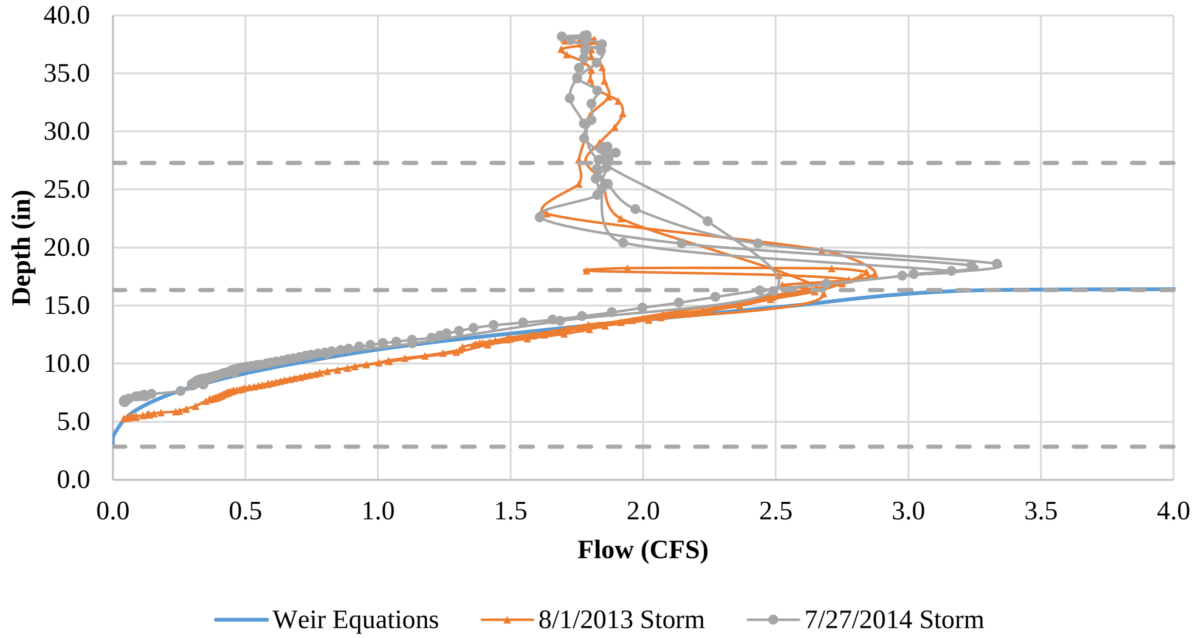

Figure A-12: 1.25" Storm Event Weir Equation Curve Validation

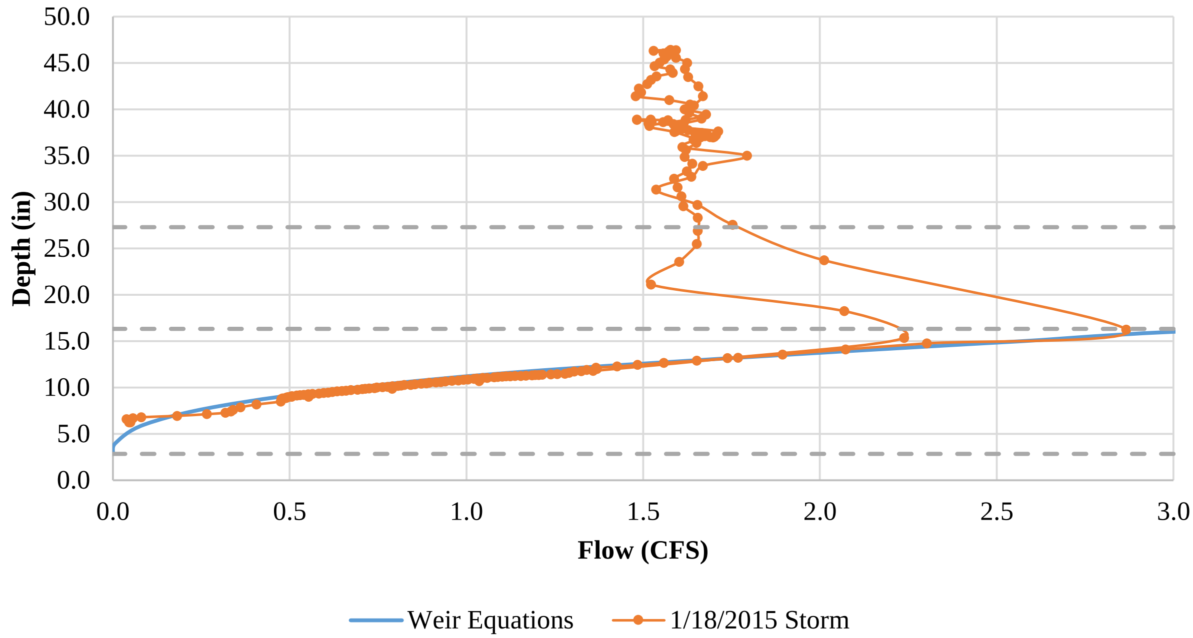

Figure A-13: 1.49" Storm Event Weir Equation Curve Validation

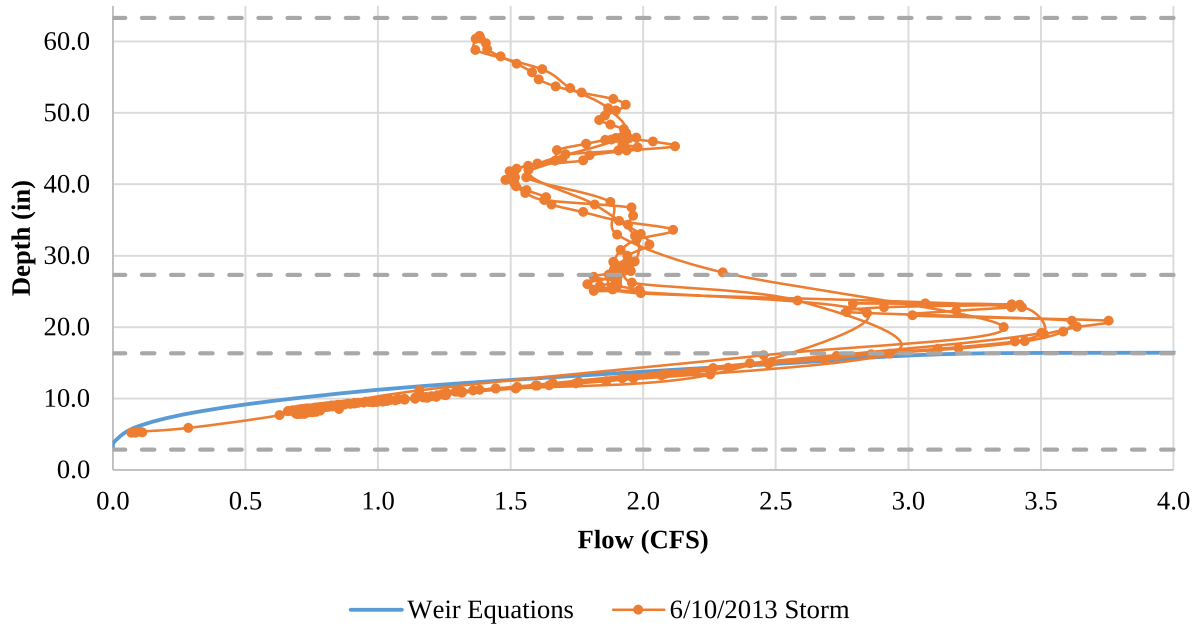

Figure A-14: 2.70" Storm Event Weir Equation Curve Validation

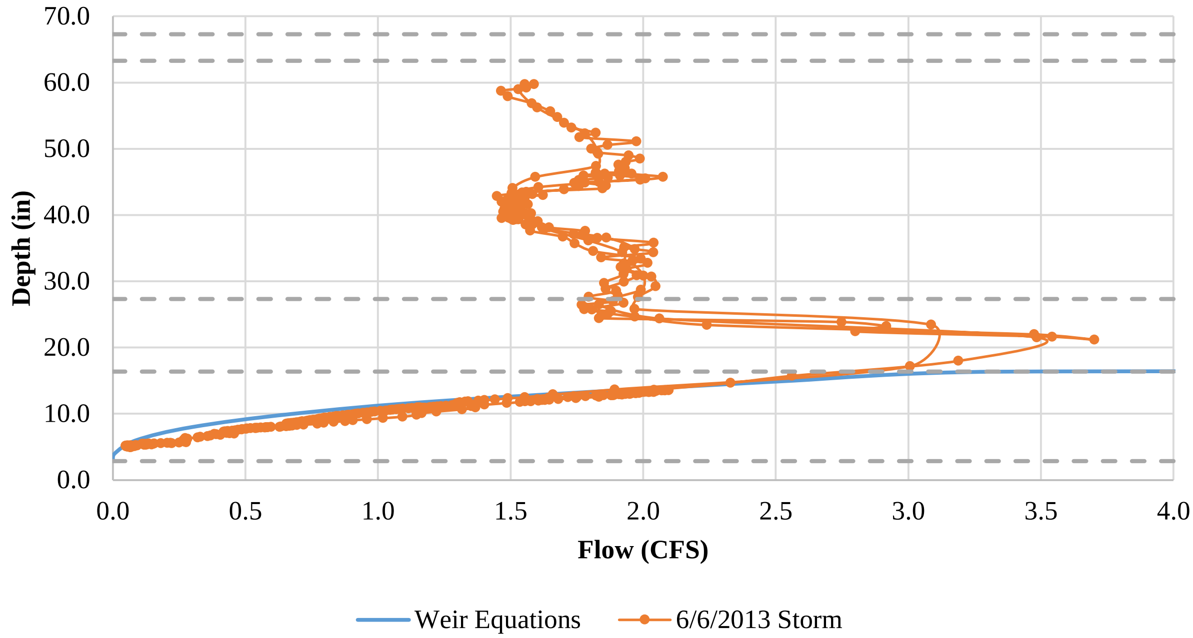

Figure A-15: 4.41" Storm Event Weir Equation Curve Validation

A.4 Outlet Structure during Storm Events

Figure A-16: Outlet Structure during Baseflow Conditions

Figure A-17: Outlet Structure during Hurricane Irene (8/28/2011)

Figure A-18: Outlet Structure on 5/14/2014 (4.23” Rainfall Event)

Figure A-19: Outlet Structure on 9/19/2016 (2.28" Rainfall Event)

A.5 Inflow and Outflow Statistical Analysis

A.5.1 Variance and Paired T-test

A.5.1.1 2012 – 2013

Yearly Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.621298501	0.581382482
Variance (V)	0.617140722	0.605800865
Observations	108	195
df	107	194
F	1.018718788	
P(F<=f) one-tail	0.45016852	
F Critical one-tail	1.315914285	

if F > Fcritical then V1 does not equal V2
1.0187 < 1.3159
Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.621298501	0.581382482
Variance	0.617140722	0.605800865
Observations	108	195
Pooled Variance	0.609831977	
Hypothesized Mean Difference	0	
df	301	
t Stat	0.426137731	
P(T<=t) one-tail	0.335156029	
t Critical one-tail	1.649931694	
P(T<=t) two-tail	0.670312059	
t Critical two-tail	1.967876531	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0
-1.97 < 0.43 < 1.97
Not different
Level of Significance - p > 0.05 accept null
0.67 > 0.05
Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.611501428	0.418833813
Variance (V)	0.89474182	0.444196696
Observations	108	195
df	107	194
F	2.01429193	
P(F<=f) one-tail	1.21049E-05	
F Critical one-tail	1.315914285	

if F > Fcritical then V1 does not equal V2
2.014 > 1.3159
Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.611501428	0.418833813
Variance	0.89474182	0.444196696
Observations	108	195
Hypothesized Mean Difference	0	
df	167	
t Stat	1.874665353	
P(T<=t) one-tail	0.031292475	
t Critical one-tail	1.654029128	
P(T<=t) two-tail	0.062584951	
t Critical two-tail	1.974270957	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0
-1.97 < 1.87 < 1.97
Not different
Level of Significance - p > 0.05 accept null
0.06 > 0.05
Not different

Yearly Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	56594.3628	53539.03408
Variance (V)	4585430763	10227511721
Observations	108	195
df	107	194
F	0.448342753	
P(F<=f) one-tail	4.0444E-06	
F Critical one-tail	0.749941749	

if F > Fcritical then V1 does not equal V2

0.4483 < 0.7499

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	56594.3628	53539.03408
Variance	4585430763	10227511721
Observations	108	195
Pooled Variance	8221855035	
Hypothesized Mean Difference	0	
df	301	
t Stat	0.280918864	
P(T<=t) one-tail	0.389482815	
t Critical one-tail	1.649931694	
P(T<=t) two-tail	0.77896563	
t Critical two-tail	1.967876531	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.28 < 1.97

Not different

Level of Significance - p > 0.05 accept null

0.779 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	50552.33057	31622.03041
Variance (V)	8836350218	1840853267
Observations	108	195
df	107	194
F	4.80013827	
P(F<=f) one-tail	1.56884E-21	
F Critical one-tail	1.315914285	

if F > Fcritical then V1 does not equal V2

4.800 > 1.3159

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	50552.33057	31622.03041
Variance	8836350218	1840853267
Observations	108	195
Hypothesized Mean Difference	0	
df	132	
t Stat	1.981623938	
P(T<=t) one-tail	0.0247995	
t Critical one-tail	1.65647927	
P(T<=t) two-tail	0.049599001	
t Critical two-tail	1.978098842	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.98 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.049 < 0.05

Different

Storm Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	1.294922714	1.291199369
Variance (V)	1.054359843	0.903225186
Observations	38	69
df	37	68
F	1.167327771	
P(F<=f) one-tail	0.285959464	
F Critical one-tail	1.585062067	

if F > Fcritical then V1 does not equal V2

1.167 < 1.585

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	1.294922714	1.291199369
Variance	1.054359843	0.903225186
Observations	38	69
Pooled Variance	0.956482161	
Hypothesized Mean Difference	0	
df	105	
t Stat	0.018846001	
P(T<=t) one-tail	0.492499861	
t Critical one-tail	1.659495383	
P(T<=t) two-tail	0.984999722	
t Critical two-tail	1.982815274	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.98 < 0.0188 < 1.98

Not different

Level of Significance - p > 0.05 accept null

0.98 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	1.205915499	0.813717434
Variance (V)	1.79566465	0.898092605
Observations	38	69
df	37	68
F	1.999420372	
P(F<=f) one-tail	0.006664726	
F Critical one-tail	1.585062067	

if F > Fcritical then V1 does not equal V2

1.999 > 1.585

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	1.205915499	0.813717434
Variance	1.79566465	0.898092605
Observations	38	69
Hypothesized Mean Difference	0	
df	58	
t Stat	1.597549218	
P(T<=t) one-tail	0.057788882	
t Critical one-tail	1.671552762	
P(T<=t) two-tail	0.115577763	
t Critical two-tail	2.001717484	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-2.00 < 1.597 < 2.00

Not different

Level of Significance - p > 0.05 accept null

0.1156 > 0.05

Not different

Storm Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	71796.64704	77122.67894
Variance (V)	6079778511	7117411072
Observations	38	69
df	37	68
F	0.854212079	
P(F<=f) one-tail	0.30509734	
F Critical one-tail	0.60655777	

if F > Fcritical then V1 does not equal V2

0.854 > 0.607

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	71796.64704	77122.67894
Variance	6079778511	7117411072
Observations	38	69
Hypothesized Mean Difference	0	
df	82	
t Stat	-0.328326665	
P(T<=t) one-tail	0.371750813	
t Critical one-tail	1.663649184	
P(T<=t) two-tail	0.743501625	
t Critical two-tail	1.989318557	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.98 < -0.328 < 1.98

Not different

Level of Significance - p > 0.05 accept null

0.74 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	77906.27527	44765.90244
Variance (V)	20678884844	2390622863
Observations	38	69
df	37	68
F	8.649998777	
P(F<=f) one-tail	1.8575E-14	
F Critical one-tail	1.585062067	

if F > Fcritical then V1 does not equal V2

8.649 > 1.585

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	77906.27527	44765.90244
Variance	20678884844	2390622863
Observations	38	69
Hypothesized Mean Difference	0	
df	42	
t Stat	1.37747164	
P(T<=t) one-tail	0.087831549	
t Critical one-tail	1.681952357	
P(T<=t) two-tail	0.175663099	
t Critical two-tail	2.018081703	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-2.00 < 1.377 < 2.00

Not different

Level of Significance - p > 0.05 accept null

0.1756 > 0.05

Not different

BF Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.255616786	0.192673235
Variance (V)	0.006070738	0.018425115
Observations	70	126
df	69	125
F	0.329481665	
P(F<=f) one-tail	6.4689E-07	
F Critical one-tail	0.696875226	

if F > Fcritical then V1 does not equal V2

0.329 < 0.696

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.255616786	0.192673235
Variance	0.006070738	0.018425115
Observations	70	126
Pooled Variance	0.014031032	
Hypothesized Mean Difference	0	
df	194	
t Stat	3.564615427	
P(T<=t) one-tail	0.000229389	
t Critical one-tail	1.652745977	
P(T<=t) two-tail	0.000458778	
t Critical two-tail	1.972267533	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 3.565 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.00046 < 0.05

Siginificantly different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.288819504	0.20258802
Variance (V)	0.1243864	0.067619497
Observations	70	126
df	69	125
F	1.839504965	
P(F<=f) one-tail	0.001585584	
F Critical one-tail	1.40577391	

if F > Fcritical then V1 does not equal V2

1.839 > 1.406

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.288819504	0.20258802
Variance	0.1243864	0.067619497
Observations	70	126
Hypothesized Mean Difference	0	
df	111	
t Stat	1.79275386	
P(T<=t) one-tail	0.037867981	
t Critical one-tail	1.658697265	
P(T<=t) two-tail	0.075735961	
t Critical two-tail	1.981566757	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.98 < 1.793 < 1.98

Not different

Level of Significance - p > 0.05 accept null

0.0757 > 0.05

Not different

BF Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	48341.69421	40624.18094
Variance (V)	3654198117	11526082844
Observations	70	126
df	69	125
F	0.317037294	
P(F<=f) one-tail	2.9504E-07	
F Critical one-tail	0.696875226	

if F > Fcritical then V1 does not equal V2

0.3173 < 0.696

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	48341.69421	40624.18094
Variance	3654198117	11526082844
Observations	70	126
Pooled Variance	8726288792	
Hypothesized Mean Difference	0	
df	194	
t Stat	0.554202972	
P(T<=t) one-tail	0.29003911	
t Critical one-tail	1.652745977	
P(T<=t) two-tail	0.580078221	
t Critical two-tail	1.972267533	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.55 < 1.97

Not different

Level of Significance - p > 0.05 accept null

0.58 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	35703.0463	24424.19572
Variance (V)	1978298436	1408917861
Observations	70	126
df	69	125
F	1.404126167	
P(F<=f) one-tail	0.050586504	
F Critical one-tail	1.40577391	

if F > Fcritical then V1 does not equal V2

1.404 < 1.406

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	35703.0463	24424.19572
Variance	1978298436	1408917861
Observations	70	126
Pooled Variance	1611429509	
Hypothesized Mean Difference	0	
df	194	
t Stat	1.884800742	
P(T<=t) one-tail	0.030475953	
t Critical one-tail	1.652745977	
P(T<=t) two-tail	0.060951906	
t Critical two-tail	1.972267533	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.88 < 1.97

Not different

Level of Significance - p > 0.05 accept null

0.0609 > 0.05

Not different

A.5.1.2 2013 – 2014

Yearly Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.5813825	0.7463329
Variance (V)	0.6058009	0.7692857
Observations	195	202
df	194	201
F	0.7874848	
P(F<=f) one-tail	0.0472251	
F Critical one-tail	0.790595	

if F > Fcritical then V1 does not equal V2

0.787 < 0.791

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.5813825	0.7463329
Variance	0.6058009	0.7692857
Observations	195	202
Pooled Variance	0.6889919	
Hypothesized Mean Difference	0	
df	395	
t Stat	-1.979448	
P(T<=t) one-tail	0.0242297	
t Critical one-tail	1.6487204	
P(T<=t) two-tail	0.0484595	
t Critical two-tail	1.9659879	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.979 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0484 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.4188338	0.4761693
Variance (V)	0.4441967	0.1751602
Observations	195	202
df	194	201
F	2.5359447	
P(F<=f) one-tail	6.173E-11	
F Critical one-tail	1.264155	

if F > Fcritical then V1 does not equal V2

2.53 > 1.264

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.4188338	0.4761693
Variance	0.4441967	0.1751602
Observations	195	202
Hypothesized Mean Difference	0	
df	324	
t Stat	-1.022372	
P(T<=t) one-tail	0.1536838	
t Critical one-tail	1.6495702	
P(T<=t) two-tail	0.3073675	
t Critical two-tail	1.9673128	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.0223 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.307 > 0.05

Not Different

Yearly Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	53539.034	78940.89
Variance (V)	1.023E+10	1.203E+10
Observations	195	202
df	194	201
F	0.8502101	
P(F<=f) one-tail	0.1278504	
F Critical one-tail	0.790595	

if F > Fcritical then V1 does not equal V2

0.850 > 0.791

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	53539.034	78940.89
Variance	1.023E+10	1.203E+10
Observations	195	202
Hypothesized Mean Difference	0	
df	394	
t Stat	-2.400247	
P(T<=t) one-tail	0.0084236	
t Critical one-tail	1.6487302	
P(T<=t) two-tail	0.0168472	
t Critical two-tail	1.9660032	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.400 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0168 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	31622.03	43782.67
Variance (V)	1.841E+09	2.57E+09
Observations	195	202
df	194	201
F	0.7153911	
P(F<=f) one-tail	0.0096033	
F Critical one-tail	0.790595	

if F > Fcritical then V1 does not equal V2

0.715 < 0.791

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	31622.03	43782.67
Variance	1.841E+09	2.57E+09
Observations	195	202
Pooled Variance	2.214E+09	
Hypothesized Mean Difference	0	
df	395	
t Stat	-2.574615	
P(T<=t) one-tail	0.0051992	
t Critical one-tail	1.6487204	
P(T<=t) two-tail	0.0103984	
t Critical two-tail	1.9659879	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.574 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0104 < 0.05

Different

Storm Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	1.2911994	1.4778371
Variance (V)	0.9032252	1.1398835
Observations	69	73
df	68	72
F	0.7923838	
P(F<=f) one-tail	0.1672247	
F Critical one-tail	0.6721047	

if F > Fcritical then V1 does not equal V2

0.792 > 0.672

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	1.2911994	1.4778371
Variance	0.9032252	1.1398835
Observations	69	73
Hypothesized Mean Difference	0	
df	140	
t Stat	-1.10159	
P(T<=t) one-tail	0.136265	
t Critical one-tail	1.6558105	
P(T<=t) two-tail	0.27253	
t Critical two-tail	1.9770537	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.102 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.273 > 0.05

Not Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.8137174	0.8761785
Variance (V)	0.8980926	0.1678784
Observations	69	73
df	68	72
F	5.3496615	
P(F<=f) one-tail	1.174E-11	
F Critical one-tail	1.4840092	

if F > Fcritical then V1 does not equal V2

5.349 > 1.484

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.8137174	0.8761785
Variance	0.8980926	0.1678784
Observations	69	73
Hypothesized Mean Difference	0	
df	91	
t Stat	-0.504711	
P(T<=t) one-tail	0.3074908	
t Critical one-tail	1.6617712	
P(T<=t) two-tail	0.6149817	
t Critical two-tail	1.9863772	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.505 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.615 > 0.05

Not Different

Storm Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	77122.679	96151.6
Variance (V)	7.117E+09	1.728E+10
Observations	69	73
df	68	72
F	0.4119043	
P(F<=f) one-tail	0.0001467	
F Critical one-tail	0.6721047	

if F > Fcritical then V1 does not equal V2

0.412 < 0.672

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	1.2911994	1.4778371
Variance	0.9032252	1.1398835
Observations	69	73
Pooled Variance	1.0249352	
Hypothesized Mean Difference	0	
df	140	
t Stat	-1.097976	
P(T<=t) one-tail	0.1370498	
t Critical one-tail	1.6558105	
P(T<=t) two-tail	0.2740996	
t Critical two-tail	1.9770537	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.0979 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.274 > 0.05

Not Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	44765.902	51679.044
Variance (V)	2.391E+09	2.322E+09
Observations	69	73
df	68	72
F	1.0295749	
P(F<=f) one-tail	0.4507609	
F Critical one-tail	1.4840092	

if F > Fcritical then V1 does not equal V2

1.030 < 1.484

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.8137174	0.8761785
Variance	0.8980926	0.1678784
Observations	69	73
Pooled Variance	0.5225539	
Hypothesized Mean Difference	0	
df	140	
t Stat	-0.514618	
P(T<=t) one-tail	0.3038156	
t Critical one-tail	1.6558105	
P(T<=t) two-tail	0.6076311	
t Critical two-tail	1.9770537	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.515 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.608 > 0.05

Not Different

BF Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.1926732	0.3323809
Variance (V)	0.0184251	0.0889663
Observations	126	129
df	125	128
F	0.2071022	
P(F<=f) one-tail	0	
F Critical one-tail	0.7453437	

if F > Fcritical then V1 does not equal V2

0.0207 < 0.745

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.1926732	0.7463329
Variance	0.0184251	0.7692857
Observations	126	202
Pooled Variance	0.4813791	
Hypothesized Mean Difference	0	
df	326	
t Stat	-7.029482	
P(T<=t) one-tail	6.1E-12	
t Critical one-tail	1.6495412	
P(T<=t) two-tail	1.21991E-11	
t Critical two-tail	1.9672675	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -7.03 < 1.97

Different

Level of Significance - p > 0.05 accept null

1.22*10^-11 < 0.05

Significantly Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.202588	0.2498075
Variance (V)	0.0676195	0.0377306
Observations	126	129
df	125	128
F	1.7921661	
P(F<=f) one-tail	0.0005652	
F Critical one-tail	1.3408688	

if F > Fcritical then V1 does not equal V2

1.792 > 1.341

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.202588	0.2498075
Variance	0.0676195	0.0377306
Observations	126	129
Hypothesized Mean Difference	0	
df	231	
t Stat	-1.639856	
P(T<=t) one-tail	0.0511981	
t Critical one-tail	1.6514767	
P(T<=t) two-tail	0.1023962	
t Critical two-tail	1.9702867	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.640 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.102 > 0.05

Not Different

BF Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	40624.181	69201.496
Variance (V)	1.153E+10	8.906E+09
Observations	126	129
df	125	128
F	1.2942248	
P(F<=f) one-tail	0.0739661	
F Critical one-tail	1.3408688	

if F > Fcritical then V1 does not equal V2

1.294 < 1.34

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	40624.181	69201.496
Variance	1.153E+10	8.906E+09
Observations	126	129
Pooled Variance	1.02E+10	
Hypothesized Mean Difference	0	
df	253	
t Stat	-2.259035	
P(T<=t) one-tail	0.0123664	
t Critical one-tail	1.6508987	
P(T<=t) two-tail	0.0247329	
t Critical two-tail	1.9693848	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.590 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0247 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	24424.196	39314.181
Variance (V)	1.409E+09	2.679E+09
Observations	126	129
df	125	128
F	0.5259185	
P(F<=f) one-tail	0.0001778	
F Critical one-tail	0.7453437	

if F > Fcritical then V1 does not equal V2

0.526 > 0.745

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	24424.196	39314.181
Variance	1.409E+09	2.679E+09
Observations	126	129
Hypothesized Mean Difference	0	
df	234	
t Stat	-2.6343	
P(T<=t) one-tail	0.0044969	
t Critical one-tail	1.6513915	
P(T<=t) two-tail	0.0089938	
t Critical two-tail	1.9701536	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.634 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.00899 < 0.05

Different

A.5.1.3 2014 – 2015

Yearly Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	0.746332868	0.962405795
Variance (V)	0.769285748	1.32088665
Observations	202	147
df	201	146
F	0.582401032	
P(F<=f) one-tail	0.000194405	
F Critical one-tail	0.778239275	

if F > Fcritical then V1 does not equal V2

0.582 < 0.778

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	Variable 2
Mean	0.746332868	0.962405795
Variance	0.769285748	1.32088665
Observations	202	147
Pooled Variance	1.00137143	
Hypothesized Mean Difference	0	
df	347	
t Stat	-1.991702166	
P(T<=t) one-tail	0.023593611	
t Critical one-tail	1.649256711	
P(T<=t) two-tail	0.047187222	
t Critical two-tail	1.966824003	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.99 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0471 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	0.476169314	0.429041298
Variance (V)	0.175160249	0.148564817
Observations	202	147
df	201	146
F	1.179015682	
P(F<=f) one-tail	0.145491291	
F Critical one-tail	1.292566721	

if F > Fcritical then V1 does not equal V2

1.179 < 1.293

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	Variable 2
Mean	0.476169314	0.429041298
Variance	0.175160249	0.148564817
Observations	202	147
Pooled Variance	0.16397024	
Hypothesized Mean Difference	0	
df	347	
t Stat	1.073540127	
P(T<=t) one-tail	0.141887409	
t Critical one-tail	1.649256711	
P(T<=t) two-tail	0.283774818	
t Critical two-tail	1.966824003	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.074 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.284 > 0.05

Not different

Yearly Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	78940.88976	130648.0464
Variance (V)	12029393499	56348429549
Observations	202	147
df	201	146
F	0.213482321	
P(F<=f) one-tail	0	
F Critical one-tail	0.778239275	

if F > Fcritical then V1 does not equal V2

0.213 < 0.778

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	78940.88976	130648.0464
Variance	12029393499	56348429549
Observations	202	147
Pooled Variance	30676595987	
Hypothesized Mean Difference	0	
df	347	
t Stat	-2.723132114	
P(T<=t) one-tail	0.003396735	
t Critical one-tail	1.649256711	
P(T<=t) two-tail	0.00679347	
t Critical two-tail	1.966824003	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.723 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.006 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	43782.6713	43691.35512
Variance (V)	2573212473	2628595361
Observations	202	147
df	201	146
F	0.978930615	
P(F<=f) one-tail	0.441771646	
F Critical one-tail	0.778239275	

if F > Fcritical then V1 does not equal V2

0.979 < 0.778

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	43782.6713	43691.35512
Variance	2573212473	2628595361
Observations	202	147
Hypothesized Mean Difference	0	
df	313	
t Stat	0.016502251	
P(T<=t) one-tail	0.49342211	
t Critical one-tail	1.649736428	
P(T<=t) two-tail	0.98684422	
t Critical two-tail	1.967572019	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.0165 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.987 > 0.05

Not different

Storm Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	1.477837079	1.891713919
Variance (V)	1.139883484	1.243496896
Observations	73	52
df	72	51
F	0.916675778	
P(F<=f) one-tail	0.363058771	
F Critical one-tail	0.656960295	

if F > Fcritical then V1 does not equal V2

0.917 > 0.657

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	Variable 2
Mean	1.477837079	1.891713919
Variance	1.139883484	1.243496896
Observations	73	52
Hypothesized Mean Difference	0	
df	107	
t Stat	-2.081696263	
P(T<=t) one-tail	0.019877984	
t Critical one-tail	1.659219312	
P(T<=t) two-tail	0.039755969	
t Critical two-tail	1.98238337	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.08 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0398 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	Variable 2
Mean	0.87617846	0.851517138
Variance (V)	0.167878399	0.116114389
Observations	73	52
df	72	51
F	1.445801851	
P(F<=f) one-tail	0.082977747	
F Critical one-tail	1.550109859	

if F > Fcritical then V1 does not equal V2

1.45 < 1.55

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	Variable 2
Mean	0.87617846	0.851517138
Variance	0.167878399	0.116114389
Observations	73	52
Pooled Variance	0.146415273	
Hypothesized Mean Difference	0	
df	123	
t Stat	0.355165892	
P(T<=t) one-tail	0.361536806	
t Critical one-tail	1.657336397	
P(T<=t) two-tail	0.723073612	
t Critical two-tail	1.979438685	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.355 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.355 > 0.05

Storm Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	96151.60013	127017.3488
Variance (V)	17279284325	12498934054
Observations	73	52
df	72	51
F	1.382460636	
P(F<=f) one-tail	0.111713794	
F Critical one-tail	1.550109859	

if F > Fcritical then V1 does not equal V2

1.382 < 1.55

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	96151.60013	127017.3488
Variance	17279284325	12498934054
Observations	73	52
Pooled Variance	15297187871	
Hypothesized Mean Difference	0	
df	123	
t Stat	-1.375241949	
P(T<=t) one-tail	0.085778048	
t Critical one-tail	1.657336397	
P(T<=t) two-tail	0.171556096	
t Critical two-tail	1.979438685	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.375 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.171 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	51679.04384	56730.13845
Variance (V)	2321951385	1745686810
Observations	73	52
df	72	51
F	1.330107653	
P(F<=f) one-tail	0.141803013	
F Critical one-tail	1.550109859	

if F > Fcritical then V1 does not equal V2

1.33 < 1.55

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	51679.04384	56730.13845
Variance	2321951385	1745686810
Observations	73	52
Pooled Variance	2083012415	
Hypothesized Mean Difference	0	
df	123	
t Stat	-0.609884603	
P(T<=t) one-tail	0.271531664	
t Critical one-tail	1.657336397	
P(T<=t) two-tail	0.543063329	
t Critical two-tail	1.979438685	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.610 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.543 > 0.05

Not different

BF Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.332380872	0.453731874
Variance (V)	0.088966277	0.637681197
Observations	129	95
df	128	94
F	0.13951529	
P(F<=f) one-tail	0	
F Critical one-tail	0.731306495	

if F > Fcritical then V1 does not equal V2

0.1395 < 0.7313

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.332380872	0.453731874
Variance	0.088966277	0.637681197
Observations	129	95
Pooled Variance	0.321305027	
Hypothesized Mean Difference	0	
df	222	
t Stat	-1.583497041	
P(T<=t) one-tail	0.057365867	
t Critical one-tail	1.651746359	
P(T<=t) two-tail	0.114731733	
t Critical two-tail	1.970707395	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -1.583 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.115 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.249807549	0.197791364
Variance (V)	0.037730597	0.0149691
Observations	129	95
df	128	94
F	2.520565525	
P(F<=f) one-tail	2.03059E-06	
F Critical one-tail	1.379686378	

if F > Fcritical then V1 does not equal V2

2.52 > 1.379

Variances are not equal

	Variable 1	*Variable 2*
Mean	0.249807549	0.197791364
Variance	0.037730597	0.0149691
Observations	129	95
Hypothesized Mean Difference	0	
df	217	
t Stat	2.451917403	
P(T<=t) one-tail	0.00749982	
t Critical one-tail	1.651905861	
P(T<=t) two-tail	0.01499964	
t Critical two-tail	1.970956301	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 2.45 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0149 < 0.05

Different

BF Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	69201.49552	132635.3756
Variance (V)	8905781246	80727281009
Observations	129	95
df	128	94
F	0.110319351	
P(F<=f) one-tail	0	
F Critical one-tail	0.731306495	

if F > Fcritical then V1 does not equal V2

0.11 < 0.731

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	69201.49552	132635.3756
Variance	8905781246	80727281009
Observations	129	95
Pooled Variance	39316686551	
Hypothesized Mean Difference	0	
df	222	
t Stat	-2.366276388	
P(T<=t) one-tail	0.009414098	
t Critical one-tail	1.651746359	
P(T<=t) two-tail	0.018828195	
t Critical two-tail	1.970707395	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -2.366 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0188 < 0.05

Different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	39314.18141	36554.33687
Variance (V)	2678966136	2990057067
Observations	129	95
df	128	94
F	0.895958196	
P(F<=f) one-tail	0.28032184	
F Critical one-tail	0.731306495	

if F > Fcritical then V1 does not equal V2

0.896 > 0.7313

Variances are not equal

	Variable 1	*Variable 2*
Mean	39314.18141	36554.33687
Variance	2678966136	2990057067
Observations	129	95
Hypothesized Mean Difference	0	
df	196	
t Stat	0.381836067	
P(T<=t) one-tail	0.351498309	
t Critical one-tail	1.652665059	
P(T<=t) two-tail	0.702996617	
t Critical two-tail	1.972141222	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.38 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.703 > 0.05

Not different

A.5.1.4 2015 – 2016

Yearly Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.962405795	0.870918495
Variance (V)	1.32088665	0.994979162
Observations	147	179
df	146	178
F	1.327552074	
P(F<=f) one-tail	0.03576171	
F Critical one-tail	1.295076366	

if F > Fcritical then V1 does not equal V2

1.33 > 1.29

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.962405795	0.870918495
Variance	1.32088665	0.994979162
Observations	147	179
Hypothesized Mean Difference	0	
df	291	
t Stat	0.75860621	
P(T<=t) one-tail	0.224351066	
t Critical one-tail	1.650106758	
P(T<=t) two-tail	0.448702132	
t Critical two-tail	1.968149554	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.759 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.449 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.429041298	0.374446829
Variance (V)	0.148564817	0.111457971
Observations	147	120
df	146	119
F	1.332922317	
P(F<=f) one-tail	0.052017114	
F Critical one-tail	1.337487512	

if F > Fcritical then V1 does not equal V2

1.333 < 1.337

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.429041298	0.374446829
Variance	0.148564817	0.111457971
Observations	147	120
Pooled Variance	0.131901742	
Hypothesized Mean Difference	0	
df	265	
t Stat	1.221847585	
P(T<=t) one-tail	0.111425517	
t Critical one-tail	1.650623976	
P(T<=t) two-tail	0.222851034	
t Critical two-tail	1.968956281	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.22 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.223 > 0.05

Not different

Yearly Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	130648.0464	102773.5867
Variance (V)	56348429549	28869122157
Observations	147	179
df	146	178
F	1.951858087	
P(F<=f) one-tail	1.11087E-05	
F Critical one-tail	1.295076366	

if F > Fcritical then V1 does not equal V2

1.952 > 1.295

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	130648.0464	102773.5867
Variance	56348429549	28869122157
Observations	147	179
Hypothesized Mean Difference	0	
df	257	
t Stat	1.194446156	
P(T<=t) one-tail	0.116702351	
t Critical one-tail	1.65080425	
P(T<=t) two-tail	0.233404702	
t Critical two-tail	1.969237496	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.194 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.233 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	43691.35512	40944.62312
Variance (V)	2628595361	1787172938
Observations	147	120
df	146	119
F	1.470811976	
P(F<=f) one-tail	0.014703819	
F Critical one-tail	1.337487512	

if F > Fcritical then V1 does not equal V2

1.47 > 1.337

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	43691.35512	40944.62312
Variance	2628595361	1787172938
Observations	147	120
Hypothesized Mean Difference	0	
df	265	
t Stat	0.47978522	
P(T<=t) one-tail	0.315887936	
t Critical one-tail	1.650623976	
P(T<=t) two-tail	0.631775872	
t Critical two-tail	1.968956281	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.479 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.631 > 0.05

Not different

Storm Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	1.891713919	1.649775052
Variance (V)	1.243496896	1.63696633
Observations	52	64
df	51	63
F	0.759634986	
P(F<=f) one-tail	0.155856443	
F Critical one-tail	0.638991813	

if F > Fcritical then V1 does not equal V2

0.7597 > 0.639

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	1.891713919	1.649775052
Variance	1.243496896	1.63696633
Observations	52	64
Hypothesized Mean Difference	0	
df	113	
t Stat	1.087533202	
P(T<=t) one-tail	0.139557734	
t Critical one-tail	1.658450216	
P(T<=t) two-tail	0.279115467	
t Critical two-tail	1.981180359	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.087 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.279 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.851517138	0.686988209
Variance (V)	0.116114389	0.100818609
Observations	52	43
df	51	42
F	1.151715845	
P(F<=f) one-tail	0.320623302	
F Critical one-tail	1.64294387	

if F > Fcritical then V1 does not equal V2

1.152 < 1.643

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	0.851517138	0.686988209
Variance	0.116114389	0.100818609
Observations	52	43
Pooled Variance	0.109206617	
Hypothesized Mean Difference	0	
df	93	
t Stat	2.415415735	
P(T<=t) one-tail	0.008836096	
t Critical one-tail	1.661403674	
P(T<=t) two-tail	0.017672193	
t Critical two-tail	1.985801814	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 2.42 < 1.97

Different

Level of Significance - p > 0.05 accept null

0.0176 < 0.05

Different

Storm Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	127017.3488	93884.66114
Variance (V)	12498934054	10953438566
Observations	52	64
df	51	63
F	1.141096833	
P(F<=f) one-tail	0.307257059	
F Critical one-tail	1.546465287	

if F > Fcritical then V1 does not equal V2

1.141 < 1.546

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	127017.3488	93884.66114
Variance	12498934054	10953438566
Observations	52	64
Pooled Variance	11644844442	
Hypothesized Mean Difference	0	
df	114	
t Stat	1.644570461	
P(T<=t) one-tail	0.051406639	
t Critical one-tail	1.658329969	
P(T<=t) two-tail	0.102813278	
t Critical two-tail	1.980992298	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.645 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.103 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	56730.13845	41562.07978
Variance (V)	1745686810	1376758730
Observations	52	43
df	51	42
F	1.267968578	
P(F<=f) one-tail	0.215392998	
F Critical one-tail	1.64294387	

if F > Fcritical then V1 does not equal V2

1.2679 < 1.643

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	56730.13845	41562.07978
Variance	1745686810	1376758730
Observations	52	43
Pooled Variance	1579074129	
Hypothesized Mean Difference	0	
df	93	
t Stat	1.851837344	
P(T<=t) one-tail	0.03361096	
t Critical one-tail	1.661403674	
P(T<=t) two-tail	0.067221921	
t Critical two-tail	1.985801814	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.852 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.0672 > 0.05

Not different

BF Averages

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.453731874	0.43746789
Variance (V)	0.637681197	0.118839962
Observations	95	115
df	94	114
F	5.365881889	
P(F<=f) one-tail	6.35585E-17	
F Critical one-tail	1.38077381	

if F > Fcritical then V1 does not equal V2

5.365 > 1.38

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.453731874	0.43746789
Variance	0.637681197	0.118839962
Observations	95	115
Hypothesized Mean Difference	0	
df	123	
t Stat	0.184796237	
P(T<=t) one-tail	0.426846607	
t Critical one-tail	1.657336397	
P(T<=t) two-tail	0.853693213	
t Critical two-tail	1.979438685	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.185 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.854 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.197791364	0.199910734
Variance (V)	0.0149691	0.032672983
Observations	95	77
df	94	76
F	0.458149166	
P(F<=f) one-tail	0.000172176	
F Critical one-tail	0.699841948	

if F > Fcritical then V1 does not equal V2

0.458 < 0.699

Variances are equal

	Variable 1	*Variable 2*
Mean	0.197791364	0.199910734
Variance	0.0149691	0.032672983
Observations	95	77
Pooled Variance	0.022883777	
Hypothesized Mean Difference	0	
df	170	
t Stat	-0.091366278	
P(T<=t) one-tail	0.463654563	
t Critical one-tail	1.653866317	
P(T<=t) two-tail	0.927309126	
t Critical two-tail	1.974016708	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.09 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.927 > 0.05

Not different

BF Volumes

Inflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	132635.3756	107720.4671
Variance (V)	80727281009	38954088119
Observations	95	115
df	94	114
F	2.072369934	
P(F<=f) one-tail	0.000108472	
F Critical one-tail	1.38077381	

if F > Fcritical then V1 does not equal V2

2.072 > 1.38

Variances are not equal

	Variable 1	*Variable 2*
Mean	132635.3756	107720.4671
Variance	80727281009	38954088119
Observations	95	115
Hypothesized Mean Difference	0	
df	163	
t Stat	0.722705159	
P(T<=t) one-tail	0.235448355	
t Critical one-tail	1.654255585	
P(T<=t) two-tail	0.470896709	
t Critical two-tail	1.974624621	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.723 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.471 > 0.05

Not different

Outflow

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	36554.33687	40599.80966
Variance (V)	2990057067	2037160054
Observations	95	77
df	94	76
F	1.467757558	
P(F<=f) one-tail	0.041888836	
F Critical one-tail	1.440347165	

if F > Fcritical then V1 does not equal V2

1.47 > 1.44

Variances are not equal

	Variable 1	*Variable 2*
Mean	36554.33687	40599.80966
Variance	2990057067	2037160054
Observations	95	77
Hypothesized Mean Difference	0	
df	170	
t Stat	-0.531513271	
P(T<=t) one-tail	0.297878486	
t Critical one-tail	1.653866317	
P(T<=t) two-tail	0.595756973	
t Critical two-tail	1.974016708	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.531 < 1.97

Not Different

Level of Significance - p > 0.05 accept null

0.596 > 0.05

Not different

A.5 Rainfall Statistical Analysis

A.5.1 Variance and Paired T-test

A.5.1.1 2012 – 2013

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.635151505	0.75942028
Variance	0.550228422	0.675546704
Observations	66	69
df	65	68
F	0.814493534	
P(F<=f) one-tail	0.203250677	
F Critical one-tail	0.665316295	

if F > Fcritical then V1 does not equal V2

0.8145 > 0.6653

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.635151505	0.75942028
Variance	0.550228422	0.675546704
Observations	66	69
Hypothesized Mean Difference	0	
df	133	
t Stat	-0.922986061	
P(T<=t) one-tail	0.178842936	
t Critical one-tail	1.656391244	
P(T<=t) two-tail	0.357685872	
t Critical two-tail	1.977961264	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.923 < 1.97

Not different

Level of Significance - p > 0.05 accept null

0.358 > 0.05

Not different

A.5.1.2 2013 – 2014

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.75942028	0.647123278
Variance	0.675546704	0.68680409
Observations	69	73
df	68	72
F	0.983609029	
P(F<=f) one-tail	0.473460548	
F Critical one-tail	0.672104653	

if F > Fcritical then V1 does not equal V2

0.984 > 0.672

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.75942028	0.647123278
Variance	0.675546704	0.68680409
Observations	69	73
Hypothesized Mean Difference	0	
df	140	
t Stat	0.810458986	
P(T<=t) one-tail	0.209525981	
t Critical one-tail	1.655810511	
P(T<=t) two-tail	0.419051962	
t Critical two-tail	1.97705372	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 0.810 < 1.97

Not different

Level of Significance - p > 0.05 accept null

0.419 > 0.05

Not different

A.5.1.3 2014 – 2015

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.647123278	0.735769218
Variance	0.68680409	0.297228798
Observations	73	52
df	72	51
F	2.310691607	
P(F<=f) one-tail	0.000991495	
F Critical one-tail	1.550109859	

if F > Fcritical then V1 does not equal V2

2.31> 1.55

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.647123278	0.735769218
Variance	0.68680409	0.297228798
Observations	73	52
Hypothesized Mean Difference	0	
df	122	
t Stat	-0.720812735	
P(T<=t) one-tail	0.236201842	
t Critical one-tail	1.657439499	
P(T<=t) two-tail	0.472403685	
t Critical two-tail	1.979599878	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < -0.721< 1.97

Not different

Level of Significance - p > 0.05 accept null

0.472 > 0.05

Not different

A.5.1.4 2015 – 2016

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	0.735769218	0.565624993
Variance	0.297228798	0.254031346
Observations	52	64
df	51	63
F	1.170047722	
P(F<=f) one-tail	0.275042028	
F Critical one-tail	1.546465287	

if F > Fcritical then V1 does not equal V2

1.17 > 1.55

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	0.735769218	0.565624993
Variance	0.297228798	0.254031346
Observations	52	64
Hypothesized Mean Difference	0	
df	105	
t Stat	1.728874251	
P(T<=t) one-tail	0.043385386	
t Critical one-tail	1.659495383	
P(T<=t) two-tail	0.086770772	
t Critical two-tail	1.982815274	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.97 < 1.73 < 1.97

Not different

Level of Significance - p > 0.05 accept null

0.087 > 0.05

Not different

A.6 Temperature Statistical Analysis

A.6.1 Variance and Paired T-test

A.6.1.1 2012 – 2013

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	11.58397824	11.96289335
Variance	67.12592553	94.17592159
Observations	316	365
df	315	364
F	0.712771634	
P(F<=f) one-tail	0.001012599	
F Critical one-tail	0.83532637	

if F > Fcritical then V1 does not equal V2

0.713 < 0.835

Variances are equal

t-Test: Two-Sample Assuming Equal Variances

	Variable 1	*Variable 2*
Mean	11.58397824	11.96289335
Variance	67.12592553	94.17592159
Observations	316	365
Pooled Variance	81.62695434	
Hypothesized Mean Difference	0	
df	679	
t Stat	-0.545810074	
P(T<=t) one-tail	0.292687883	
t Critical one-tail	1.647100848	
P(T<=t) two-tail	0.585375766	
t Critical two-tail	1.963463887	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.96 < -0.546 < 1.96

Not different

Level of Significance - p > 0.05 accept null

0.585 > 0.05

Not different

A.6.1.2 2013 – 2014

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	11.96289335	11.23864589
Variance	94.17592159	102.7846967
Observations	365	365
df	364	364
F	0.916244583	
P(F<=f) one-tail	0.202218425	
F Critical one-tail	0.841429586	

if F > Fcritical then V1 does not equal V2

0.916 > 0.841

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	11.96289335	11.23864589
Variance	94.17592159	102.7846967
Observations	365	365
Hypothesized Mean Difference	0	
df	727	
t Stat	0.98592463	
P(T<=t) one-tail	0.162249052	
t Critical one-tail	1.646952285	
P(T<=t) two-tail	0.324498105	
t Critical two-tail	1.963232428	

if - t critical 2 tail < t < t critical 2 tail then mean1 - mean 2 = 0

-1.96 < 0.986 < 1.96

Not different

Level of Significance - p > 0.05 accept null

0.3245 > 0.05

Not different

A.6.1.3 2014 – 2015

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	11.23864589	12.5420153
Variance	102.7846967	106.8105656
Observations	365	365
df	364	364
F	0.962308327	
P(F<=f) one-tail	0.357091464	
F Critical one-tail	0.841429586	

if F > Fcritical then V1 does not equal V2

0.962 > 0.841

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	11.23864589	12.5420153
Variance	102.7846967	106.8105656
Observations	365	365
Hypothesized Mean Difference	0	
df	728	
t Stat	-1.719979323	
P(T<=t) one-tail	0.042930597	
t Critical one-tail	1.646949399	
P(T<=t) two-tail	0.085861193	
t Critical two-tail	1.963227931	

if – t critical 2 tail < t < t critical 2 tail then mean1 – mean 2 = 0

-1.96 < -1.72 < 1.96

Not different

Level of Significance – p > 0.05 accept null

0.086 > 0.05

Not different

A.6.1.4 2015 – 2016

F-Test Two-Sample for Variances

	Variable 1	*Variable 2*
Mean	12.5420153	15.12996292
Variance	106.8105656	106.9214136
Observations	365	366
df	364	365
F	0.998963276	
P(F<=f) one-tail	0.49607171	
F Critical one-tail	0.841519431	

if F > Fcritical then V1 does not equal V2

0.998 > 0.841

Variances are not equal

t-Test: Two-Sample Assuming Unequal Variances

	Variable 1	*Variable 2*
Mean	12.5420153	15.12996292
Variance	106.8105656	106.9214136
Observations	365	366
Hypothesized Mean Difference	0	
df	729	
t Stat	-3.384263472	
P(T<=t) one-tail	0.000375938	
t Critical one-tail	1.64694652	
P(T<=t) two-tail	0.000751877	
t Critical two-tail	1.963223447	

if – t critical 2 tail < t < t critical 2 tail then mean1 – mean 2 = 0

-1.96 < -3.38 < 1.96

Not different

Level of Significance – p > 0.05 accept null

0.00075 > 0.05

Not different

A.7 Grain Size Distribution Analysis and Soil Wash Data

Table A-2: Grain Size Distribution July 2016

Sieve	D (mm)	D (μm)	% Retained	% Passing
4	4.80	4800	26.14	73.86
10	2.00	2000	51.95	48.05
20	0.850	850	79.63	20.37
40	0.420	420	91.54	8.46
100	0.160	160	97.71	2.29
200	0.0750	75	98.70	1.30

Table A-3: Soil Wash Results July 2016

Soil Before Wash (g)	578.8
Sieve + Soil Wash (g)	905.7
Sieve Weight (g)	337.1
Dry Soil After Wash (g)	568.6
% < #200 sieve	1.76

Table A-4: Grain Size Distribution October 2016

Sieve	D (mm)	D (μm)	Run 1		Run 2		Run 3	
			% Retained	% Passing	% Retained	% Passing	% Retained	% Passing
4	4.80	4800	2.75	97.25	3.08	96.92	6.37	93.63
10	2.00	2000	12.77	87.23	13.28	86.72	17.17	82.83
20	0.850	850	53.96	46.04	52.57	47.43	53.69	46.31
40	0.420	420	87.01	12.99	86.62	13.38	83.83	16.17
100	0.160	160	98.33	1.67	98.19	1.81	96.60	3.40
200	0.0750	75	99.15	0.85	99.20	0.80	97.97	2.03

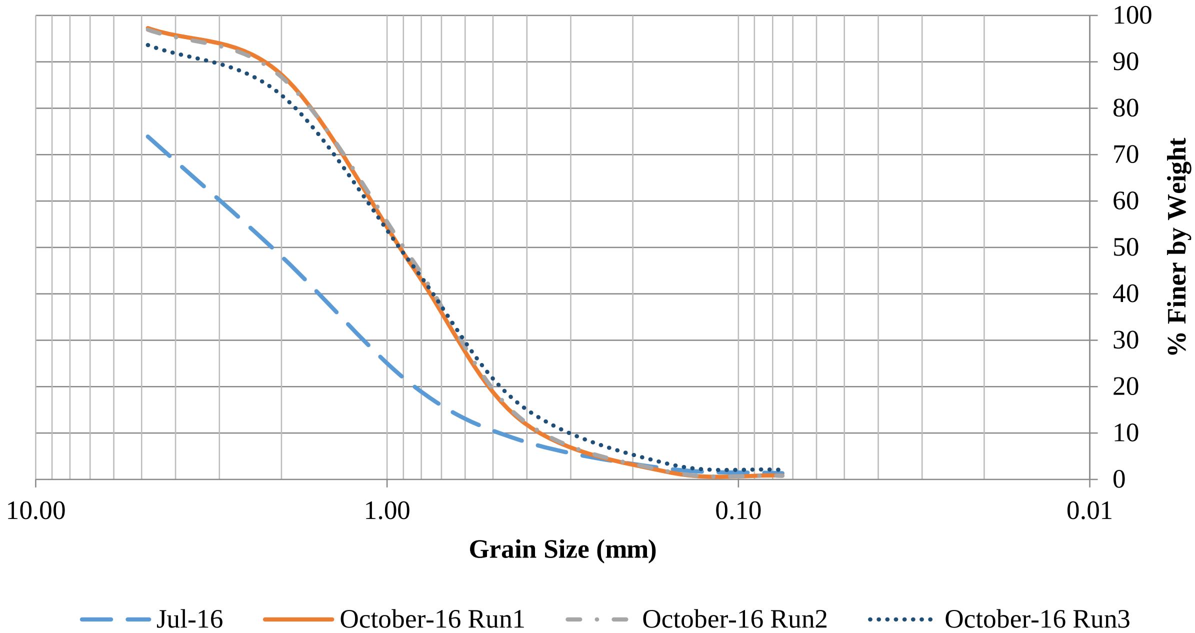

Figure A-19: Grain Size Distribution Results

A.9 TSS Standard Information

A.9.1 Pan Standards

Table A-5: Grams of Soil from the Pan in 1000 mL of Water

Concentration (mg/L)	Weight Soil (g)
0	0
3	0.0030
5	0.0051
10	0.0105
15	0.0152
20	0.0206
25	0.0257
50	0.0522
100	0.1214
200	0.2029
500	0.5042
1000	1.0078

A.9.2 No. 200 sieve Standards

Table A-6: Grams of Soil from the No. 200 Sieve in 1000 mL of Water

Concentration (mg/L)	Weight Soil (g)
0	0
3	0.0033
5	0.0047
10	0.0107
15	0.0153
20	0.0202
25	0.0255
50	0.0497
100	0.1037
200	0.2009
500	0.4992
1000	0.9991