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Quantifying and Modeling Surface Inflow and Groundwater Infiltration into Sanitary Sewers in Southern Pinellas County, FL

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by

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DEDICATION

This work is dedicated to my family, Aaron, Ben, Toni, Jeff, Chris, and Rick for their endless patience and support. Thank you for encouraging me through this process.

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ABSTRACT

Following large rain events, excess flow in sanitary sewers from inflow and infiltration (I/I) cause sanitary sewer overflows (SSO), resulting in significant problems for Pinellas County and the Tampa Bay area. Stormwater enters the sanitary sewers as inflow from improper or illegal surface connections, and groundwater enters the system as infiltration through cracks in subsurface infrastructure. This pilot study was designed to develop methods to separate and quantify the components of I/I and to build a predictive model using flowmeter and rainfall data.

To identify surface inflow, daily wastewater production and groundwater infiltration patterns were filtered from the flow data, leaving a residual signal of random variation and possible inflow. The groundwater infiltration (as base infiltration, BI) was calculated using the Stevens-Schutzbach method, and daily wastewater flow curves were generated from dry weather flow (DWF) data. Filtered DWF values were used to construct a range of expected residuals, encompassing 95% of the variability inherent in the system. Filtered wet weather flows were compared to this range, and values above the range were considered significant, indicating the presence of surface inflow.

At all 3 flow meters in the pilot study site, no surface inflow was detected, and the I/I was attributed to groundwater infiltration (as BI). Flow data from 2 smaller sub-sewersheds within the greater sewershed allowed analysis of the spatial variability in BI and provided a method to focus in on the most problematic areas. In the sub-sewershed with the shallowest water table and most submerged sanitary sewer infrastructure, an average of 56% of the average daily flow consisted of groundwater, compared to 44% for the entire study site.

Cross-correlation analysis suggests that rain impacts the water table for up to 9 days, with the highest impact 1 to 3 days after rain events, and the water table, in turn, impacts infiltration for up to 6 days. The highest correlation between rainfall and infiltration occurs 3 to 5 days after a rain event, which corroborates observations from Pinellas County that severe flows to the reclamation facility continue for 3 to 5 days after severe storms. These results were used to build a linear regression model to predict base infiltration (per mile of pipeline) during the wet season using the previous 7 days of daily rainfall depths. The model tended to under-predict infiltration response to large storm events with a R^2 value of 0.52 and standard error of regression of 5.3.

The results of the study show that inflow can be detected using simple time series analysis instead of traditional smoke and dye testing. In this study site, however, groundwater infiltration is the only significant source of I/I. Additionally, water table and sewer invert elevations serve as useful indicators of potential sites of groundwater infiltration. Infiltration can be modeled as a function of the previous 7 days of rainfall, however simple linear regression cannot fully capture the complexity of the system response.

CHAPTER 1: INTRODUCTION

1.1 Inflow and Infiltration in the U.S.

The useful design life of sewer collectors and pumping stations is from 50 to 100 years, and much of the United States' wastewater infrastructure is either approaching, or has surpassed its design life (ASCE, 2011). Symptoms of aging or damaged sewer pipes include sanitary sewer overflows (SSO) or combined sewer overflows (CSO). These occur when there is a blockage in the conveyance system or when the sewage flow rate exceeds the capacity of its conduits or treatment facility, causing the sewage to backup and spill into basements, or out of manholes or outfalls. In cases of treatment capacity exceedance, operators must purposely dump untreated sewage into bodies of water to prevent it from backing up into streets or homes. These exceedance sewage discharges are most often associated with extreme storm events and rainfall-related contributions to the sewer system. In combined sewers, the pipes are designed to carry both stormwater and wastewater, and CSOs occur when the rain and runoff exceed the maximum capacity. However, separate sanitary sewers are designed to carry only wastewater, meaning the excess flows from rain events must be from unintentional freshwater contributions. These freshwater contributions to sanitary sewer flow are referred to as inflow and infiltration (I/I).

Inflow is traditionally associated with freshwater from surface sources that enter the sanitary sewer system through improper or illegal direct connections to the sanitary sewer pipes. These surface sources include rain or stormwater runoff that enters the sanitary sewer through open manholes or wet wells, as well as rain gutters, sump pumps, or other stormwater collection devices that are directly connected to the sanitary sewer instead of the storm sewer. Because surface inflow sources have a direct connection to the sanitary sewer system, the inflow contribution to fresh water sewer flow occurs on a timescale that matches urban stormwater runoff, typically minutes to hours. Because of this quick timescale, surface inflow is generally associated with relatively acute rain or storm events, although discrete events such as an above-ground water main rupture could potentially contribute to inflow as well.

Infiltration is associated with soil water or groundwater that seeps into the sanitary sewer through cracks or openings in the pipes, manholes, or wet wells. Groundwater infiltration occurs when a pipe or well is submerged beneath the water table. The water in the saturated soils of the water table is under positive pressures that are greater than the atmospheric pressure of the sewer pipe. This creates a pressure gradient that drives the ground water through cracks and holes into the pipe. The quantity of groundwater infiltration depends on the depth of the water table and the length of pipeline submerged. As the groundwater table elevation rises, the pressure head above the pipe increases, increasing the flow of water into the pipe. Additionally, as the water table rises, more of the pipe system will become submerged, which will increase the area subject to groundwater infiltration. Depending on the condition of the pipes, the hydraulic conductivity of the surrounding soil, the depth of the water table, and amount of submerged infrastructure, groundwater infiltration can start several hours after the rain but may last for several days after the passage of the storm, as cracked or leaking sewer lines gradually drain the water table.

Inflow and infiltration leading to SSOs create significant problems for cities nationwide. A 2001 study estimated that sewer overflows occur 40,000 times per year, and sanitary sewer laterals backup into basements 400,000 times per year (Petrequin, 2011). The American Society of Civil Engineers (ASCE) estimated in 2011 that aging and outdated sewer pipes lead to 900 billion gallons of untreated sewage discharge every year (ASCE, 2011).

Sewage overflows violate the Clean Water Act (CWA), and the responsible utility can face fines and injunctions from the Environmental Protection Agency (EPA) or other local regulatory agencies. From 2003 to 2008, at least one third of the nation's publicly owned wastewater treatment authorities faced fines or disciplinary measures for sewage violations (Petrequin, 2011).

From 2008 to 2013, hundreds of SSOs occurred due to aging pipes in the city of Greenville, Mississippi, which resulted in the EPA filing a lawsuit against the city for violating the CWA (Campbell, 2017). In June 2016, Greenville and the EPA reached a settlement that the city would complete early action projects and invest approximately $22 million in sewer system rehabilitation (Campbell, 2017) (Greenville, MS Clean Water Settlement, 2016). If Greenville does not complete repairs within 6 years, the EPA will reevaluate the case and consider civil penalties or fines (Campbell, 2017).

In December 2016, the EPA settled a lawsuit with the city of Gary, Indiana for longstanding violations of the CWA through sewer overflows. In addition to implementing a 25-year plan to remediate polluted waters and update all components of their sewer system to increase treatment capacity, the Gary Sewage District must also pay a civil penalty of $75,000 (EPA, 2016).

The costs to environmental and human health caused by SSOs and CSOs are often much greater than the costs of regulatory fines. Sewage overflows have been linked to roughly 8.6 million cases per year of waterborne illness or microbial infection and roughly 900 deaths per year from waterborne microbial infections (Petrequin, 2011). Annual medical costs from exposure to water contaminated by SSOs can total from $591 million to $4.1 billion (Petrequin, 2011). The EPA estimates that the annual cost of responding to SSOs ranges from $1.1 billion to

$6.1 billion, and that the annual cost to mitigate both CSOs and SSOs ranges from $305 million to $654 million (Petrequin, 2011). The American Society of Civil Engineers (ASCE) estimated that to correct these issues by repairing and updating America's sewer pipes, nearly $230 billion in capital investments will be necessary over the next 20 years (ASCE, 2013).

1.2 Inflow and Infiltration in Pinellas County

1.2.1 Background

Serving over 250,000 customers, the southern municipal sanitary sewer collection network for Pinellas County, Florida, contains over 1,150 miles of sewer pipes and over 140 wet wells that collect and carry sanitary wastes to the South Cross Bayou Water Reclamation Facility (SCBWRF). Once delivered to this advanced treatment facility, the wastewater undergoes primary, secondary, and tertiary treatment, preparing it for municipally distributed non-potable reuse or discharge into a nearby creek. The sanitary sewer collection network is designed to be completely separate from storm sewer systems, conveying solely wastewater flows composed of wastes generated from homes and businesses that are flushed or drained directly into the sewer. Any fresh water (including groundwater, rainwater, floodwater, or naturally occurring saline water) should be confined to stormwater collection infrastructure. However, due to aging or inappropriate infrastructure and regional hydrology, groundwater and rainwater often contribute to increased sanitary sewer flow.

The reclamation facility is permitted for an average load of 33 million gallons per day (mgd), with a maximum capacity of 60 mgd, and typically operates at an average daily load of 22 mgd (Pinellas County, 2013). However, during rain events and wet weather, the SCBWRF can receive average daily loads of 67 mgd with peak loads over 100 mgd, causing many issues for the county, including severe SSOs. These extreme loading cases are caused by the unintentional contribution of fresh water into the sanitary sewer system through I/I.

1.2.2 Pinellas County Characteristics that Exacerbate I/I

While Pinellas County shares some characteristics with other cities and areas plagued by I/I, it also has unique characteristics that make I/I especially difficult to measure and manage. The age of the wastewater infrastructure, the regional topography, and the depth of the water table contribute to the problem of I/I in Pinellas County.

1.2.2.1 Aging Infrastructure

As is the case in many other regions dealing with significant I/I issues, much of Pinellas County's sewer infrastructure is approaching its intended design life. The American Society of Civil Engineers (ASCE) Infrastructure Report Card for 2013 rated Florida's wastewater infrastructure at a C (mediocre). While this rating is higher than the national average of a D (poor), ASCE estimates that Florida must spend $19.6 billion on wastewater projects and repairs over the next 20 years to meet ecological standards and societal needs (ASCE Florida Section, 2012). According to the Clean Watershed Needs Survey (CWNS) of 2012, Pinellas County would need to spend $463 million in repairs and projects to provide optimal wastewater services, with $116 million (25% of the total) dedicated to rehabilitation of existing sanitary sewer lines and dealing directly with I/I (EPA, 2012).

The need for sewer line repair and rehabilitation stems primarily from the age and condition of the system. Many sewers in southern Pinellas County are up to 100 years old, and are vitrified clay pipe (VCP), a material more likely to crack and break than newer polyvinyl chloride (PVC) pipe (Pinellas County, 2013). As the system ages, both the pipes and wet wells are more likely to contain cracks and openings, introducing potential sites for groundwater infiltration. Additionally, older homes and buildings may have been constructed before the county mandated separate storm and sanitary sewers, and consequently may have improper or illegal connections from sump pumps or rain gutters to the sanitary sewer system.

Another potential issue created by older infrastructure is that of flooding. In older parts of town developed prior to adequate stormwater management practices, large storm events can lead to significant flooding. In some areas, this flooding may lead residents to open sanitary sewer manholes to prevent flood damage to their homes, which can contribute significant surface inflow to the sanitary sewer system.

1.2.2.2 Flat Topography

Most sanitary sewer collection channels utilize gravity driven flow, and depend on changing elevation to convey wastewater from one location to another. The state of Florida, including Pinellas County, has a relatively flat topography, limiting the elevation gradient available to drive the flow. Due to this limitation, the sewer network drains, by gravity or through a force main, to a number of wet wells throughout the sewershed. The sewage collects in each wet well until it reaches a specified fill level, when it then triggers a water level sensor that activates a pump. The pump uses pressurized flow to add head to the flow, essentially lifting it to a higher elevation so that the sewage can then travel by gravity to its next destination. A network of 141 wet wells or “lift stations” convey the sanitary sewer flow to its final destination at the SCBWRF, where it finally undergoes wastewater treatment. These 141 wet wells introduce many potential sites for groundwater or surface flow to enter into the sanitary sewer system.

1.2.2.3 High Water Table

The water table in Pinellas County varies, but on average is quite shallow, which means that much of the sanitary sewer infrastructure is submerged beneath the water table for much of the year. For example, the wells in the study area show the water table to be on average between 2 and 6 feet below the land surface. In the study area, an estimated average of 70% of the sewer pipes are submerged below the water table. Because the sanitary sewer pipes and wet wells are unpressurized, if the infrastructure is below the water table, the pressure outside the pipe or well is higher than the pressure inside the pipe or well. This pressure gradient drives the water into the pipe or well, contributing to freshwater infiltration component of sanitary sewer flow. Separating constant groundwater contribution from rainfall-derived groundwater infiltration may prove difficult because the soils in Pinellas County exhibit high hydraulic conductivity, meaning that when rainfall infiltrates into the soil, it quickly raises the water table.

Additionally, the water table along Pinellas County's 588 miles of coastal shoreline (Pinellas County, 2017) will be significantly affected by changing tides. As the coastal water table rises and falls with high and low tides, discerning surface inflow from groundwater contribution may become more difficult. Brackish groundwater infiltration will also require different treatment processes than typical freshwater infiltration, again complicating and raising the cost of wastewater treatment and potentially limiting its potential for reuse.

1.2.3 Problems Caused by I/I in Pinellas County

Inflow and Infiltration (I/I) cause many costly problems for Pinellas County Utilities and their residents. During typical, smaller rain events, the excess sewer flow from I/I must undergo excess transport and treatment. All of the fresh water introduced to the sanitary sewer system through I/I is conveyed through the rest of the piping system until it reaches the treatment facility. Pinellas County Utilities pays the electricity costs to pump this fresh water from 141 wet wells and through each corresponding pressurized force main, and the excess costs continue through to the end of the treatment process. Primary, secondary, and tertiary water treatment processes are carefully calibrated for typical concentrations of wastewater solids and pollutants. During rain events, the ratio of sewage to fresh water entering the treatment facility changes rapidly, impeding optimal calibration and reducing the efficacy of the treatment processes, so not only is the freshwater being unnecessarily treated, it may also reducing the quality of treatment of the actual wastewater. Excess sewage transport and treatment can occur during small rain events and for typical water table elevations and are often considered insignificant when compared to the cost of replacing or rehabilitating sewer infrastructure. The most significant problems occur during large rain events and severe storms.

During severe storm events, extreme excess sewer flows can cause SSOs and can exceed the maximum capacity of treatment and storage facilities. A sanitary sewer overflow occurs when one or many sanitary sewer pipes are clogged or filled to capacity, causing sewage flow to back up and spill out of service laterals or manholes (EPA Office of Water Management, 1996). This spilling of untreated sewage into homes, yards, streets, and waterways creates significant human health hazards, severely degrades water quality, and damages public and personal property. The bacteria and viruses present in untreated sewage can cause diseases like hepatitis, meningitis, encephalitis, giardia, cryptosporidiosis, Legionnaire's disease, and many others (EPA Office of Water Management, 1996). SSO can lead to direct contact with these pathogens in homes and yards and can also introduce them into the water supply. In addition to pathogens, untreated wastewater contains organic matter and nutrients, which, when consumed by marine bacteria, can lead to algal blooms and depletion of oxygen in water bodies. If a SSO occurs inside a home or business, disinfection and replacement of carpeting and other furnishings can cost thousands of dollars.

The most concerning consequence of I/I from severe storms is the exceedance of treatment and storage facility capacity. When extreme flows enter the treatment facility, systems such as screens and clarifiers can be hydraulically overloaded, and hydraulic residence time is decreased, leading to ineffective treatment. When the flow volumes exceed capacity, in order to preserve vital functions of the treatment equipment, excess sewage flow must be diverted into natural water bodies, the most common in which for Pinellas County, is the Tampa Bay. In September 2016, Hurricane Hermine delivered up to 22 inches of rain in some parts of the Tampa Bay area over three days, which resulted in ten straight days of sewage discharges from municipalities surrounding the bay (Neuhaus, 2016). An estimated combined volume of 240 million gallons of partially or untreated sewage was discharged into the Tampa Bay or its tributaries by the four counties bordering the Tampa Bay: Hillsborough, Hernando, Pasco, and Pinellas (Neuhaus, 2016). Pinellas County, served by six separate utilities companies, dumped over 210 million gallons (Yeargan, 2016). The most severe sewage dumps were reported by St. Petersburg Utilities, totaling over 152 million gallons (Yeargan, 2016) or 223% of the system's permitted daily treatment capacity. Additionally, during the 2016 wet season, St. Petersburg accounted for 58% of the total SSOs for the entire state of Florida (Yeargan, 2016). After Hurricane Hermine, three environmental organizations threatened to file a suit against St. Petersburg for violating the CWA if environmental mitigation and infrastructure repair plans were not released within 60 days (Lonon, 2016). Municipalities surrounding the Tampa Bay also face possible fines from the EPA and Florida Department of Environmental Protection (FDEP).

The sewage dumps into the Tampa Bay create economic problems for local businesses as well as municipalities. When Tampa Bay is in good condition, the region generates an estimated $22 million per year (Frago & Reeves, 2016) from water-related industries, from kayak rentals and paddleboard yoga classes to large-scale commercial fishing operations. The smell and sight of untreated sewage in the water and the fear of contracting illnesses drives customers away from beach and waterfront activities, even without formal beach closures. A researcher from the University of South Florida (USF) detected strains of antibiotic-resistant bacteria, previously only found in medical wastes (Frago & Reeves, 2016). The bacteria and viruses can directly cause serious illness in humans and can also make local fish and filter-feeders unsafe for consumption. Additionally, the large amounts of organic matter and nutrients in wastewater create conditions that support large algal blooms. In addition to creating aesthetically unpleasant water quality, algal blooms lead to oxygen depletion in the water and consequently, fish kills and dead zones. Accounting for business losses, infrastructure and environmental damage, hurricane Hermine cost roughly $1 billion in economic loss in the state of Florida (Neuhaus, 2016).

Excess I/I flows into an aging sanitary sewer system costs the municipalities, residents, and businesses of Pinellas County millions of dollars every year in energy costs, operation and maintenance costs, fines, and local business losses, in addition degrading the environment, and creating unsafe public health conditions. However, proper management and rehabilitation of infrastructure can prevent or curb the devastating effects of I/I.

There are several options to mitigate the effects of SSOs and large sewage discharges to bodies of water. If the quantity of excess sewer flow is known, these options include increasing the capacity of treatment facilities or installing equalization basins. However, construction and land acquisition to increase capacity are costly and can take many years. Additionally, the large quantities of fresh water from I/I flows would drastically change the composition of the waste flows during rain events and limit the efficiency of treatment procedures. The best way to prevent the devastating effects of SSOs from I/I are to prevent the I/I flows from ever entering the sanitary sewer, which requires knowing the source of I/I at each site. If the excess flow comes from surface runoff sources, such as open manholes or illegal connections, the county would mitigate the issue with enforcement measures such as notices or fines. If the excess flow stems from groundwater penetrating cracks in pipes or wet wells, the county would need to plan for replacement or rehabilitation of the faulty infrastructure. Consequently, to guide management and investment plans, Pinellas County needs an economically feasible method to separate surface inflow from groundwater infiltration and quantify the two separately. Once the existing I/I flows have been separated and quantified, a model can predict the sewer system response to future storms and further help with management decisions.

CHAPTER 2: LITERATURE REVIEW

The problem of excess fresh water flowing into sewer pipes has been studied for many years and is most often referred to as inflow and infiltration (I/I) or rainfall-derived inflow and infiltration (RDII). Observing unusually high flows into treatment facilities can identify possible I/I problems, but more information is needed to make infrastructure and management decisions. Because knowing the source of the excess flow is imperative for management decisions, many methods have been developed either to separate the surface and subsurface components of I/I or to calculate each separately. Physical detection methods like smoke tests, dye tests, and video footage can show where I/I may be entering the pipe system, however these methods are costly, time consuming, and often require taking the system offline for periods of time. For these reasons, researchers have been developing mathematical approaches to determining I/I to assist municipalities with more convenient and cost-effective decision making. These approaches fall under two overall categories: flow separation methods and modeling.

2.1 Flow Separation Methods

The most common approach to quantifying I/I or RDII is to monitor dry weather sewer flows (DWF), use the DWF data to determine an expected flow pattern, often referred to as baseflow, then monitor wet weather flows (WWF). The difference of the WWF during rain events and the DWF baseflows is considered to be I/I or RDII (Vallabhaneni, Chan, & Burgess, 2007). The challenge is then to discern surface sources from subsurface sources by calculating either infiltration or inflow, then subtracting it from the RDII total to solve for the remaining quantity. Groundwater infiltration occurs more slowly and predictably than surface inflow, so groundwater infiltration is generally the chosen variable to calculate, although some methods compute both inflow and infiltration simultaneously. The three general families of groundwater infiltration calculation methods are average minimum flow estimation, empirical equation methods, and methods that include Darcy's Law and hydraulic gradient.

2.1.1 Average Minimum Flow

One approach to separating groundwater infiltration from the RDII total is to assume that during nighttime hours wastewater is not being produced, so the minimum nightly flow can be assumed equal to the groundwater infiltration. The EPA recommends averaging the low nighttime flow during the period from midnight to 6:00 A.M. for each day (EPA, 2014), but some studies use other minimum flow estimations, such as the monthly average of minimum nightly flow values (Staufer, Scheidegger, & Rieckermann, 2012), however, in a region with a shallow, dynamic water table, such as Pinellas County, daily, rather than monthly average low nighttime flows are more appropriate. Depending on the size and demographics of the sewershed, these methods may not be accurate, as they fail to account for travel time of flows from distant laterals, equipment such as water softeners that run overnight, waste streams from overnight industrial processes, or utility customers with atypical schedules who may be producing wastewater during the nighttime minimum periods.

2.1.2 Empirical Equation Methods

Empirical groundwater infiltration methods, including the Wastewater Production method (WWPM), Minimum Flow Factor method (MFFM) and Stevens-Schutzbach method

(SSM), calculate the groundwater infiltration component of excess sewer flow, referred to as base infiltration (BI), using daily average and daily minimum sewer flow values during dry weather periods (Mitchell, Stevens, & Nazaroff, 2007). These methods are cost-effective, yielding accurate results using only flowmeter data. Using data from domestic water use studies, the WWPM estimates that 12% of the daily flow occurs at night, during the minimum flow period. The daily volume of wastewater produced is calculated from this ratio and the difference between average daily flow (ADF) and minimum daily flow (MDF). The base infiltration (BI) is the difference between the average daily flow in the sewer pipe and the actual wastewater produced. This WWPM overestimates BI for very large or very small basins, so the MFFM and SSM were developed to correct these issues. Like the WWPM, the MFFM and SSM equations calculate BI from ADF and MDF, but these empirical equations use curve fitting techniques to effectively scale the result by sewershed size. The MFFM requires iterative calculations to achieve more exact results, so the Stevens-Schutzbach method is preferred for its relative ease and accuracy for all basin sizes (Mitchell, Stevens, & Nazaroff, 2007).

2.1.3 Darcy's Law Methods

Other methods of separating and quantifying I/I adopt a physical, rather than purely empirical approach, most commonly applying and adapting Darcy's law and hydraulic conductivity. One method by Karpf and Krebs (2011) uses groundwater level data, treatment plant flow data, local stream flow data, rainfall volume and intensity, air temperature, and pipe cracks and condition from a test sewershed to calculate both groundwater infiltration and surface inflow. The groundwater infiltration component is modeled based on Darcy's law and requires estimating detailed data including soil conductivity, thickness of surrounding soil, area of pipe leaks, and the elevation difference between the pipe and ground water level. The surface inflow is modeled with two components: permanent inflows and flood inflows. Permanent inflows are empirically related to runoff in local creeks. Flood inflows are calculated based on Torricelli's approach, relating pressure heads and cross sections of surface-connected openings. After accounting for dry weather flow versus wet weather flow, the inflow and infiltration components are combined in a multiple linear regression model. While the model yields favorable results, it requires detailed data at a high resolution, which can be costly for a municipality to obtain and monitor over large sewer networks.

Similarly, a second model by Karpf and Krebs (2013) is also based on Darcy's law, but instead uses 3-dimensional MODFLOW groundwater modeling software to predict the groundwater infiltration into a sewer pipe. While this approach uses an existing software for complex calculations, it requires complex, user-defined boundary conditions including soil hydraulic conductivity, size of soil layer and fill, size and shape of pipe leaks, and depth of water table relative to leak location. The data required for this method is much too costly to obtain and enter for an entire county's pipe system. The authors include a simplified 1-dimensional model, but applying it to an entire sewershed requires assuming homogeneous soils, pipe conditions, rainfall patterns, and water table depths, which is not a fair assumption in many locations.

Zhang and Guo (2013) developed a method for modeling 2-dimensional infiltration using Darcy's law and the LaPlace equation, approximated with the equivalent circumference method and Mobius transformation, to solve for the groundwater infiltration into cracks in a sewer pipe. Like the other Darcy's law models, it requires detailed soil conductivity, pipe condition and defect locations, and water level data, making it impractical for large municipal projects.

2.2 Estimating I/I with Models

Another approach to determining the source and quantity of I/I is to use models to estimate I/I using a variety of input variables and calibration techniques. Aside from quantifying existing I/I, models are also useful for predicting the impact of future rain events on the sanitary sewer system, which can further help the county prevent or prepare for I/I-related SSOs. Methods for modeling I/I can be broken down into two main categories: adapted rainfall-runoff models and regression models. Selection of a method is primarily based on availability and cost of input data and the desired level of accuracy of I/I prediction.

2.2.1 Adapted Rainfall-Runoff Models

Unit hydrographs are used frequently in rainfall-runoff modeling to show flow responses, as a function of time, for one unit of rainfall, and synthetic unit hydrographs approximate these responses using a predefined shape, often a triangle (Vallabhaneni, Chan, & Burgess, 2007). The RTK method of synthetic unit hydrograph modeling is the most widely used method for estimating and modeling I/I in research, literature, and industry. The "R" is the percentage of rainfall that enters the sewer system as I/I and is also the volume under the hydrograph, "T" is the time to peak for the I/I event, and "K" is the ratio of the time to recession to the time to peak (T) (Vallabhaneni, Chan, & Burgess, 2007). Because surface inflow and groundwater infiltration occur on different time scales, multiple RTK hydrographs can be utilized to capture the complex response of sewer flow to rainfall. The EPA Sanitary Sewer Overflow Planning and Analysis (SSOAP) toolbox and other similar sewer flow modeling software packages fit three RTK hydrographs to the data, one for a fast response, one for a medium response, and one for a slow response (Vallabhaneni, Chan, & Burgess, 2007). In the SSOAP toolbox, the user iteratively fits and calibrates the fast, medium, and slow R's, T's, and K's (nine parameters total) for significant rain events to create the best fit total hydrograph (summation of fast, medium, and slow triangular hydrographs). Dynamic modeling software with built-in RTK methods, such as SewerCAD, perform these calibrations automatically (Bentley Systems, 2014). The nine RTK parameters that make up the best fit total hydrograph can then be used to analyze the current sewer response and predict the response to other rainfall events. The results of the RTK method can provide an accurate model of total RDII, however, determining if the flow is attributed to surface or subsurface sources is left to user discretion. While fast, medium, and slow responses are provided, in an area with a complex, dynamic water table, interpreting the physical meaning of these timed responses becomes difficult.

Soil moisture accounting (SMA) models are often used in rainfall-runoff modeling to capture the complex relationship between rain, soil moisture, groundwater, and resulting runoff. Renaud, Joannis, Schoefs, and Billard (2008) created a modified SMA rainfall-runoff model for the city of Nantes that models inflow and infiltration flow rates using data inputs of precipitation and estimated evapotranspiration. The model estimates I/I by accounting for groundwater storage and evapotranspiration in the calculation of infiltration and by applying a calibrated scaling factor to calculate surface inflow. Groundwater infiltration is separated into a fast response and a slow response. For each response, infiltration flow rate is calculated with a groundwater storage value and two scaling parameters that are dependent on the rainfall input. Surface inflow is calculated by multiplying rainfall input by an estimated inflow parameter. The model also calculates a total I/I flow rate by combining the output flow rates for fast groundwater infiltration, slow groundwater infiltration, and surface inflow. Using flow data from a specific monitored catchment, the model parameters are then calibrated using statistical and practical criteria for measures of accuracy and fit. The model functions well for rain events up to the 95% quantile, but for more extreme rain events, the model underestimates the flows by 5 to 20%. The accuracy of this method is strongly dependent on the quality and availability of the data used to calibrate the many parameters and requires a long data collection period for multiple catchments.

2.2.2 Regression Models

Although it cannot initially calculate the existing I/I, linear regression can develop simple models that predict I/I responses for future rain events or conditions using observed flow monitoring data and correlated input variables such as rainfall or water table depth (Crawford, Eckley, & Pier, 1999). While the accuracy of linear regression models may be limited, one major benefit is the flexibility allowed in selecting input data and desired outputs. Data availability can differ with municipality and catchment. For example, one study in Dresden, Germany found that I/I flow rates were highly correlated with flow rates in a local creek and the height of the water table above the sewer system rather than rainfall, so only the creek flow and water table head were included as independent variables in the multiple linear regression model (Karpf, Franz, & Krebs, 2007). For other sanitary sewer catchments, available input data may include daily rainfall totals, peak intensities, or groundwater elevations, and desired outputs may include total I/I volumes or flow rates, or separate surface inflow or groundwater infiltration volumes or flow rates. Accuracy and fit of regression models is strongly dependent on quality of collected data and inclusion of highly correlated variables. Because of their empirical nature, regression models are generally not applicable to other sites with vastly different physical characteristics.

The ultimate goal of the Fairview Estates Pilot study was to provide Pinellas County Utilities with the information to make managerial decisions and to guide infrastructure improvement plans, which depend on the source and quantity of the excess sewer flows for current and future rain events. After reviewing the existing methods to quantify and model I/I in the context of the needs and characteristics of Pinellas County, no one method seemed to fit the constraints of data availability, cost, scope, or project size, and few had been tested in areas with similar topography or hydrogeology. Multiple concepts from previous studies were combined to produce the methods for quantifying and modeling I/I for Pinellas County.

CHAPTER 3: OBJECTIVES, SITE, AND DATA COLLECTION

3.1 Objectives of Study

The objective of the Fairview I/I pilot study was to develop standard methods for separating surface inflow from groundwater infiltration, for quantifying them separately, and for modeling and predicting future excess sewer flows. The primary goal was for Pinellas County Utilities to use the methods developed in this pilot study to guide any future I/I studies at other sites and to direct their management decisions, policies, and infrastructure refurbishment plans.

3.2 Fairview Environment and Infrastructure

Fairview Estates is a small residential neighborhood, south of Sawgrass Lake Park in Pinellas County, FL, spanning 72 acres, and containing 215 houses of primarily permanent residents (Pinellas County, 2009). The ground elevation of the site ranges between 14 and 22 feet NAVD with an average water table of 2 to 6 feet below the land surface. As shown in Table 1, the soils of the study area are mostly Myakka fine sands containing silt and organic matter (NRCS, 2016). The neighborhood is mostly developed land, which has low permeability but is well drained by modern stormwater infrastructure. Sawgrass Lake Park, at the north end of the site, is a Southwest Florida Water Management District (SWFWMD) study site, equipped with water level control structures and subsurface drain tiles. The Fairview neighborhood contains approximately 2.3 miles of 8-inch diameter, gravity-driven sanitary sewer pipeline (VCP and PVC) that feeds into a wet well at pump station #119 (PS119). PS119 serves as a lift station to temporarily pressurize and ultimately direct the wastewater to SCBWRF for treatment.

3.3 Instrumentation

3.3.1 Flow Meters

Isco 2150 flow meters were installed in three locations within the sewer pipeline of Fairview Estates: one in the pipe just before the wet well at PS119, and two in manholes throughout the neighborhood. The flow meter at PS119 captures the flow for the entire neighborhood sewershed, and the two others capture flow of sub-sewersheds. The flowmeters measure and record the water level (within ±0.008ft) and velocity (within ±0.1ft/s) in the sewer pipe every 15 minutes to give a fine resolution for identifying potential surface inflow. (One additional sub-sewershed flow meter was initially installed, but the data it collected was unrealistic, so it was excluded from analysis). Flow meter data was collected from October 2015 to October 2016.

Table 1: Soil Composition of Fairview Study Site and Map Locations (NRCS, 2016)

Map Unit Symbol	Map Unit Name	Acres in Site	Percent of Site
11	*Felda soils and urban land*	0.2	0.2%
16	*Matlacha and St. Augustine soils and Urban land*	0.1	0.1%
17	*Myakka soils and Urban land*	62.5	75.2%
18	*Okeechobee, frequently ponded, 0 to 1 percent slopes*	11.6	14.0%
29	*Tavares soils and Urban land, 0 to 5 percent slopes*	2	2.4%
31	*Wabasso soils and Urban land*	6.7	8.0%

3.3.2 Groundwater Monitoring Wells

Two 15-foot deep, 2-inch diameter, PVC groundwater level monitoring wells, equipped with Solinist Levelogger® pressure transducer water level sensors, were installed within the study area (Detailed installation shown in Figures A1 and A2 in Appendix A). The first monitoring well (MW1) was installed in the northwest corner of the neighborhood, directly next to the pump station (PS119). The second monitoring well (MW2) was installed in the southeast corner of the neighborhood. The pressure transducer water level sensors in the monitoring wells measure and record the water level every hour within 0.05% accuracy. Groundwater data was collected from February 2016 to July 2016.

3.3.3 Rain Gauges

Data from three separate rain gauges were used in this study. One tipping bucket rain gauge on top of the wet well at PS119 was already in place as part of the Pinellas County Utilities SCADA system. Historically, this rain gauge provided daily rain depth readings, but for the pilot study project, the gauge was refined to provide hourly readings beginning in February, 2016. For calculations requiring a 15-minute time resolution, publically available rain data were accessed from the nearby Southwest Florida Water Management District (SWFWMD) Sawgrass Lake 2 rain gauge, roughly 0.4 miles north of the Fairview neighborhood. If gaps in the rainfall record from either of the first two gauges occurred, data were gathered from the United States Geological Survey (USGS) rain gauge at St. Joe Creek, 2 miles southwest of Fairview Estates. Rain data was collected from October 2015 to October 2016, which encompassed a strong El Niño period and an extreme hurricane season (Collins & Roache, 2017).

CHAPTER 4: SEPARATING AND QUANTIFYING I/I

4.1 Components of Sewer Flow

The flow in the sanitary sewer pipe is made up of sewage and freshwater. The sewage component of the flow follows daily diurnal patterns, but the data will also contain variations from that diurnal pattern due to the inherent variability of a system with many users. The freshwater component of the flow is made up of surface inflow and groundwater infiltration. Daily groundwater infiltration (base infiltration) and diurnal wastewater flow patterns can be estimated with straightforward equations and methods, but the inflow component and random system variations are more difficult to quantify. Because surface inflow occurs on a short timescale, it will appear as a sharp spike in the time series of flow data, and due to the highly variable nature of wastewater production in a residential neighborhood, similar spikes are observed on days with no rainfall, making it difficult to discern inflow signals from random variations (Figure 1). For this reason, a method to screen the data for significant inflow signals was developed using time series analysis.

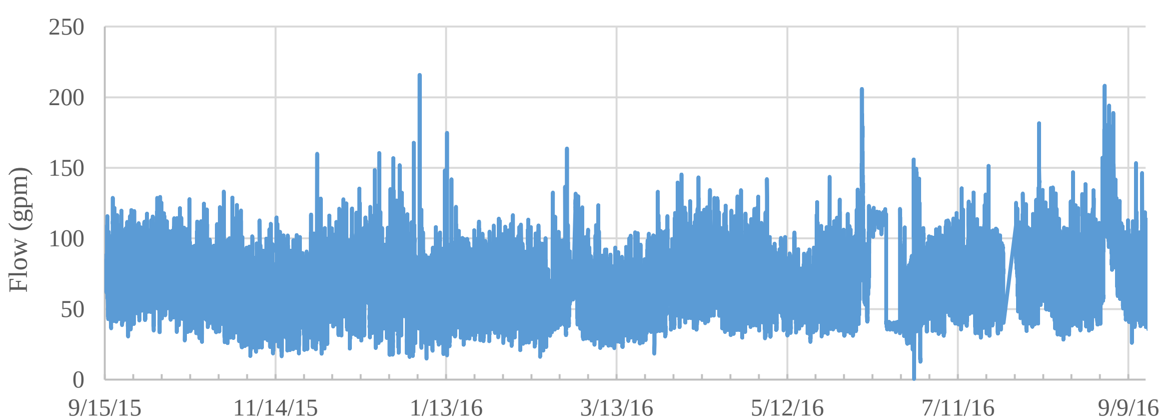

Figure 1: Raw sewer flow signal for the PS119 sewershed

4.2 Time Series Analysis

The time series analysis method filters base infiltration and diurnal patterns from the flow data, leaving behind a residual signal that could be attributed to either random variation or surface inflow. A residual signal of purely random variation with a mean of zero is called white noise. During dry weather flow (DWF), there is no rainfall, so surface inflow is not a possibility. When the filters are applied to DWF data, the residual is attributed completely to random variations in the sanitary sewer system. When the same filters are applied to wet weather flow, the residual will still contain random variations, but may also include inflow. By determining representative statistics of the dry weather residual and applying a significance limit, a range of expected system variation can be developed. Wet weather residual values that fall outside of this range are not explained by normal system variability and are considered statistically significant inflow contribution.

4.2.1 Filtering Out Patterns

4.2.1.1 Base Infiltration

In a shallow groundwater environment, sewer flow includes a consistent groundwater infiltration component referred to as base infiltration (BI). The first step in filtering the flow data for time series analysis involves calculating base infiltration using the Stevens-Schutzbach method described in previous sections (chosen for its accuracy in both small and large sewersheds). Using the average daily flow (ADF) and the minimum daily flow (MDF) in an empirical relationship, the Stevens-Schutzbach method produces one BI value for each day (Equation 1) (Mitchell, Stevens, & Nazaroff, 2007). The inputs and outputs of the equation are in flow units of million gallons per day (mgd), and the empirical equation uses the ADF value to essentially scale BI result for sewershed size.

$$BI = \frac{0.4(MDF)}{(1 - 0.6\left(\frac{MDF}{ADF}\right)^{ADF^{0.7}})}$$

Equation 1: Stevens-Schutzbach Base Infiltration (BI) (Mitchell, Stevens, & Nazaroff, 2007)

4.2.1.2 Diurnal Patterns

When examining a single day of sewer flow data, there is a high level of variation, but the flow tends to follow a diurnal pattern that closely matches typical water use throughout the day (Figure 2). The data from dry weather periods were used to establish the typical flow patterns because inflow only occurs during rainfall events. However, the raw DWF data include BI, artificially inflating the sewage flow values. To get a true wastewater flow value, BI was subtracted from the DWF data.

The typical daily diurnal patterns for each Fairview sub-sewershed were determined by compiling the flow data from every dry weather day in the 11-month study record. The flowmeters provided a sewer flow value at 15-minute time increments throughout the day. By averaging the adjusted flow values (sewer flow - base infiltration) for every 15-minute time interval for every weekday or weekend day, respectively, in the 11 month study period, a curve was produced to show the average sewage production throughout a typical day. Separate curves were generated for weekdays and weekends because the typical user follows a different water use routine on weekdays and weekends (Figure 3) (Additional flow meter patterns shown in Appendix A). Wastewater production patterns were assumed constant throughout the year.

The typical daily wastewater flow pattern is classified as diurnal because of the two peaks observed each day. The flow reaches a minimum between midnight and 4:00 AM, when most users are sleeping, consequently not producing wastewater. The flow values begin to rise to a peak between 6:00 AM and 9:00 AM when most people wake up, shower, and get ready for school or work. The flow values reach a second peak between 6:00 PM and 9:00 PM when people return home to produce wastewater through cooking, cleaning, laundry, or other household activities. On weekends, the diurnal pattern shifts as users tend to wake up later and produce wastewater more steadily throughout the day.

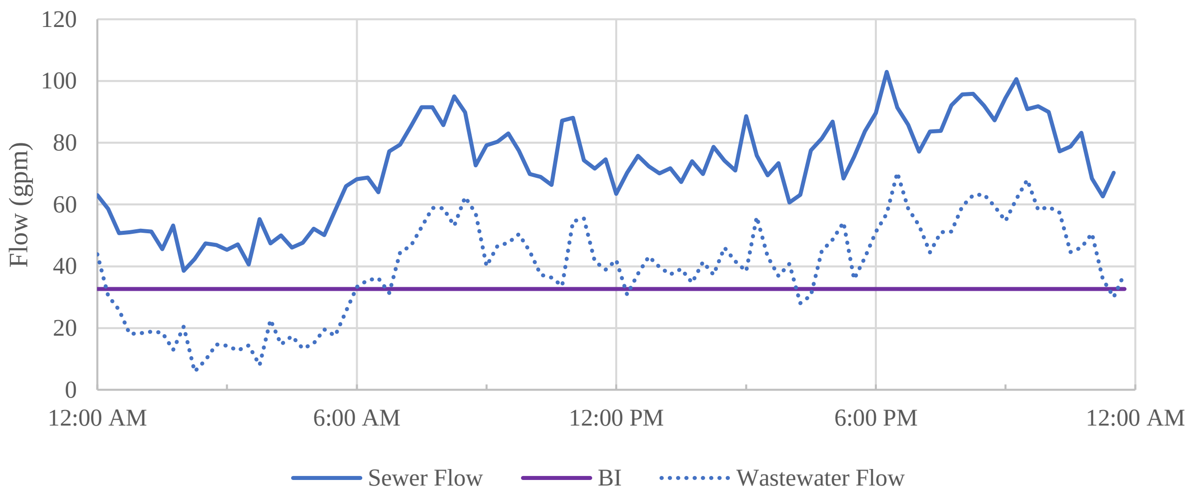

Figure 2: Sewer flow, BI, and wastewater flow for one dry weather day. (Monday, 9/21/15).

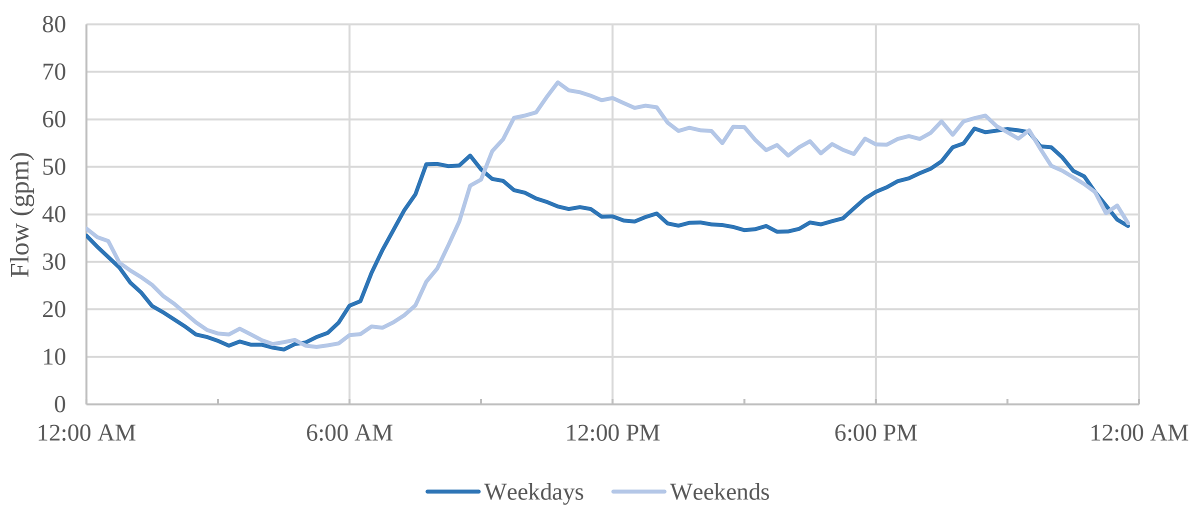

Figure 3: Daily diurnal wastewater production pattern for PS119.

4.2.2 Calculating Residual Flow

The raw sewer flow data, given in 15-minute intervals, were filtered by subtracting the BI value for each corresponding day and subtracting the typical flow value for that time of day (from the adjusted diurnal curve for either weekdays or weekends). Applying these filters reduced the raw 15-minute flow values to 15-minute residual flow values.

$$Residual\ Flow = (Raw\ sewer\ flow)_{15\ min} - (BI)_{daily} - (Diurnal\ Pattern\ value)_{15\ min}$$

Equation 2: Residual Flow

For dry weather flow, the residual flow values are a result of system variability (different number of water users at any given time), as there is no rainfall to cause surface inflow (Figure 4). Over the entire record of data, the average of the dry weather residuals was zero (for all flowmeters), suggesting that the residuals are attributed solely to random system variations.

To test if the DWF residual signal was pure white noise, a Ljung-Box Test was run for the daily average residual time series. In the Ljung-Box Test (Serra & Rodriguez, 2012), the null hypothesis (H_o) is that the series is purely random with no correlation, and the alternate hypothesis (H_a) is that the series exhibits serial correlation, and therefore is not purely random. The test statistic (Q), shown in Equation 3, is compared to the chi square statistic ($\chi^2_{1-\alpha,h}$) for h degrees of freedom, at significance level α (set to 0.05). The value r_k is the autocorrelation (detailed in Section 5.1) of the series at a time lag of k. If $Q > \chi^2_{1-\alpha,h}$, then H_o is rejected, and the series exhibits serial correlation. The Ljung-Box test was conducted with h values ranging from

$$Q = n(n+2)\sum_{k=1}^{h}\frac{r_k^2}{n-k}$$

Equation 3: Ljung-Box Test for Randomness (Serra & Rodriguez, 2012)

3-12 days, and in all cases, H_o was rejected, meaning the average daily residual signals exhibit serial correlation and cannot be considered pure white noise, as initially expected.

The serial correlation is due to rounding and averaging inherent in the Stevens-Schutzbach Method and calculation of diurnal patterns. Consequently, the average of residuals for any given day or week is not necessarily zero, and the Ljung-Box Test cannot be used to determine whether the wet weather residuals contain inflow. Each flowmeter's sewershed had a different range and standard deviation of daily average residual values summarized in Table 2.

Table 2: Range of Average Residual Flow Values for Each Sewershed (gpm)

Sewershed	PS119	FM2506	FM2520
Residual High	33	21	18
Residual Low	-35	-7	-15
Standard Deviation	8.7	4.1	5.7

4.2.3 Developing Expected Range of Variability

Ultimately, the purpose of calculating dry weather residual is to provide test values, that when compared to wet weather residuals, will determine which spikes in residual flow can be attributed to surface inflow. Because the dry weather residual signals contain serial correlation and have varying daily averages, they cannot be easily compared to the wet weather residual values for any given rain day, leading to need for a range of expected dry weather values that encompasses the inherent system variability and accounts for serial errors.

To create the range of expected variability in residuals, the 15-minute DWF residuals were converted to average daily values, and the standard deviation was calculated for the series (8.7 for PS119). To capture 95% of the variability, two standard deviations were added and subtracted to the series average of zero to provide the top and bottom limits of the expected residual variation range (assuming standard normal distribution) (Figure 5). For PS119, the expected variability in DWF residuals ranges from +17.3 to -17.3 gpm. (Additional flow meter residuals and ranges provided in Appendix A).

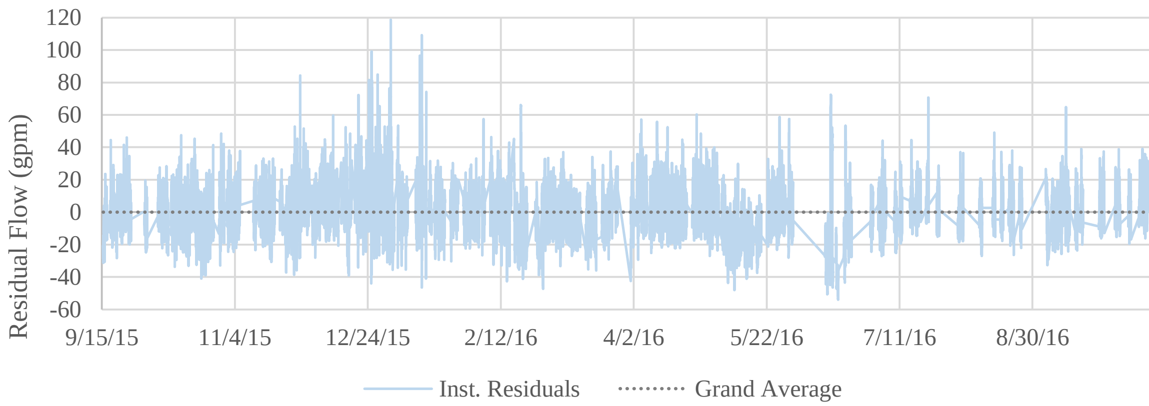

Figure 4: 15-minute residual flow values for DWF at PS119. (Inst. Residuals at 15-minute time step).

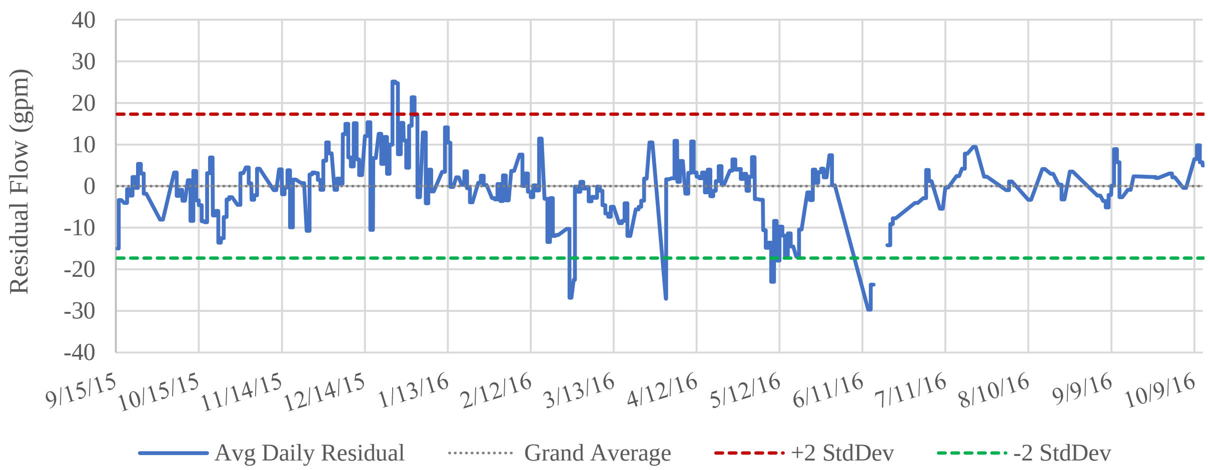

Figure 5: Average daily residuals and expected range of variability for DWF (PS119)

4.2.4 Screening for Inflow on Rain Days

Following the same process as that of dry weather flow, the daily base infiltration and diurnal patterns were filtered from the flow data on rain days, resulting in a series of 15-minute residual data points, which were then converted to average daily values. Each rain day corresponded to one average residual value to compare to the DWF range of expected variability (Figure 6). For this study, rain events with daily rainfall totals greater than or equal to 1 inch are considered significant events and selected for comparison. If the rain day residual falls within or below the expected range, it cannot be discerned as inflow, and therefore is not considered significant. If the rain day residual falls above the upper limit, it is statistically significant and considered a result of surface inflow.

In the Fairview Estates study site, the significant rain event daily average residual values for all flowmeters fell within the ranges of expected variation, leading to the conclusion that there is no significant surface inflow at this site (Additional flow meter graphs in Appendix A).

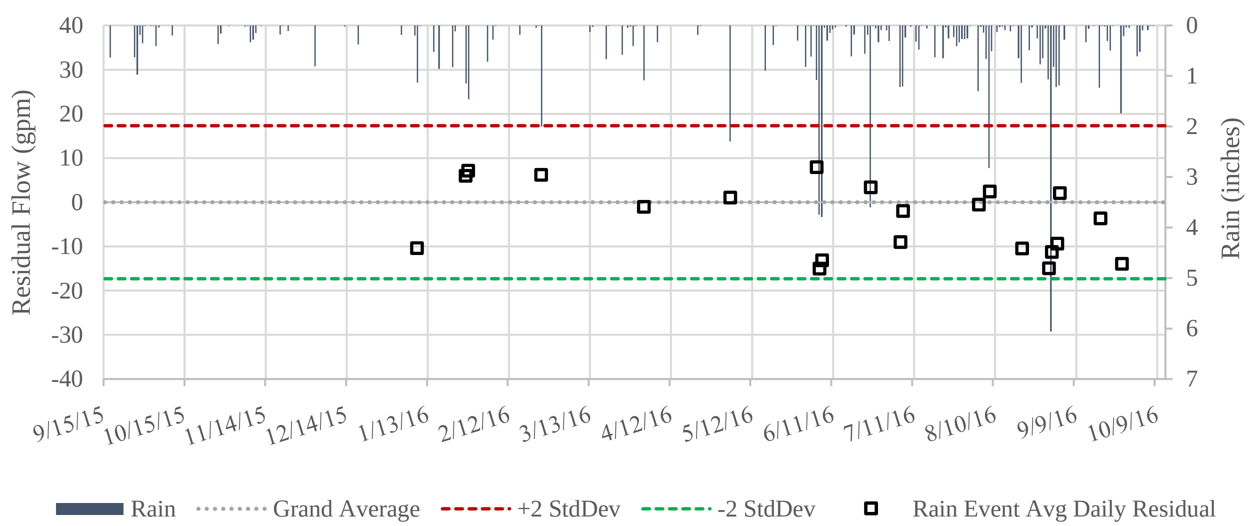

Figure 6: Average daily residuals for significant rain events. (Compared to range of expected residual flows for DWF in PS119).

CHAPTER 5: RESULTS AND ANALYSIS

5.1 Results

Because the screening process ruled out surface inflow as a significant source of excess flow, the I/I flow in the Fairview neighborhood can be attributed to groundwater sources, or base infiltration (BI). Further analysis is required to better understand the severity of groundwater contribution to excess flow in the PS119 sewershed.

During the study period, the Fairview neighborhood produced an average of 245 gallons of wastewater per household per day, which is in line with the Florida average of 200-300 gallons per household per day (ACS, 2015) (FDEP, 2016). However, when groundwater base infiltration (BI) is included in these values, the average sewer flow is 464 gallons per household per day, almost double the actual wastewater value. The average infiltration rate for the study site was 2,420 gpd/idm (gallons /day/inch of pipe diameter/mile of pipe), which is greater than the 1,500 gpd/idm considered to be excessive (EPA, 2014). For the entire PS119 sewershed, an average of 44% of the average daily sewer flow (ADF) was composed of groundwater (as BI). Table 3 shows the BI as percent of ADF values for each flow meter's sewershed in the dry season (November-May), in the wet season (June-October), and on average. Groundwater contribution to daily sewer flow is highest during the wet season, but even during the dry season, 26% to 52% of the sewer flow is composed of BI.

Over the year of the study period (10/12/2015 to 10/12/2016), the study area received 70 inches of rain, and the water budget for this study period (rainfall*sewershed area) was 18.3 million cubic feet of water. In the same period, the sanitary sewer pipes of the PS119 sewershed experienced 2.7 million gallons of base infiltration (BI), which means the sewer pipes drained 14.7% of the annual water budget.

Table 3: Base Infiltration (BI) as Percent of Average Daily Flow (ADF).

Base Infiltration as Percent of Average Daily Flow			
	PS119	**FM2506**	**FM2520**
Dry Season	40%	26%	52%
Wet Season	49%	32%	68%
Average	44%	29%	56%

5.2 Temporal Analysis

The most severe I/I problems at the waste reclamation facility occur after large storm events, so to understand how BI will ultimately affect the Pinellas County Utilities' plans to prepare for these events, it is important to understand the response of BI to rainfall.
By plotting daily rainfall with ground water elevations of the monitoring wells, it can be shown that, during the wet season (June-October), the water table responds to rainfall within one day, causing a 1ft to 6ft rise in water table elevation (Figures 7 and 8). This water table rise then dissipates within 3 to 5 days. The drainage response at Monitoring Well 1 (MW1) is more predictable than that of Monitoring Well 2 (MW2) partly due to drainage tiles installed near Sawgrass Lake that drain the water table near MW1, and partly due to instrumentation failure at MW2 during the largest rain events.

A cross-correlation analysis (detailed in Chapter 6) of water table and rainfall also shows that the average water table response is highest from 1 to 5 days after rainfall (Figure 9). Cross-correlation shows more clearly that while the water table does respond within one day rainfall, the strongest response occurs 1 to 2 days after the rain event. In Florida, rain takes 1 to 2 days to travel through the unsaturated zone to raise the water table (Nachabe, Masek, & Obeysekera, 2004), so the analysis is consistent with the expected response. The water table response to rainfall is significant for 9 days; so even though much of the rainfall-induced rise in water table dissipates after 5 days, the average seasonal water table will increase after repeated rain events.

By plotting the base infiltration (BI) of the PS119 sewershed with the water table elevations, it is clear that the BI response is closely tied to the water table, especially during large rain events such as Topical Storm Colin (6/6/16) (Figure 10). These results confirm the observations of the reclamation facility operators that the extreme flows to the facility continue from 3 to 5 days after a major rain event.

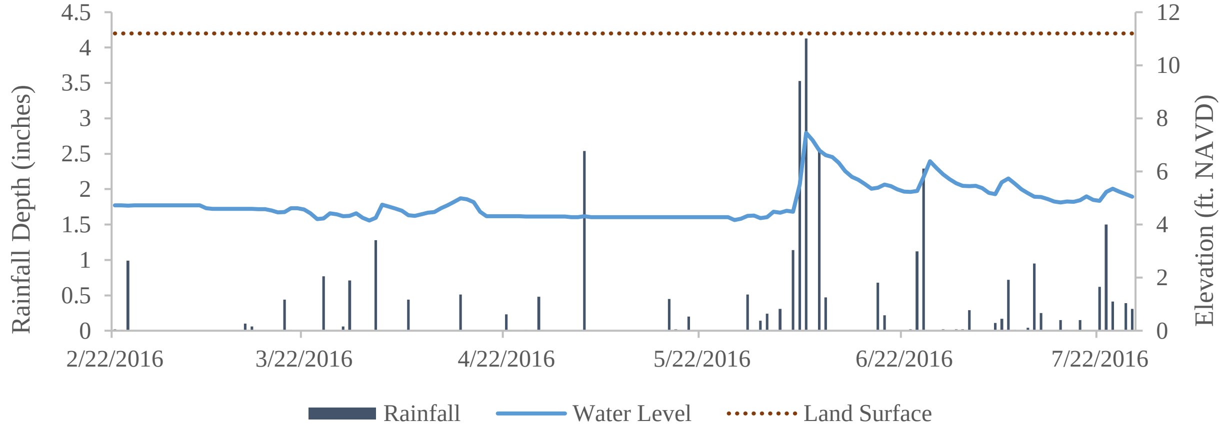

Figure 7: Monitoring Well 1 (MW1) water table response to rainfall

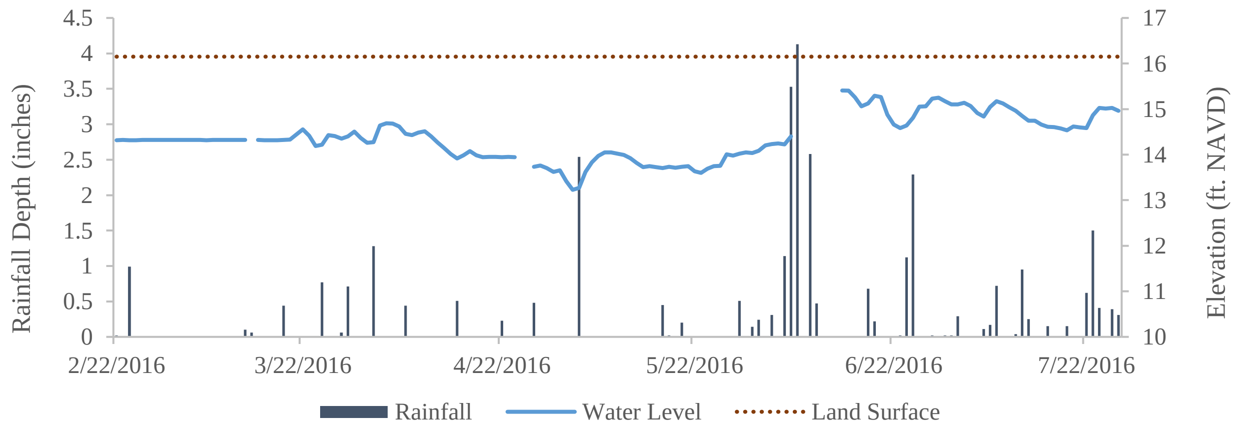

Figure 8: Monitoring Well 2 (MW2) water table response to rainfall

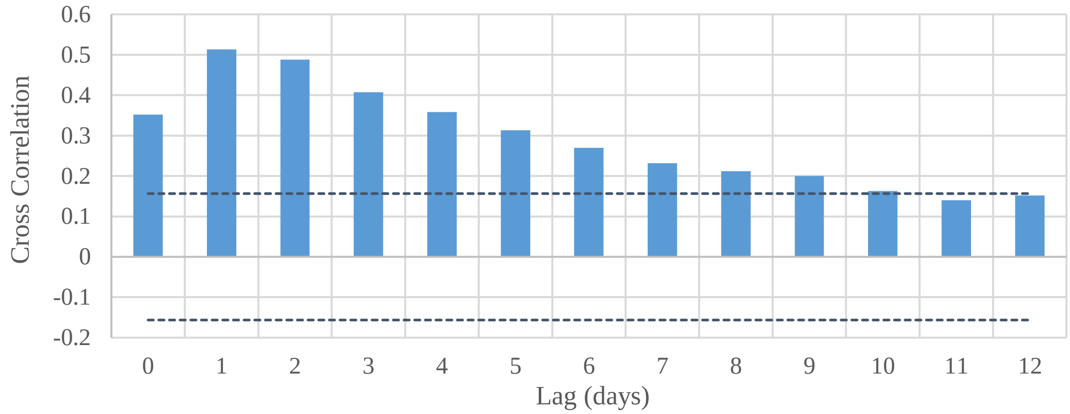

Figure 9: Cross-correlation of WT elevation at MW1 and rainfall. (Daily WT elevation in ft. NAVD and daily rainfall totals in inches. 95% significance limits ±0.16)

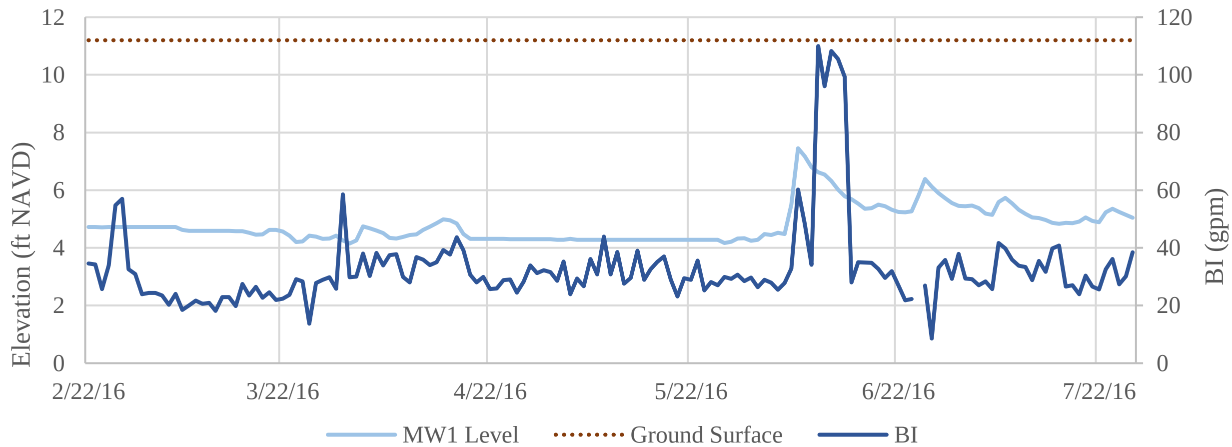

Figure 10: Base Infiltration at PS119 and water table elevation of MW1.

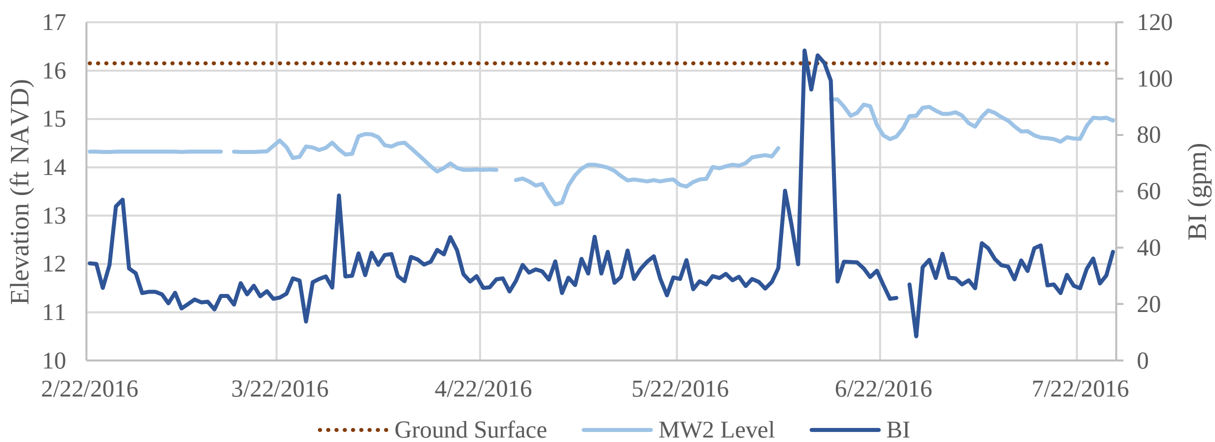

Figure 11: Base Infiltration at PS119 and water table elevation of MW2.

5.3 Spatial Analysis

While it had been determined that the PS119 sewershed has a base infiltration (BI) problem, the BI may not be uniform throughout all the pipes of the system. By determining which areas contribute the most BI, costs for rehabilitating the pipes can be minimized. The data from the 2 sub-sewersheds and 2 monitoring wells helped isolate the most problematic BI area.

As shown in Figure 12, the land surface gradient slopes upward from north to south, while the water table becomes shallower from north to south. By comparing the water table elevation gradient to the estimated invert elevations of manholes, a rough calculation showed that on average, throughout the year, 75% of the Fairview pipes are submerged beneath the water table, with 60% in the northern half of the neighborhood, and nearly 100% in the southern half. The neighborhood average of 75% submergence increases to 83% with a 1ft rise in water table, 88% with a 2ft rise, and 98% with a 3ft rise. As shown in the previous section, Monitoring Well 1 (MW1) experienced almost a 6ft rise in water table during Tropical Storm Colin, which indicates that nearly 100% of the entire sewershed's pipes were submerged beneath the water table, consequently subject to potential groundwater infiltration.

The sub-sewershed with the most submerged infrastructure, in this case FM2520, will have the highest potential for groundwater infiltration into the sewer pipes, but actual infiltration would depend on soil characteristics and pipe conditions. Analyzing the spatial layout and the groundwater infiltration (BI) statistics for each sub-sewershed (Table 4) indicated that the sewershed with the most submerged infrastructure (FM2520) was also the sewershed with the highest BI, or groundwater contribution, even when accounting for sewershed size, average daily flow, and malfunctioning of the flowmeter during rain events. These results suggest that percent of submerged sewer infrastructure is a good indicator of potential groundwater infiltration problems, but a specific relationship could not be calculated in this study due to insufficient pipe elevation and rain event flow meter data.

Table 4: Summary of Base Infiltration (BI) into Each Sewershed

Sewershed	**Length of Pipe** *(ft)*	**Avg BI/mi** *(gpm/mi)*	**Avg BI as Percent of ADF**
FM2506	2,870	4.5	29%
FM2520	4,087	16.1	56%
PS119	11,936	13.6	44%

Figure 12: Layout of flowmeters, corresponding sewersheds, and monitoring wells. (Land surface elevations in ft. NAVD)

CHAPTER 6: REGRESSION MODELING OF BASE INFILTRATION

6.1 Autocorrelation

A regression model is useful for predicting the sanitary sewer system's response to severe storm events and can guide management and design decisions for the future. The ideal predictive model would require easily attainable inputs, such as rainfall and historic groundwater data, to avoid construction and installation costs for future data collection. Correlation analysis was conducted to determine which terms would build a useful model to accurately represent expected base infiltration (BI).

In a discrete time series, autocorrelation is the degree to which each observation depends on the previous observations, and the memory of the system is the length of time for which the values remain correlated (Haan, 2002). The autocorrelation coefficient, r_k, is the measure of the strength of correlation between an observation at time t, and another observation at time $t+k$, where k is a number of time intervals between events, also known as the lag (Equation 4). The value of the autocorrelation coefficient can range from -1 to 1, with an absolute value of 1 indicating strong correlation, and absolute value of 0 indicating no correlation. The autocorrelation coefficient can also be considered the covariance between the event at time t and the event at time $t+k$ divided by the variance of the series (Haan, 2002).

$$r_k = \frac{\sum_{t=1}^{N-k}((x_t - \overline{x})(x_{t+k} - \overline{x}))}{\sum_{t=1}^{N-k}(x_t - \overline{x})^2}$$

Equation 4: Autocorrelation Coefficient for a Time Series
(Salas, Delleur, Yevjevich, & Lane, 1988)

A correlogram is a plot showing the strength of the autocorrelation (y-axis) as lag time increases (x-axis). Figure 13 shows a correlogram for base infiltration per mile of pipeline (BI/mi) for the sewershed of PS119, with lag times in days. The BI/mi of the previous day is strongly tied to the BI/mi one day later, and the strength of that correlation diminishes as the lag increases. An increase in BI will persist throughout the memory of the system, which in this case reflects the time to drain the water table and remove the cause of infiltration. After a lag time of 7 days, the autocorrelation drops below zero, meaning the BI/mi from 8 days ago has no correlation with the BI/mi today. The 95% confidence limit of the series also shows a significant drop in strength of autocorrelation after 4 days, so 4 days would be considered the significant memory of the system. For modeling purposes, adding terms past 4 days to an autoregressive model would only add complexity to the model without significantly increasing accuracy.

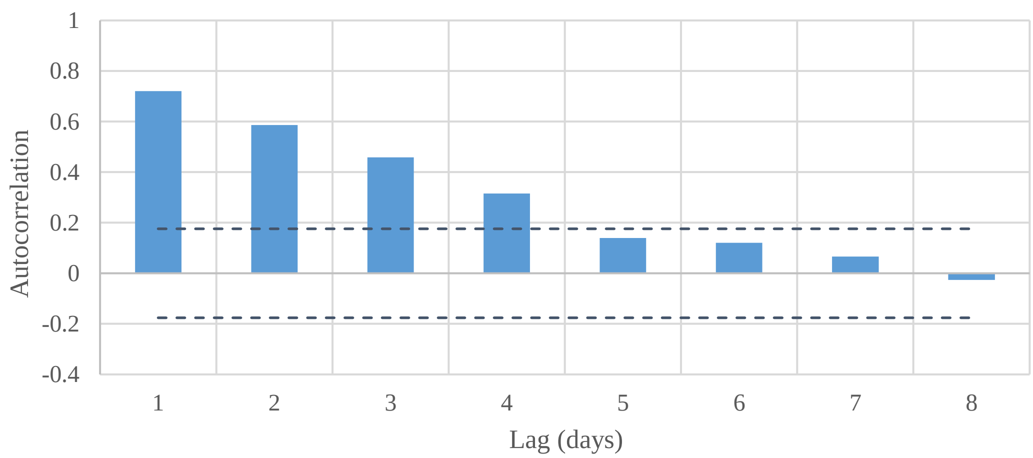

Figure 13: Autocorrelation correlogram for BI/mi in PS119. (95% significance limits ± 0.18)

6.2 Cross-Correlation

Cross-correlation is a measure of the strength of the relationship between observations of two different variables in a time series. A strong cross-correlation is not necessarily due to a cause-and-effect relationship between two variables, but it does imply that, through some external factors, each variable can serve as a predictor of the other (Haan, 2002). Shown in

Equation 5, the cross-correlation coefficient, r_k^{xy}, is the strength of the correlation between observations of variables x and y at time lag k, with r_k^{xy} again ranging between -1 and 1. Similar to autocorrelation, the cross-correlation equation calculates the covariance between the two variables at time lags in the numerator and a form of the variance of the series in the denominator.

$$r_k^{xy} = \frac{\sum_{t=1}^{N-k}((x_t - \overline{x}_t)\,(y_{t+k} - \overline{y}_{t+k}))}{\left[\,\sum_{t=1}^{N-k}(x_t - \overline{x}_t)^2 * \sum_{t=1}^{N-k}(y_{t+k} - \overline{y}_{t+k})^2\,\right]^{1/2}}$$

Equation 5: Cross-Correlation Coefficient for two Variables (x and y) in a Time Series (Salas, Delleur, Yevjevich, & Lane, 1988)

Also similar to autocorrelation, correlograms for cross-correlation show the strength of the correlation between the two variables at each lag time in the series. Observing the changing correlation throughout the time series can helps discern which variables and lag times will be useful inputs for a regression model to predict base infiltration (as BI/mi).

The head above pipe invert elevations is an important variable to consider because physical understanding of the problem reveals that BI/mi is highly dependent on water table fluctuations; the amount of pipes submerged and the head that forces groundwater into the pipes vary according to the water table. Because pipe elevation data for PS119 was not available, head above the pipes was not possible to measure, and water table (WT) elevation was chosen as the variable to represent the changing head above the pipes. The time series from Monitoring Well 1 (MW1) was chosen because it contains the most complete record of data, especially during rain events. In the correlogram in Figure 14, there is a strong (nearly 50%) correlation between WT elevation and BI/mi from 0 to 4 days lag time, implying that a rise in the water table will result in higher BI for at least 4 days, tapering off after 6 days.

Groundwater characteristics can vary drastically from site to site, and studies in other locations would likely need different groundwater data. Because installation of groundwater monitoring wells is costly, and well construction is not permitted in some parts of the county, readily available groundwater data from the NRCS Web Soil Survey (WSS) (NRCS, 2016) were also analyzed for correlation with BI/mi. The WSS reports seasonal high water tables as depth to water table (DTW) for each soil type in the PS119 sewershed at a monthly time step. Because over 75% of the study area was made up of Myakka soils, the Myakka monthly DTW values (converted to water table elevations) were chosen for the time series values. The correlogram (Figure 15) shows a relatively weak correlation with little variability, due to the course resolution of the available WSS data.

Because Pinellas County experiences I/I problems after severe rain events, and rainfall data are easily accessible from existing SCADA systems and public record rain gauges, rainfall is the most important variable to consider for cross-correlation analysis and use in a regression model to predict base infiltration (as BI/mi). The correlogram for daily rainfall totals (in inches) and BI/mi in the PS119 sewershed (Figure 16) shows that the strength of the correlation between BI/mi and rainfall decreases substantially after 7 days, implying that BI will be significantly impacted by rainfall for one week. The correlogram also shows that on the day lag=0, rainfall has almost no correlation with BI/mi, and that the most significant correlations occur between 3 and 5 days. These results are intuitive, as rainfall often takes 1 to 2 days to infiltrate the unsaturated zone of the soil and raise the water table, which then forces groundwater into the submerged pipes. It then takes water from the furthest reaches of the sewershed an average of 2 hours to reach the flowmeter at PS119. The results also correlate with observations at the reclamation facility that the excessive sanitary sewer flows continue for 3 to 5 days after a large rain event.

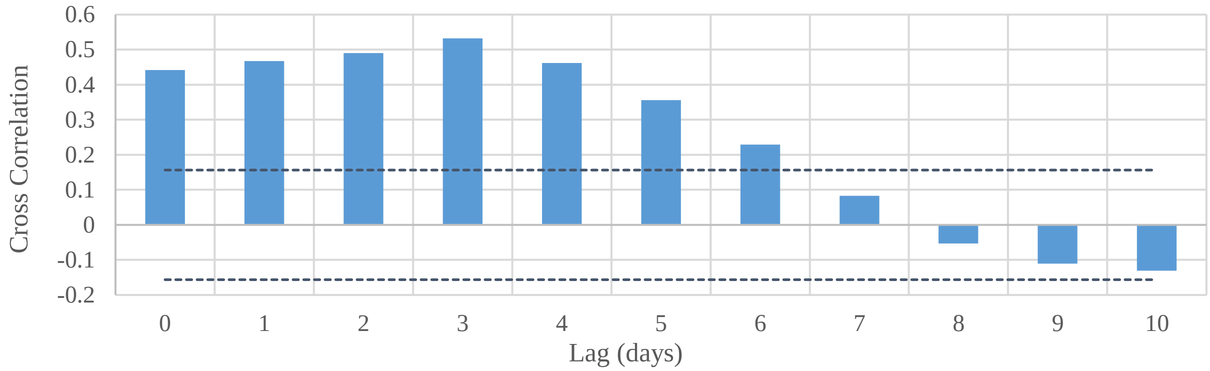

Figure 14: Cross-correlation between WT elevation at MW1 and BI/mi (PS119). (95% significance limits ±0.16)

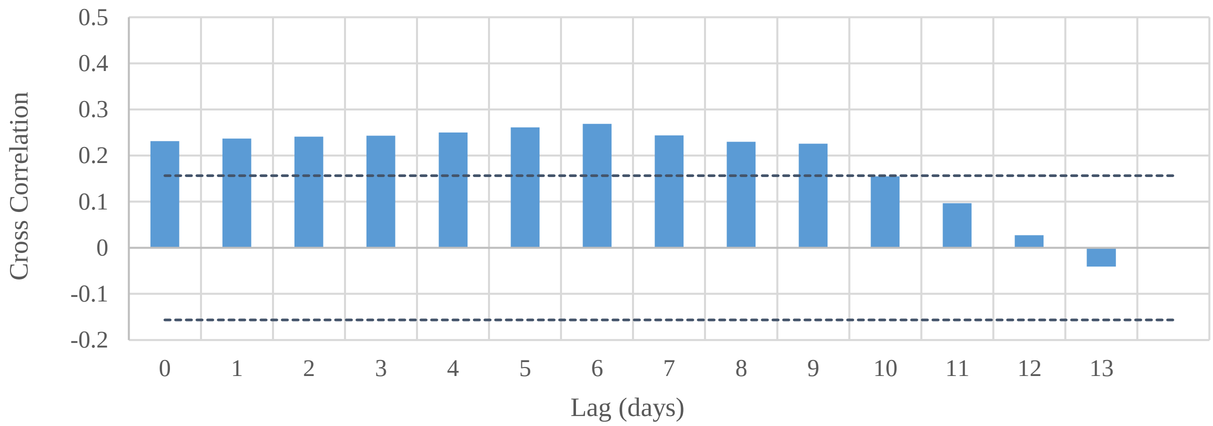

Figure 15: Cross-correlation between WT elevation from NRCS WSS and BI/mi (PS119). (95% significance limits ±0.16)

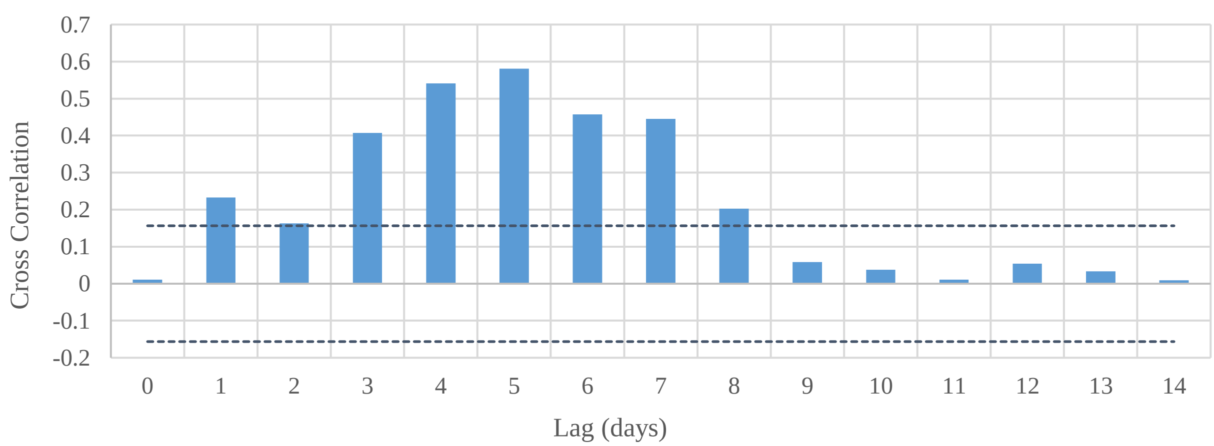

Figure 16: Cross-correlation between BI/mi at PS119 and rainfall. (95% significance limits ±0.16)

6.3 Regression Models

The purpose of the regression model is to serve as a practical predictive tool to estimate the amount of base infiltration that can be expected as a result of rain events. The base infiltration per mile of pipeline in the sewershed (BI/mi) was used for correlation analysis and regression to allow the model to be more applicable to other sewersheds of interest. Readily available data inputs and simplicity of the model were two main design criteria for the regression model. While the physical processes that cause infiltration may not be linear, a linear regression model based on cross-correlation analysis may represent the BI response to rain events with sufficient accuracy. A wide variety of other factors may influence BI, however water table and rainfall depth were chosen for their relative ease of measurement. Because any new sewershed modeled would need its own, site specific groundwater data, the NRCS water table data are preferred over monitoring well data for accessibility and low cost.

The depth to water table values from the NRCS WSS only change seasonally (Table A1 in Appendix A), so the values would not be useful as direct inputs to a regression model with a daily time step. Instead, the WSS data were used to help determine how best to separate the dry season from wet season to make separate regression models for each. By also using regional knowledge of storm seasonality, the wet season was defined as June through October, and the dry season as November through May. Splitting the model into seasons applies an underlying assumption about water table depth instead of requiring a direct input in the model.

Cross-correlation analysis of BI/mi and rainfall was performed separately for the dry season and wet season data. In the dry season (Figure 17), BI/mi shows a weak and sporadic correlation with rainfall, indicating that a dry season regression model would have low accuracy. A test regression model for BI/mi during the dry season was developed using daily rainfall for the previous seven days as inputs, and the resulting coefficient of determination (R^2) was 0.06, indicating a poor fit and low accuracy. With more sporadic rainfall and deeper groundwater tables, the conditions contributing to BI in the dry season appear to be too complex for a simple linear regression model to capture the relationship. Additionally, severe sanitary sewer overflows (SSO) do not occur during the dry season, so for the purposes of predicting severe SSOs, only a wet season model is necessary.

The pattern of cross-correlation of BI/mi and rainfall for the wet season data (Figure 18) is similar to the pattern for the total study period (Figure 16). There is almost no correlation on day lag=0, as the rain takes about one day to raise the water table significantly, and the strength of the correlation drops substantially after 7 days, as the water table has a chance to drain. However, the correlation for the lag times of 1 and 2 days are stronger during the wet season, presumably because the water table is closer to the land surface, and with a shallower unsaturated zone, the infiltrating rain can raise the water table more quickly. For a wet season regression model, including inputs of rainfall from the previous seven days will produce the most accurate result.

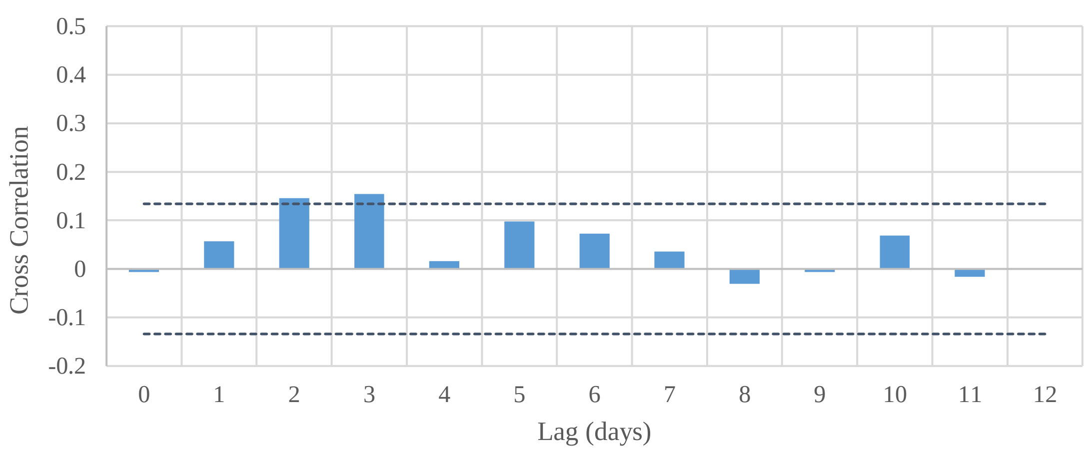

Figure 17: Cross-correlation between BI/mi at PS119 and rainfall (dry season). (95% significance limits ±0.13)

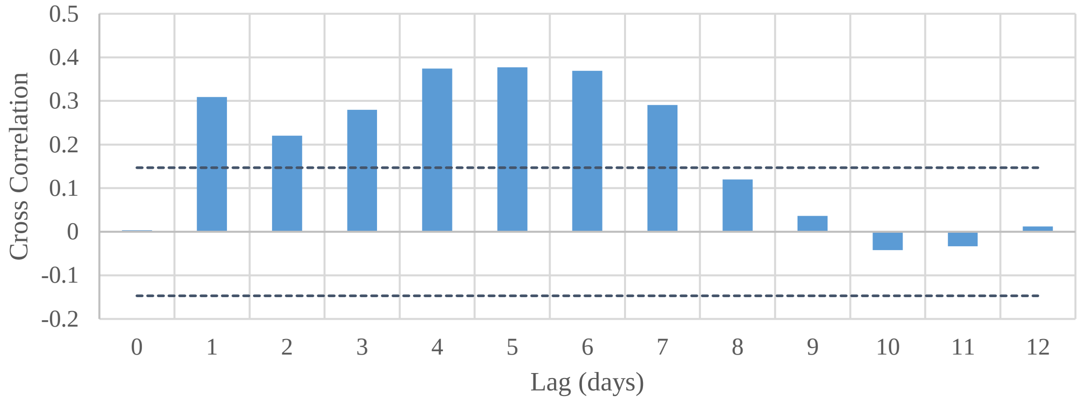

Figure 18: Cross-correlation between BI/mi at PS119 and rainfall (wet season). (95% significance limits ±0.15)

Using the rainfall totals from the previous seven days as inputs and daily BI/mi at PS119 as the target output, a preliminary multiple linear regression model was developed to predict BI/mi during the wet season at PS119. Due to equipment malfunction, the period from 6/23/2016 to 6/27/2016 contained unrealistic BI data values, but the regression analysis requires a continuous data series, so the BI/mi values from the preliminary regression model were used to replace the corrupted values from 6/23 to 6/27. The final regression model to predict BI/mi using rainfall from the previous seven days during the wet season at PS119 is shown in Equation 6 and Figure 19.

$$BI/mi_i = 11.71 + 2.98R_{i-1} + 1.11R_{i-2} + 1.34R_{i-3} + 2.08R_{i-4} + 2.06R_{i-5} + 2.16R_{i-6} + 2.17R_{i-7}$$

Equation 6: Regression Equation of BI/mi at PS119 (gpm). Inputs are rainfall totals from previous 7 days (inches)

The coefficients for each variable in the model are related to the strength of the cross-correlation at that lag time, but differ slightly because the regression accounts for 7 days at a time instead of the average response of the entire study period. The lowest coefficients correspond to lag times of 2 and 3 days, as was predicted by the correlogram. The coefficient for lag time of 1 day is highest, accounting for quick changes to the soil and groundwater, then after dropping for a lag time of 2 days, the coefficients steadily increase and level off as lag time approaches 7 days, corresponding to the time for rain to move through the unsaturated zone and raise the water table and the time for the water table to drain.

The R^2 value for the model is 0.52, which means roughly half of the variability of the BI/mi response is not captured by the model. The standard error of regression is 5.3, meaning that on average, the model will predict the BI/mi response within 5.3gpm/mi of the exact value. The model drastically under-predicts the BI response to Tropical Storm Colin (6/6/2016) and slightly under-predicts the peak response to Hurricane Hermine (8/31/2016). It is clear that the system's response to rainfall is complex, and varies with the rainfall patterns of different storms. Tropical Storm Colin presented two consecutive days of nearly 4-inch rainfall with very little rain afterward, whereas Hurricane Hermine produced over 6 inches of rain on one day, followed by 3 more days of 1-inch rainfall. Only two significant storms occurred during the measured study period, but ideally, future models would include data from more storm events and capture more of the complex response to rainfall patterns. While the magnitude of BI response is only somewhat accurate, the time response appears to fit the data well, so the model can still be useful to predict and prepare for the approximate BI load to the sewer system for upcoming storms.

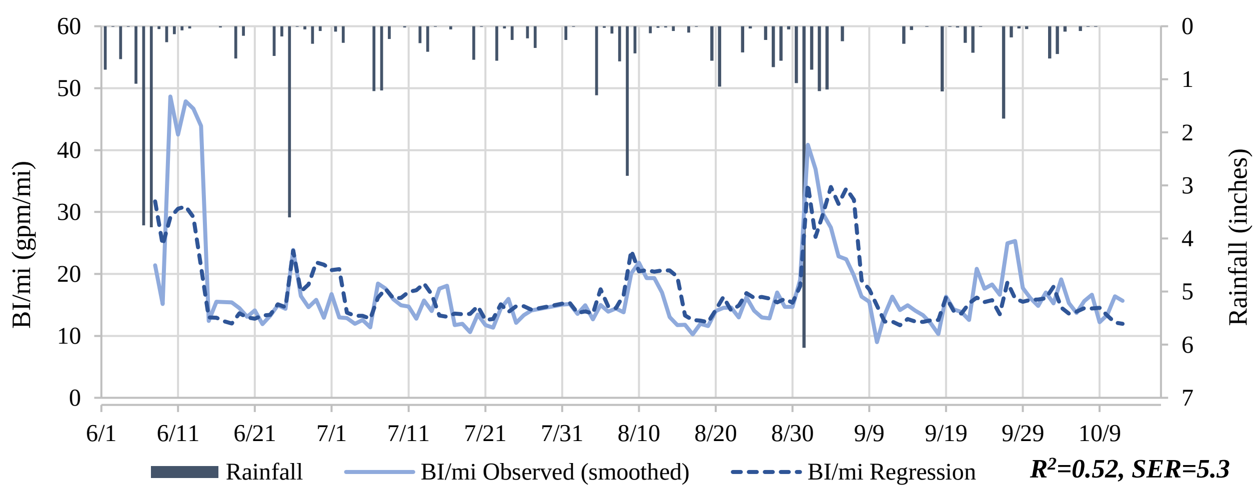

Figure 19: Regression model to predict BI/mi at PS119 (wet season)

CHAPTER 7: CONCLUSIONS

Sanitary sewer overflows (SSO) from inflow and infiltration (I/I) cause financial and public health problems for Pinellas County and the Tampa Bay area. The pilot study of the sewershed of PS119 has helped to determine the main sources of I/I in PS119 and develop procedures for quantifying and modeling I/I in other locations throughout the county.

The time series analysis method developed to screen for inflow can be used to determine whether or not a sewershed experiences significant surface inflow using only two data inputs: 15-minute flow readings and daily rainfall totals. The calculation and filtering of base infiltration (BI) and daily diurnal patterns to produce residuals and the construction of a 95% confidence interval for comparing dry weather to wet weather flows can all be performed in simple excel sheets or further automated in a programming platform. Unlike traditional physical testing methods such as smoke and dye testing or video footage, this statistical method allows the sewershed to maintain full service to utility customers because flowmeters do not require disconnecting or isolating sewer lines. The statistical method also circumvents substantial costs associated with physical I/I detection methods. The screening method can quickly determine whether the I/I issues in the monitored sewershed are attributed to surface or groundwater sources, which can guide enforcement or infrastructure rehabilitation or decisions.

By monitoring flows of sub-sewersheds within the study site and using elevation, soil, and water table data, the different sections of the sewershed can be prioritized for more detailed study or rehabilitation based on the highest I/I flow rates, amount of submerged infrastructure, and condition of the pipes. However, it is recommended that in any future studies, flow meters be more carefully monitored to avoid malfunction and large gaps in data.

In the pilot study sewershed, PS119, the screening process ruled out surface inflow as a significant source of excess sewer flow and indicated that groundwater is the primary source of I/I at this site. Using the Stevens-Schutzbach method to calculate groundwater infiltration (as BI) showed that an annual average of 44% of the flow in the pipes was composed of groundwater, and that the sanitary sewer pipes are essentially draining the water table year round.

Correlation analysis suggests that rainfall takes 1 to 2 days to raise the water table, which in turn increases base infiltration (BI) into the sewer pipes, peaking 3 days after significant rain events. The water table then drains within 5 to 7 days after the rainfall, and BI decreases accordingly. The analysis showed that heightened BI persists in the system for about one week, peaking from 3-5 days after a large rain event, which corresponds to the observations of the waste reclamation facility operators that significant flows to the facility and SSO risks persist for 3-5 days after a storm. While PS119 may not be representative of every sewershed in Pinellas County, the flow monitoring and correlation analysis suggests that groundwater infiltration is likely the main source of I/I throughout the county. However, this inference should be verified with further flow monitoring studies in sewersheds with different physical characteristics.

Pinellas County Utilities is currently considering building a GIS-based dynamic sanitary sewer model to help predict I/I and plan for infrastructure rehabilitation, but until it is finished, the simple linear regression method used in this pilot study can serve to model and predict BI flows for projected rain events. While the model for the PS119 sewershed during the wet season only had a coefficient of determination (R2) of 0.52, it can still be used to provide a rough estimate of the quantity and timing of excess sewer flows.

LIST OF REFERENCES

ACS. (2015). Household Size by Number of Workers in Household. *United States Census Bureau American Fact Finder*. Florida: American Comunity Survey. Retrieved from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_15_5YR_B08202&prodType=table

ASCE. (2011). Failure to Act: The Economic Impact of Current Investment Trends in Water and Wastewater Treatment Infrastructure. Reston, Virginia: American Society of Civil Engineers. Retrieved 2016, from http://www.asce.org/water_and_wastewater_report/

ASCE. (2013). Wastewater Report. *Report Card for America's Infrastructure*. Reston, Virginia: American Society of Civil Engineers. Retrieved 2016, from http://www.infrastructurereportcard.org/wastewater/

ASCE Florida Section. (2012). Report Card for Florida's Infrastructure. Lake Worth, Florida: American Society of Civil Engineers. Retrieved from http://www.fla-asce.org/Documents/2012-Florida-Section-Report-Card-Brochure.pdf

Bentley Systems. (2014). *The Water Project Showcase.* Exton, Pennsylvania: Bentley Systems Inc. Retrieved from https://www.bentley.com/~/asset/14/3893.ashx

Campbell, L. (2017, April 7). Greenville, EPA resolve to cut off raw sewage spills. Ridgeland, Mississippi. Retrieved from http://mississippitoday.org/2016/04/07/greenville-epa-resolve-to-cut-off-raw-sewage-spills/

Collins, J. M., & Roache, D. R. (2017, May). The 2016 North Atlantic hurricane season: A season of extremes. *Geophysical Research Letters, 44*. doi:10.1002/2017GL073390

Crawford, D., Eckley, P., & Pier, E. (1999). Methods for Estimating Inflow and Infiltration into Sanitary Sewers. In W. James, *New Applications in Modeling Urban Water Systems.* Guelph, Ontario.

EPA. (2012). Clean Watersheds Needs Survey: Report and Data. Washington, DC: U.S. Environmental Protection Agency. Retrieved from https://www.epa.gov/cwns

EPA. (2014). *Quick Guide for Estimating Infiltration and Inflow for Region 1 NPDES Annual Reporting.* Water Infrastructure Outreach, U.S. Environmental Protection Agency.

EPA. (2016). *Gary Sanitary District and City of Gary Clean Water Settlement.* Chicago: USEPA. Retrieved from https://www.epa.gov/enforcement/gary-sanitary-district-and-city-gary-clean-water-settlement

EPA Office of Water Management. (1996). Sanitary Sewer Overflows. Washington, DC: U.S. Environmental Protection Agency. Retrieved 2016, from https://www.epa.gov/npdes/sanitary-sewer-overflow-sso-additional-resources#factsheets

FDEP. (2016, November). *Domestic Wastewater*. Retrieved from Florida Department of Environmental Protection: http://www.dep.state.fl.us/water/wastewater/dom/index.htm

Frago, C., & Reeves, M. (2016, September 9). While St. Petersburg waits for sewage details, health risks emerge. *Tampa Bay Times*.

Haan, C. T. (2002). *Statistical Methods in Hydrology* (Second ed.). Ames, Iowa: Iowa State Press.

Karpf, C., & Krebs, P. (2011). Quantification of groundwater and surface water inflows in urban sewer networks based on a multiple model approach. *Water Research*, 3129-3136.

Karpf, C., & Krebs, P. (2013). Modelling of groundwater infiltration into sewer systems. *Urban Water Journal, 10*(4), 221-229.

Karpf, C., Franz, T., & Krebs, P. (2007). Fractionation of Infiltration and Inflow (I/I) components in urban sewer systems with regression analysis. *Novatech,* (pp. 1227-1234). Lyon, France.

Lonon, S. (2016, September 30). St. Petersburg Facing Sewage-Rlated Lawsuit. *St. Pete Patch*. St. Petersburg, Florida: Patch.com. Retrieved 2016, from http://patch.com/florida/stpete/st-petersburg-facing-sewage-related-lawsuit

Mitchell, P. S., Stevens, P. L., & Nazaroff, A. (2007, December). A Comparison of Methods and a Simple Empirical Solution to Quantifying Base Infiltration in Sewers. *Water Practice, 1*(6).

Nachabe, M., Masek, C., & Obeysekera, J. (2004). Observations and Modeling of Profile Soil Water Storage above a Shallow Water Table. *Soil Science Society of America Journal*, 719-724.

Neuhaus, L. (2016, Septemer 16). Sewage Overflow Again Fouls Tampa Bay After Storm. *The New York Times*.

NRCS. (2016). *Web Soil Survey.* United States Department of Agriculture, Natural Resources Conservation Service. USDA. Retrieved from https://websoilsurvey.sc.egov.usda.gov/

Partial Consent Decree, 4:16-cv-0018-DMB-JMV (United States District Court for the Northern District of Mississippi Greenville Division January 28, 2016). Retrieved from https://www.epa.gov/enforcement/greenville-mississippi-clean-water-settlement

Petrequin, M. (2011, May 3). The Crisis in U.S. Wastewater Infrastructure: History, Issue, and Solutions. (R. Siegrist, Ed.) Golden, Colorado: Colorodo School of Mines, Department of Environmental Science and Engineering. Retrieved from http://www.academia.edu/1786909/The_Crisis_in_U.S._Wastewater_Infrastructure

Pinellas County. (2009). *Permanent, Seasonal, and Tourist Population Forecast Report.* Metropolitan Planning Organization. Clearwater, FL: Pinellas County. Retrieved from https://www.pinellascounty.org/mpo/docs/Demographics/StaffReport_Oct2008.pdf

Pinellas County. (2013). Potable Water Supply, Wastewater and Reuse Element. In *Comprehensive Plan.* Florida, Pinellas County: Board of County Commissioners. Retrieved from http://www.pinellascounty.org/Plan/comp_plan/9water/ch2.pdf

Pinellas County. (2017, April). *Facts About Pinellas*. Retrieved from http://www.pinellascounty.org/facts.htm

Raynaud, O., Joannis, C., Schoefs, F., & Billard, F. (2008). A model-based assessment of infiltration and inflow in the scope of controlling separate sanitary overflows at pumping stations. *11th International Conference on Urban Drainage.* Edinburgh, Scotland.

Salas, J., Delleur, J., Yevjevich, V., & Lane, W. (1988). *Applied Modeling of Hydrologic Time Series.* Littleton, Colorado: Water Resources Publications.

Serra, R., & Rodriguez, A. C. (2012). The Ljung-Box Test as a Performance Indicato for VIRCs. *International Symposium on Electromagnetic Compatibility (EMC Europe).* Rome, Italy: IEEE. Retrieved from http://ieeexplore.ieee.org/document/6396834/

Staufer, P., Scheidegger, A., & Rieckermann, J. (2012, July). Assessing the performance of sewer rehabilitation on the reduction of infiltration and inflow. *Water Research, 46*, 5185-5196.

Vallabhaneni, S., Chan, C. C., & Burgess, E. H. (2007). *Computer Tools for Sanitary Sewer System Capactiy Analysis and Planning.* Washington, DC: U.S. EPA.

Yeargan, M. E. (2016, September 20). Domestic Waste Water Issues and Challenges. Florida, Pinellas County: Florida Department of Environmental Protection. Retrieved from https://www.pinellascounty.org/delegation/

Zhang, Y.-p., & Guo, S. (2013, November). An approximate solution for two-dimensional groundwater infiltration into sewer systems. *Water Science & Technology*, 347-352.

APPENDIX A: ADDITIONAL FIGURES AND TABLES

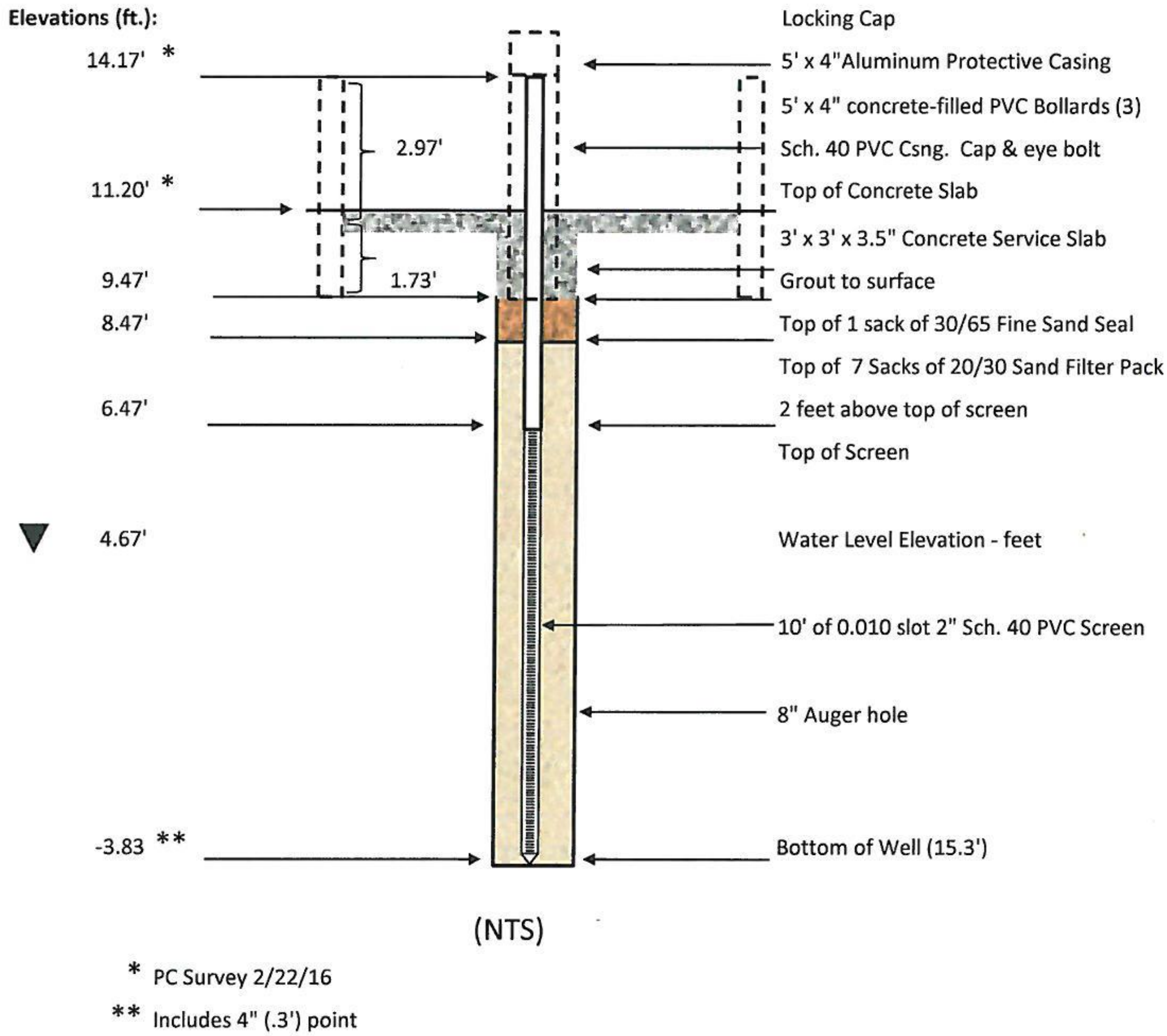

Figure A1: Groundwater Monitoring Well 1 (MW1) installation

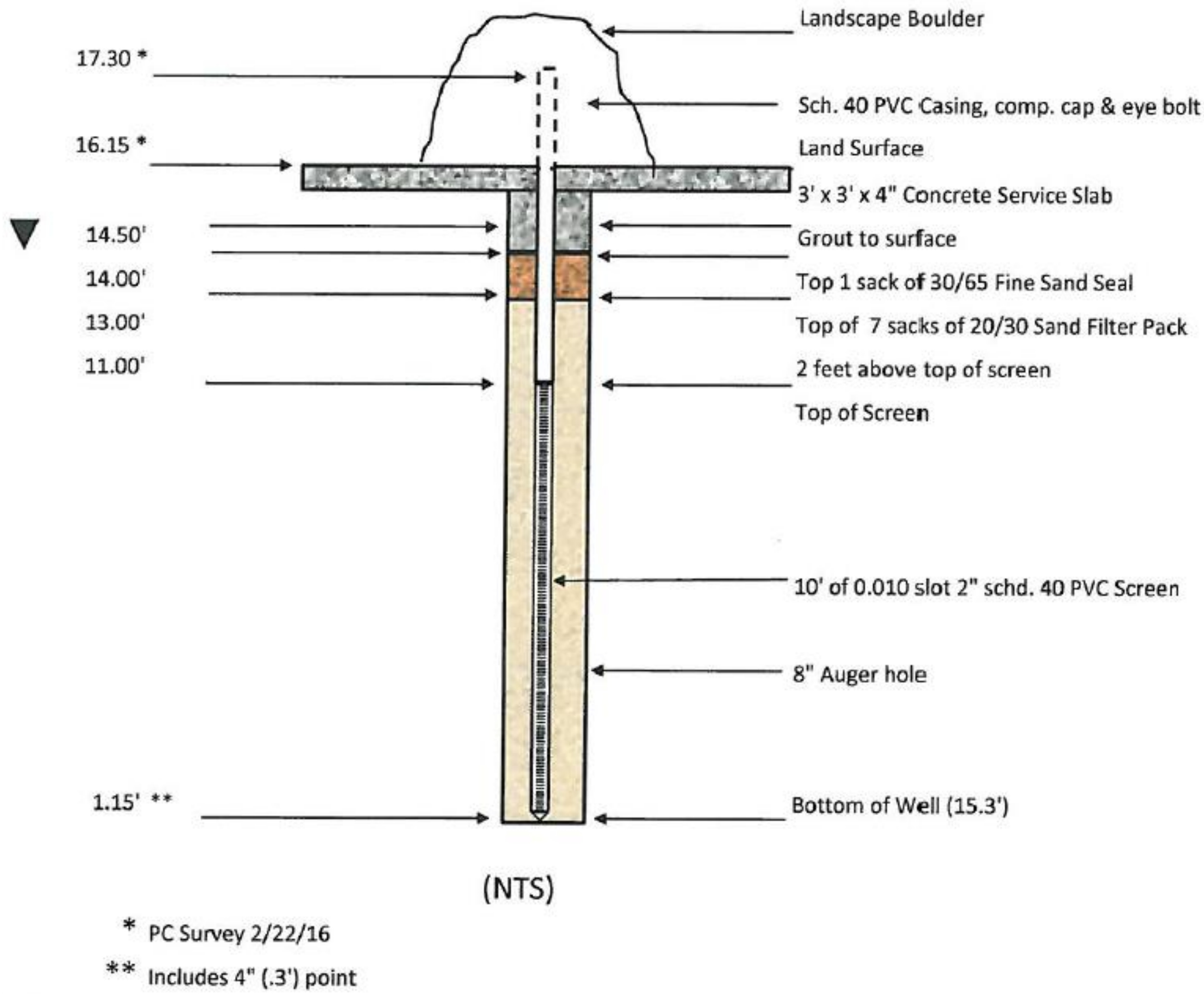

Figure A2: Groundwater Monitoring Well 2 (MW2) installation

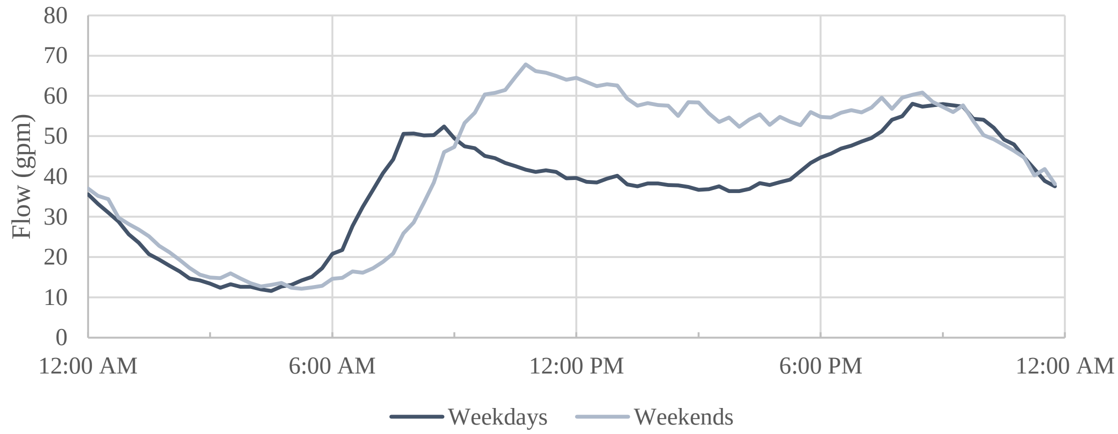

Figure A3: Diurnal pattern of wastewater flow in PS119 sewershed

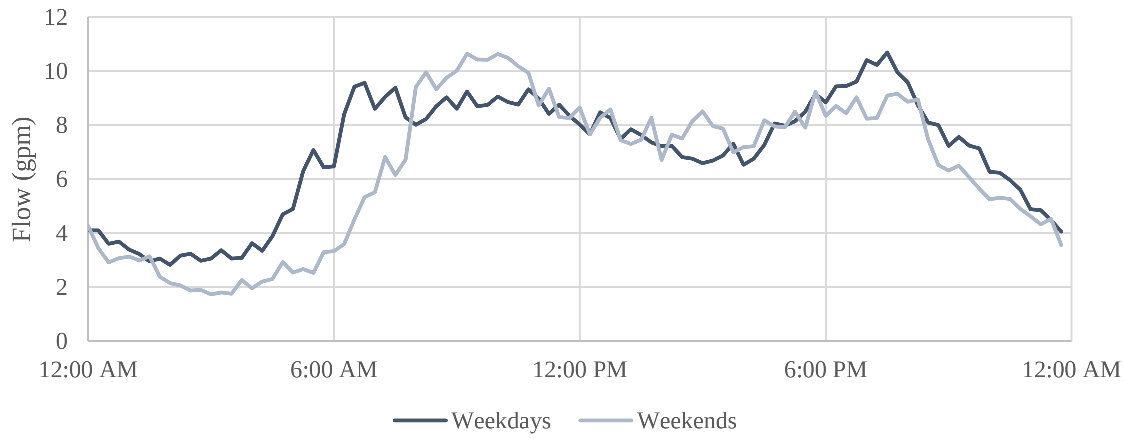

Figure A4: Diurnal pattern of wastewater flow in FM2506 sewershed

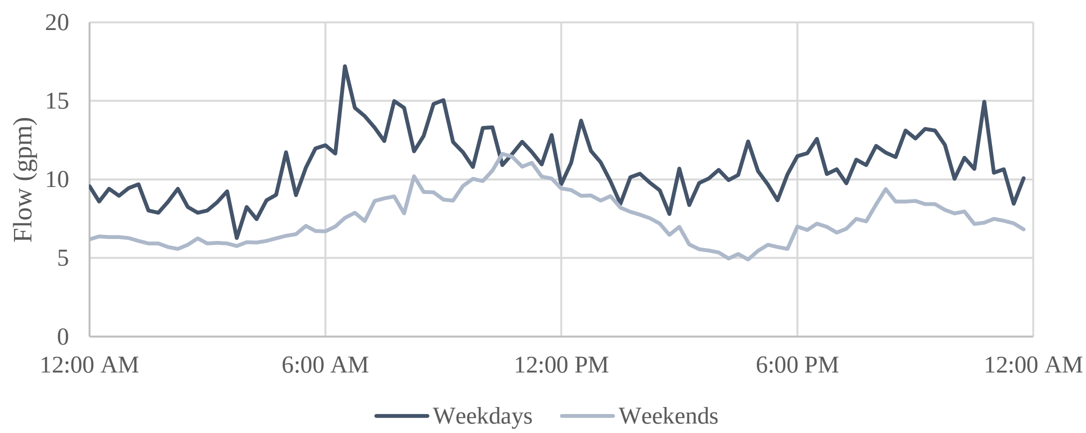

Figure A5: Diurnal pattern of wastewater flow in FM2520 sewershed

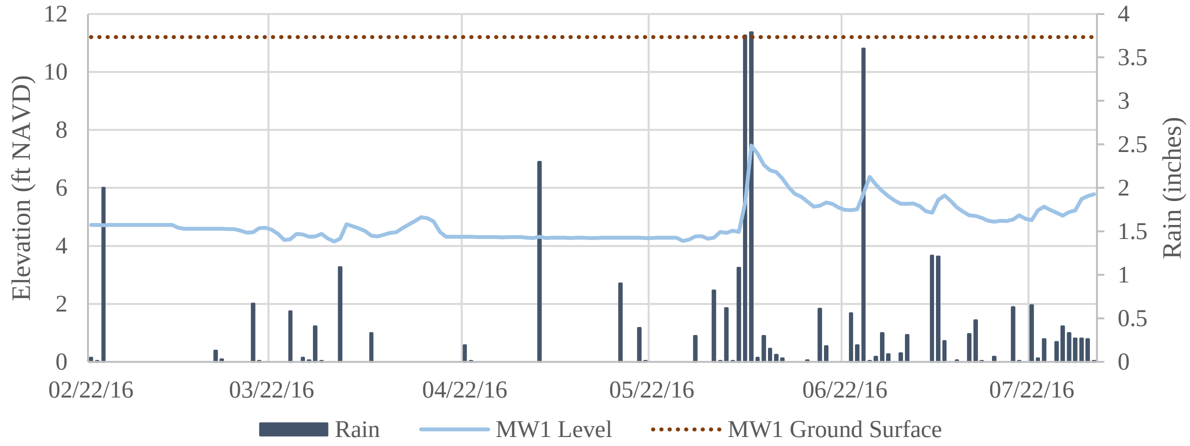

Figure A6: Rainfall and elevation of water table at MW1 and land surface

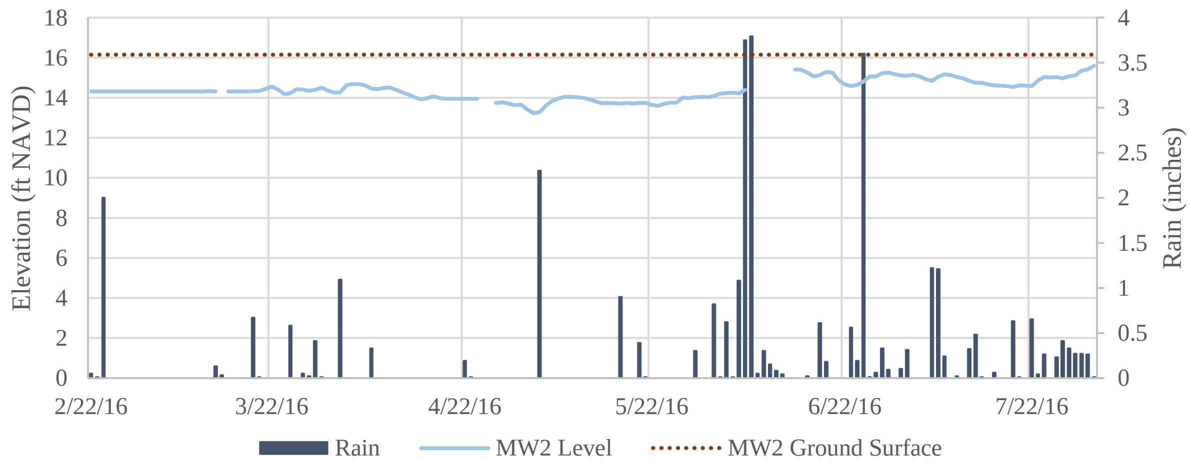

Figure A7: Rainfall and elevation of water table at MW2 and land surface

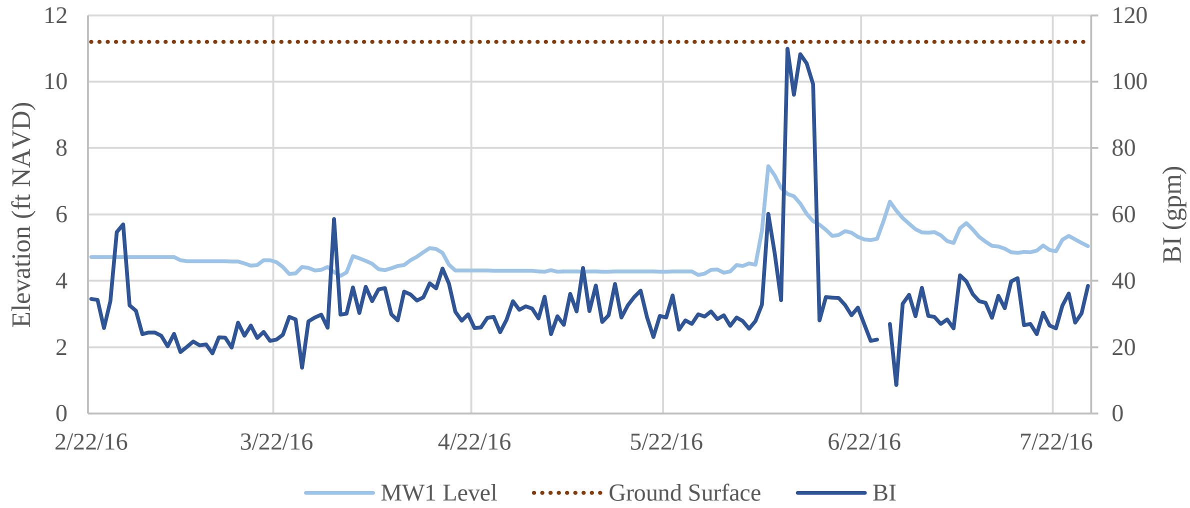

Figure A8: BI at PS119 and elevation of land surface and water table at MW1

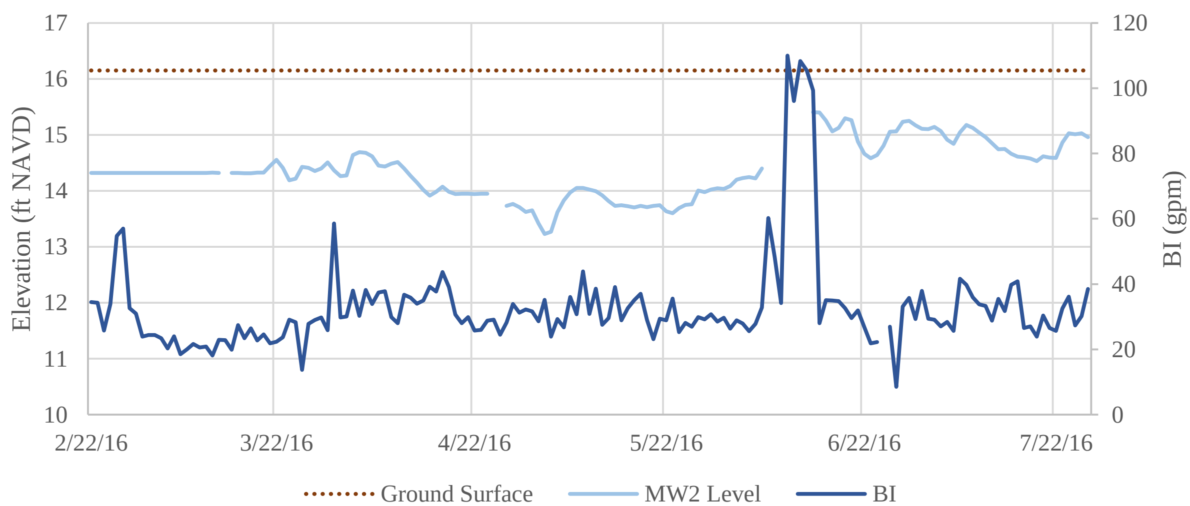

Figure A9: BI at PS119 and elevation of land surface and water table at MW2

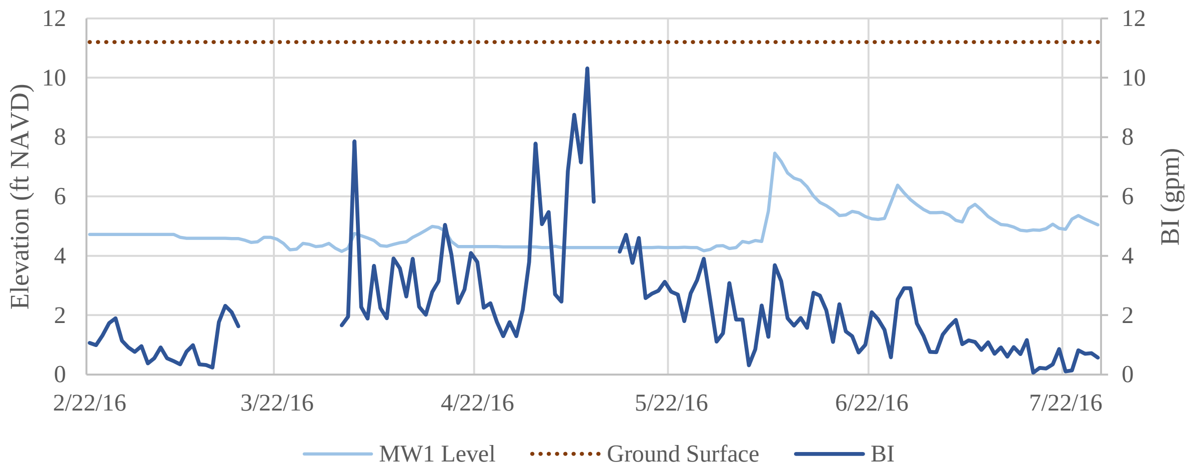

Figure A10: BI at FM2506 and elevation of land surface and water table at MW1

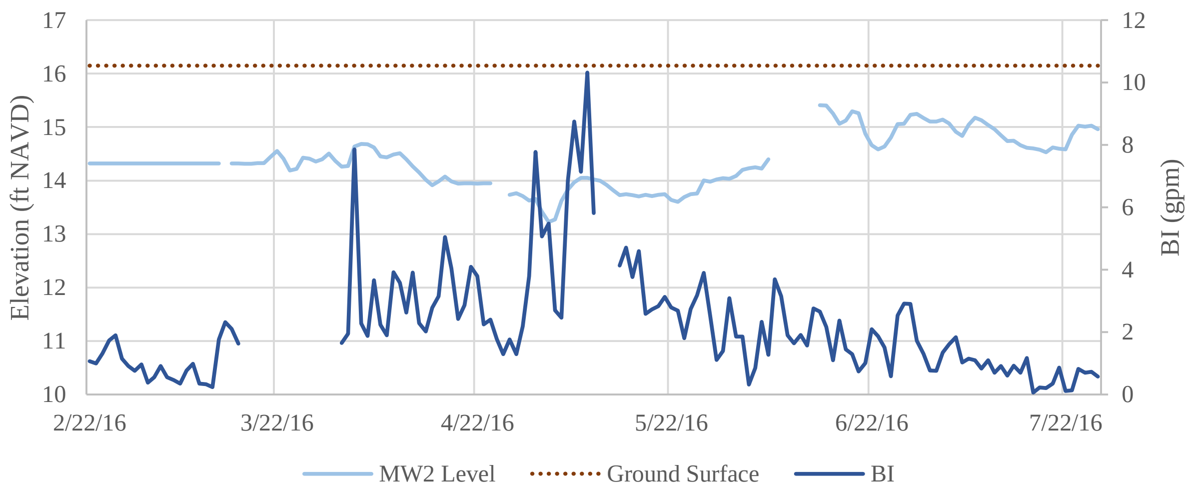

Figure A11: BI at FM2506 and elevation of land surface and water table at MW2

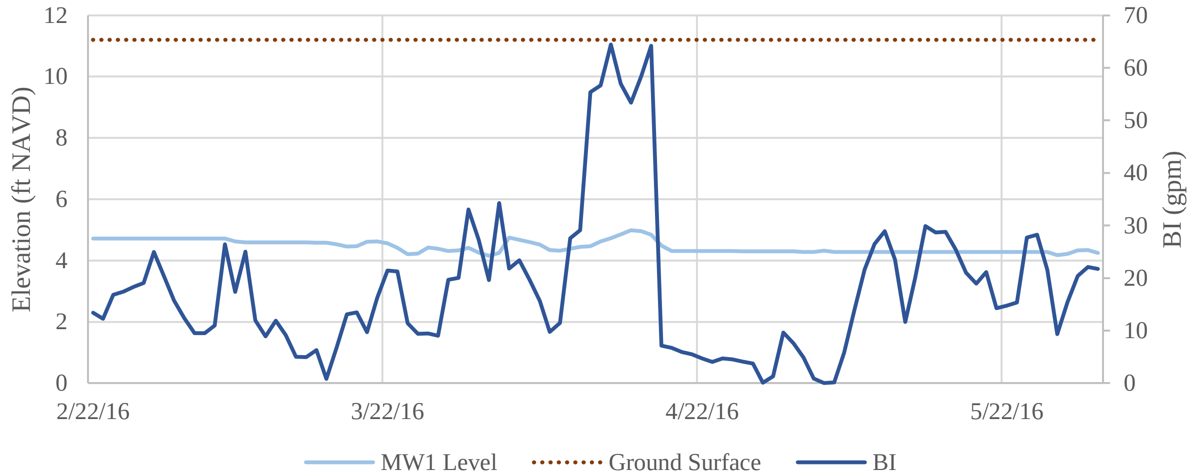

Figure A12: BI at FM2520 and elevation of land surface and water table at MW1

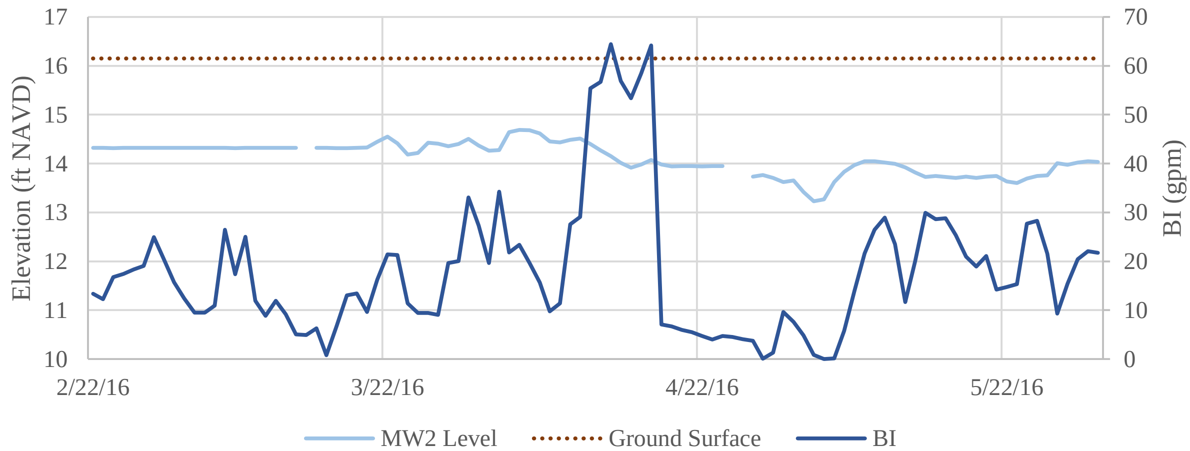

Figure A13: BI at FM2520 and elevation of land surface and water table at MW2

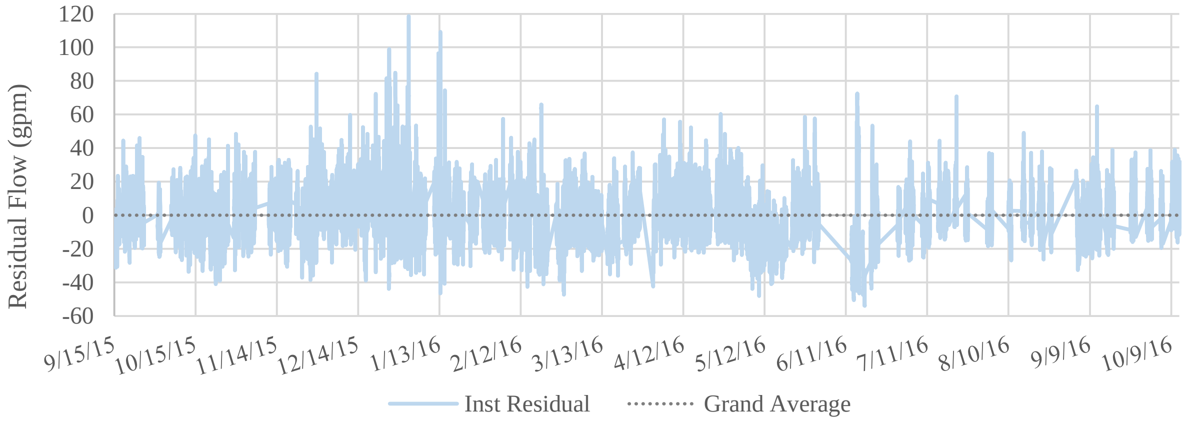

Figure A14: 15-minute residual flow values for DWF at PS119

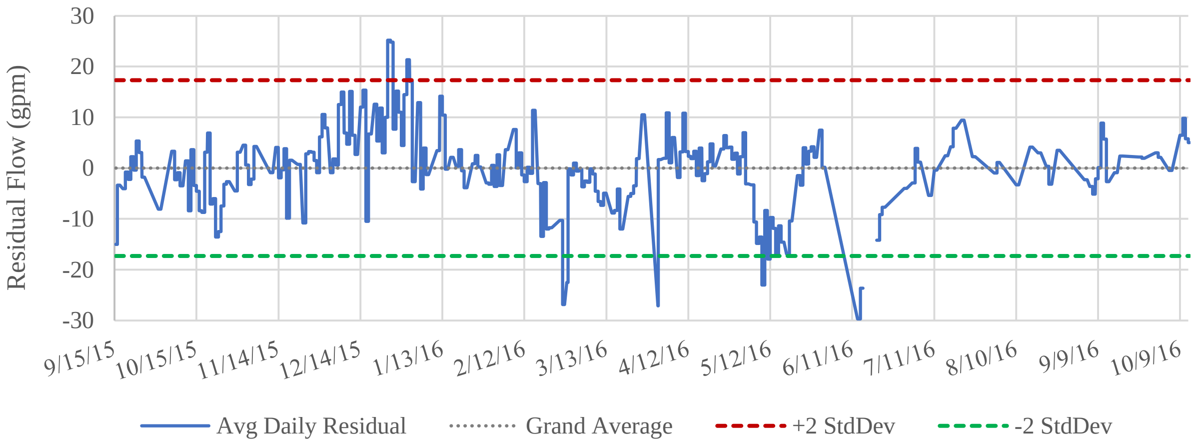

Figure A15: Average daily residual flow values and range of expected variation PS119. (DWF)

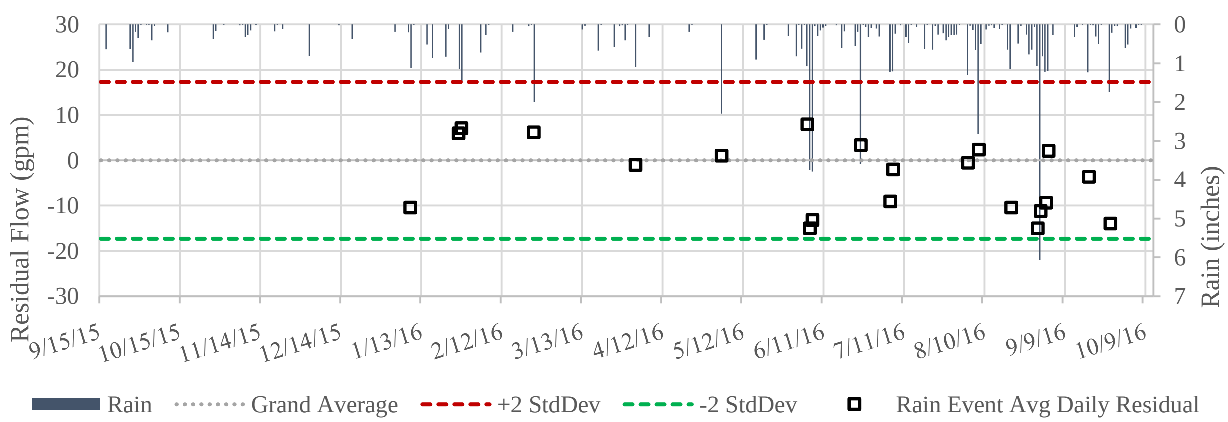

Figure A16: Daily residuals for significant rain events at PS119. (Range of expected variability from DWF)

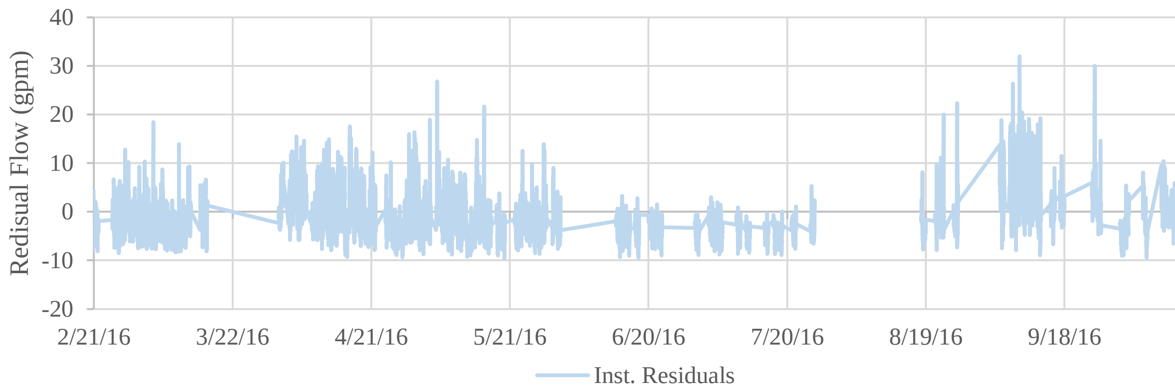

Figure A17: 15-minute residual flow values for DWF at FM2506

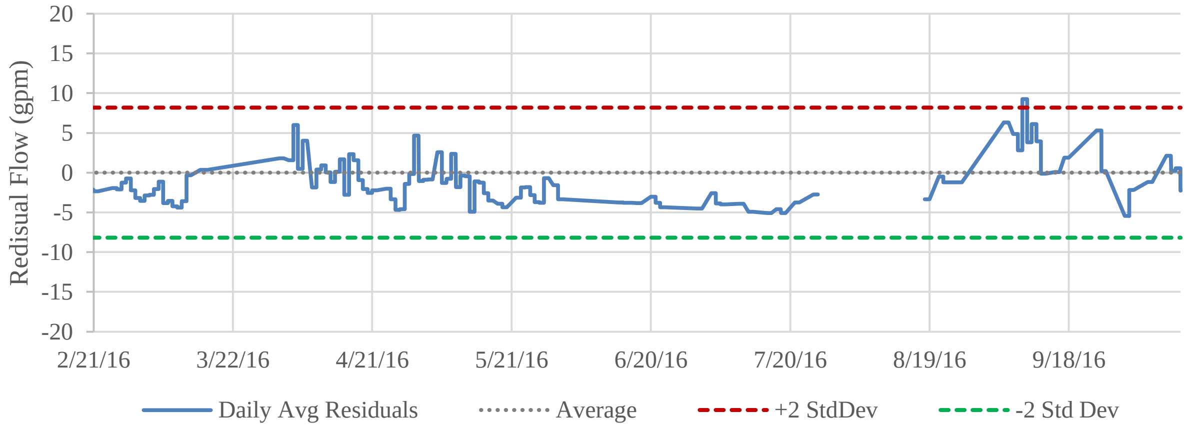

Figure A18: Average daily residual flow values and range of expected variation FM2506. (DWF)

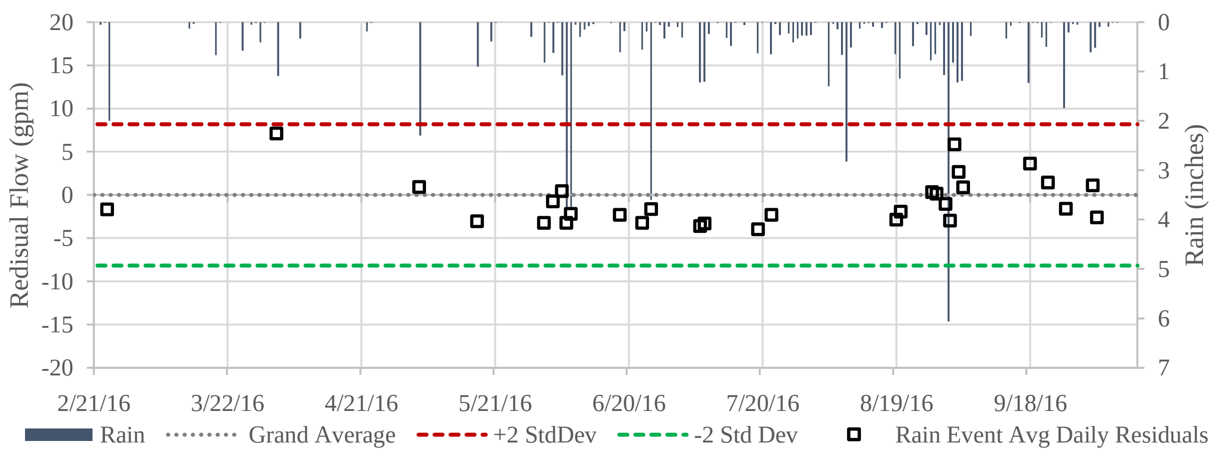

Figure A19: Daily residuals for significant rain events in FM2506. (Range of expected variability from DWF)

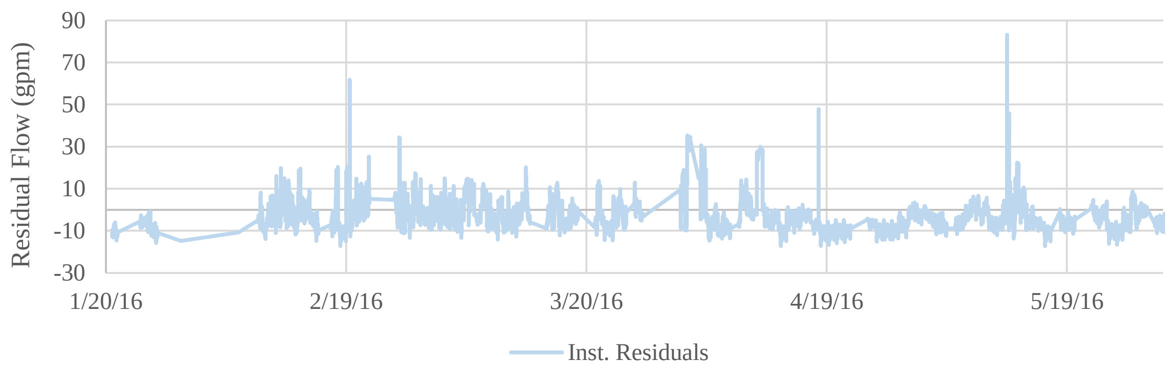

Figure A20: 15-minute residual flow values for DWF at FM2520

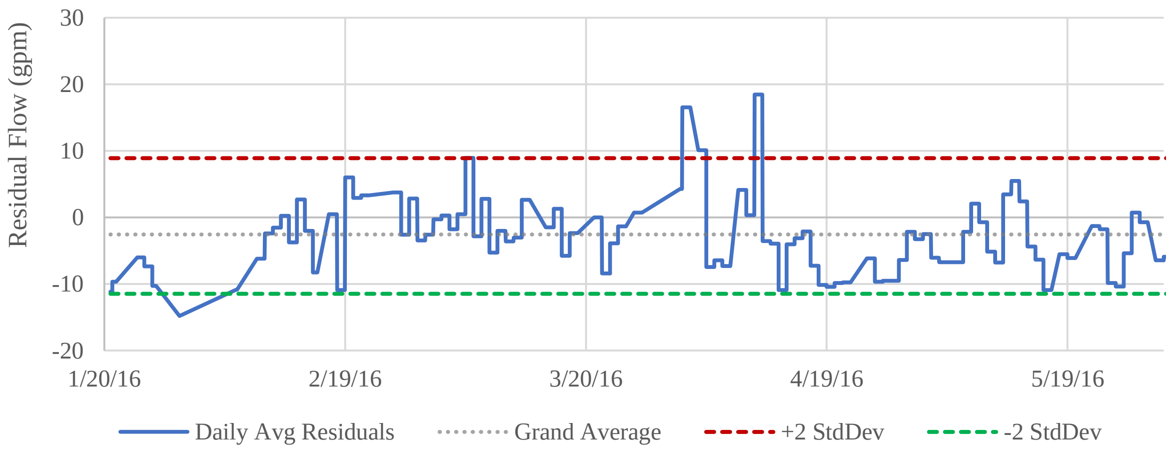

Figure A21: Average daily residual flow values and range of expected variation FM2520. (DWF)

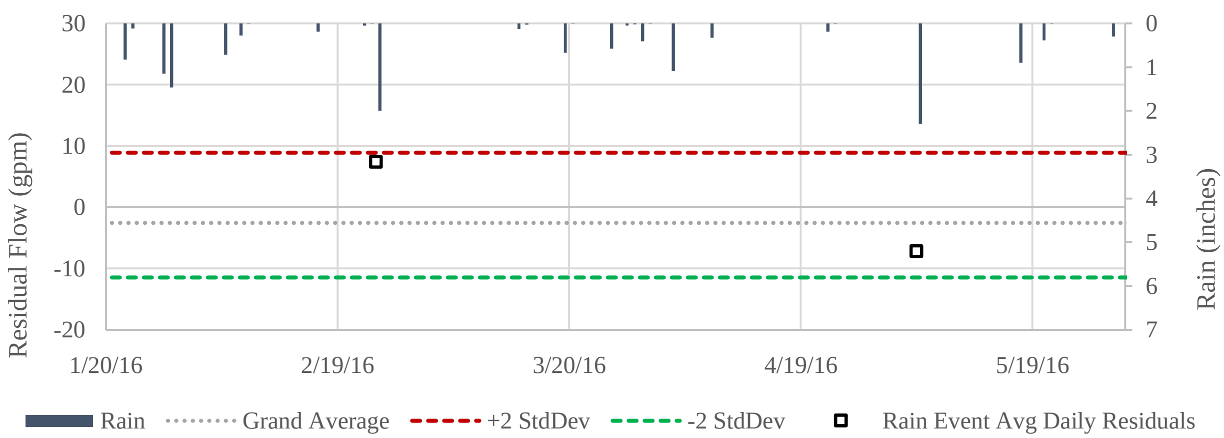

Figure A22: Daily residuals for significant rain events in FM2520. (Range of expected variability from DWF

Table A1: Depth to Water Table in Myakka Soils from NRCS WSS (NRCS, 2017).

Depth to Water Table in Myakka Soils	
Month	**DTW (ft)**
1	6.56
2	6.56
3	6.56
4	6.56
5	6.56
6	1.18
7	1.18
8	1.18
9	1.18
10	1.18
11	**1.18**
12	6.56

APPENDIX B: LIST OF ABBREVIATIONS

ADF: Average daily flow

ASCE: American Society of Civil Engineers

BI: Base infiltration

BI/mi: Base infiltration per mile of pipeline

CSO: Combined sewer overflow

CWA: Clean Water Act

CWNS: Clean Watersheds Needs Survey

DTW: Depth to water table

DWF: Dry weather flow

EPA: Environmental Protection Agency

FDEP: Florida Department of Environmental Protection

FM: Flow meter

gpm; gallons per minute

I/I: Inflow and infiltration

MDF: Minimum daily flow

MFFM: Minimum Flow Factor Method

mgd: Million gallons per day

MW: Monitoring well

NRCS: Natural Resources Conservation Service

PCU: Pinellas County Utilities

PS: Pump station

PVC: Polyvinyl chloride

R^2: Coefficient of determination

RDII: Rainfall derived inflow and infiltration

SCADA: Supervisory control and data acquisition

SCBWRF: South Cross Bayou Water Reclamation Facility

SER: Standard error of regression

SMA: Soil moisture accounting

SSM: Stevens-Schutzbach Method

SSO: Sanitary sewer overflow

SWFMWD: Southwest Florida Water Management District

USF: University of South Florida

USGS: United States Geological Survey

VCP: Vitrified clay pipe

WT: Water table

WSS: Web soil survey

WWF: Wet weather flow

WWPM: Wastewater Production Method