8-2021

Impact and Application of Real-Time Control on Stormwater Systems

Aaron A. Akin
University of Tennessee, Knoxville, aakin4@vols.utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Aaron A. Akin entitled "Impact and Application of Real-Time Control on Stormwater Systems." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

Jon M. Hathaway, Major Professor

We have read this dissertation and recommend its acceptance:

Branko Kerkez, Anahita Khojandi, John S. Schwartz

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Impact and Application of Real-Time Control on Stormwater Systems

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Aaron Alexander Akin

August 2021

ACKNOWLEDGEMENTS

This work would not be possible without the financial support from the United States Geological Survey 104b Program and the National Science Foundation (Award # 1737432).

I would like to thank Dr. Jon Hathaway, Dr. Branko Kerkez, Dr. Anahita Khojandi, and Dr. John Schwartz for their help and feedback during this journey. Each of your expertise helped to shape and make my research better. I would especially like to thank Dr. Jon Hathaway who served as my major advisor during my time here at the University of Tennessee. Thank you for giving me the flexibility to explore and grow as a researcher and to pursue projects that I was genuinely passionate about. Having the freedom to design and apply smart stormwater infrastructure will not be an experience that I will soon forget. I am also grateful to the lifelong friends I have made during my time here and I was fortunate enough to be in the right time at the right place to meet each of you. Whether it was surviving the heat of the greenhouse with Padmini, storm chasing with Vic-tree-a, or moving equipment with Gillian, the HRG team felt like an ever-growing family.

I would most importantly like to thank my fiancée, Dr. Claire Bennett, for being an unwavering bastion of support throughout this journey as well as providing the motivation I needed to keep going when things got tough. Especially during the last few months, jokingly mentioning that if I had not defended by our wedding that she would have them introduce us as “Mr. and Dr. Akin.” I am excited for the life we are going to build together in this next chapter.

ABSTRACT

Stormwater control measures (SCMs) such as dry extended detention basins and wet ponds are common practices implemented by engineers and designers to mitigate the impact of stormwater runoff. These practices are designed based on historical rainfall data to attenuate runoff to pre-development conditions and, once they are installed, are unable to adapt to changing rainfall patterns or watershed restoration objectives. To solve these climate resiliency issues, several studies were conducted which investigated the impact of retrofitting such systems with a controllable outlet to increase or change detention times during rainfall events along with the novel instrumentation and methodologies necessary for its operation.

The first of these studies explored the development, deployment, and validation of a low-cost, accurate stream gauging station capable of remotely sensing stream stage as an alternative to more traditional, but cost prohibitive, systems. Not only can these stations be deployed to cover gaps in existing networks, but the real-time data can also be used to inform the control decisions of SCMs outfitted with real-time control (RTC). The next study analyzed the performance of a dry extended detention basin outfitted with RTC which incorporated real-time water quality data in the decision framework in order to meet water quality objectives more consistently. The results of this study proved that this novel methodology was not only successful but performed better than static stormwater infrastructure or a RTC strategy utilizing predetermined detention times. While the hydrologic impact to a receiving stream once water is released from a RTC equipped SCM has begun to be explored, little is known about the impact to in-stream water quality. Results from the third study of this dissertation investigating these impacts

concluded that while noticeable impacts to many parameters were observed, the only concerning impacts were thermal impairments during warm weather. Finally, a comprehensive modeling investigation was undertaken to provide contextualization and explore the advantages and disadvantages of different RTC strategies. Results from this investigation concluded that both wet ponds and dry extended detention basins would be able to further attenuate stormwater during and following rainfall events with wet ponds especially benefiting from additional control.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1. Introduction to Stormwater

Stormwater runoff generation is a significant process in the urban hydrologic regime. As precipitation occurs, a portion of the water infiltrates into the watershed's soil, is intercepted by vegetation, or reenters the atmosphere through evapotranspiration processes (Huffman et al. 2013; The Federal Interagency Stream Restoration Working Group 2001). Precipitation which is not intercepted by one of these processes flows across the landscape as stormwater runoff and collects in receiving streams and waterbodies (Pyzoha 1994; The Federal Interagency Stream Restoration Working Group 2001). Watershed topography, soil type, and land use/management alter the rate and intensity at which stormwater runoff is generated and travels across a landscape. Alterations in land use and management are the primary methods by which humans have exacerbated this process (Dunne and Leopold 1978; Huffman et al. 2013). Through urbanization, natural landcover is converted to impervious surfaces with reduced rates of infiltration and evapotranspiration resulting in increased runoff (Figure 1.1). This increased intensity and volume of stormwater runoff causes rapid accumulation in drainage networks (such as streams and rivers) creating flooding in the watershed and erosive flows in stream channels. Compounding on these hydrologic issues are the pollutants that stormwater runoff washes off and carries to receiving waterbodies. Pollutants such as nutrients, bacteria, heavy metals, and sediment are detrimental to biological and ecological systems (Huffman et al. 2013; Pyzoha 1994). In order to mitigate these impacts, planners and engineers implement stormwater control measures (SCMs) within the watershed to attenuate flows or intercept pollutants (Dunne and Leopold 1978). While SCMs are diverse in their design and objectives, this literature review will explore the use and impact of two common practices, wet ponds and dry extended detention basins, as solutions for stormwater management in urban watersheds.

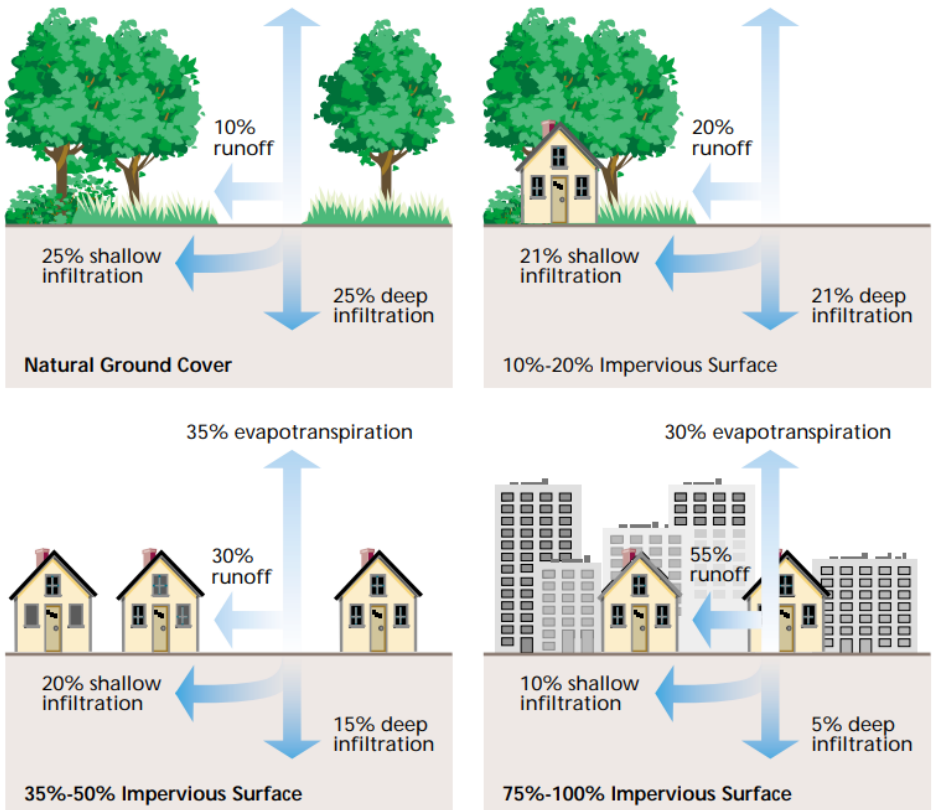

Figure 1.1. Relationship between impervious cover and surface runoff (image created by The Federal Interagency Stream Restoration Working Group 2001).

1.2. Stormwater Control Measures

1.2.1. Dry Extended Detention Basins

Dry extended detention basins are surface storage facilities installed with the primary purpose of attenuating flows generated by stormwater runoff to provide channel and flood protection for the receiving waterbody (Figure 1.2; Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). This SCM accomplishes these objectives by temporarily detaining runoff during rainfall and slowly releasing it over the next 1 to 3 days (dependent on local guidance) while remaining dry between rainfall events (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Flow attenuation of this SCM is achieved by sizing the basin's outlet structure (riser, bypass orifices, and overflow weir) appropriately so that the peak flow is attenuated to match pre-development conditions (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). However, once these SCMs are installed, they are unable to adapt to changing rainfall or landcover conditions.

While the primary benefit of these systems is peak flow attenuation and volume capture, by extending the time water is detained within the basin, minor pollutant removal and improvement in water quality is possible through trapping and settling of suspended sediment (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Clary et al. (2020) completed a recent review of stormwater infrastructure performance studies and concluded that dry extended detention basins had significant pollutant removal efficiencies for TSS (total suspended sediment), bacteria (*E. coli* and fecal coliform), total phosphorous, ammonia, and metals (arsenic, cadmium, chromium,

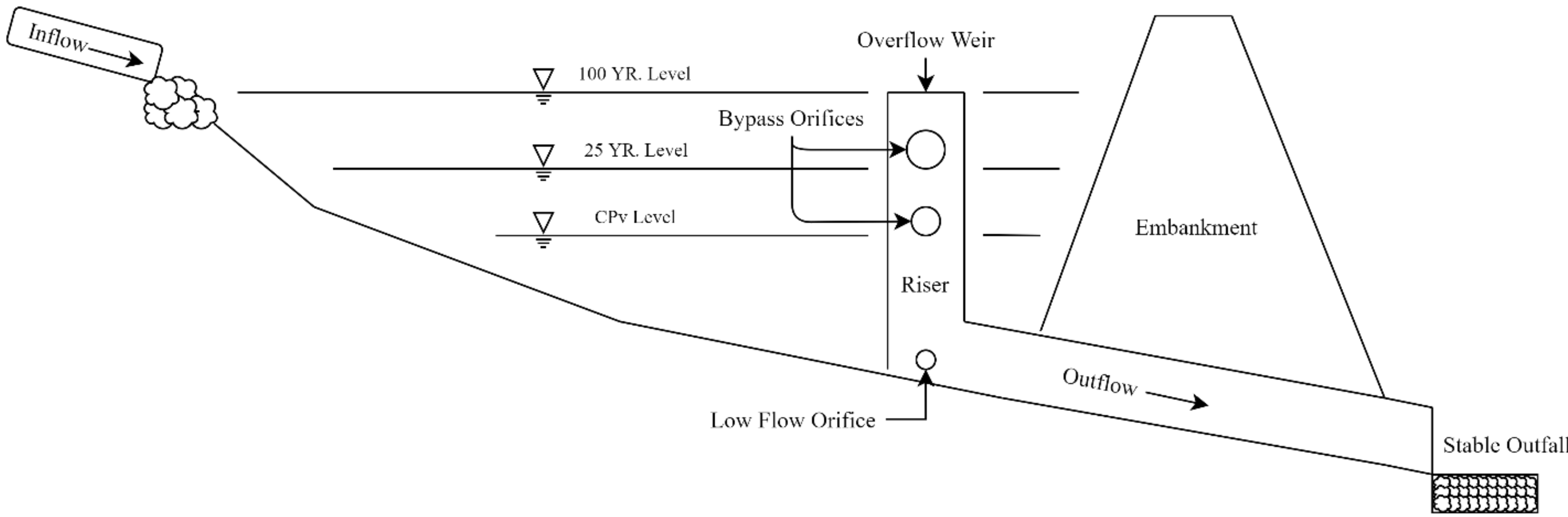

Figure 1.2. Profile view of a dry extended detention basin (adapted from Knox County, Tennessee Stormwater Management Manual 2008).

copper, lead, nickel, and zinc). These removal efficiencies are also reflected in the technical guidance for this SCM with several design manuals suggesting the ability to remove TSS, phosphorous, nitrogen, and metals (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008).

1.2.2. Wet Ponds

Similar to dry extended detention basins, wet ponds (also referred to as retention ponds or stormwater ponds) are surface storage facilities for stormwater runoff but include a permanent pool for retention in addition to a temporary storage zone for runoff quantity control (Figure 1.3; Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). During rainfall events, stormwater runoff up to the site's water quality volume is retained within the permanent pool through displacement of existing water (which travels through the reverse drain). Additional storage for larger events is available in the temporary storage zone (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Channel and flood protection for the receiving water body is provided by sizing the wet pond's outlet structure (riser, bypass orifices, reverse drain, and overflow weir) for appropriate peak flow attenuation to match pre-development conditions (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). A drain and valve are installed at the base of the pond to allow the permanent pool to be drained if maintenance is required; during normal operation this valve stays closed. As was the case with the dry extended detention basin, once this practice is installed it is unable to adapt to changing rainfall or landcover conditions.

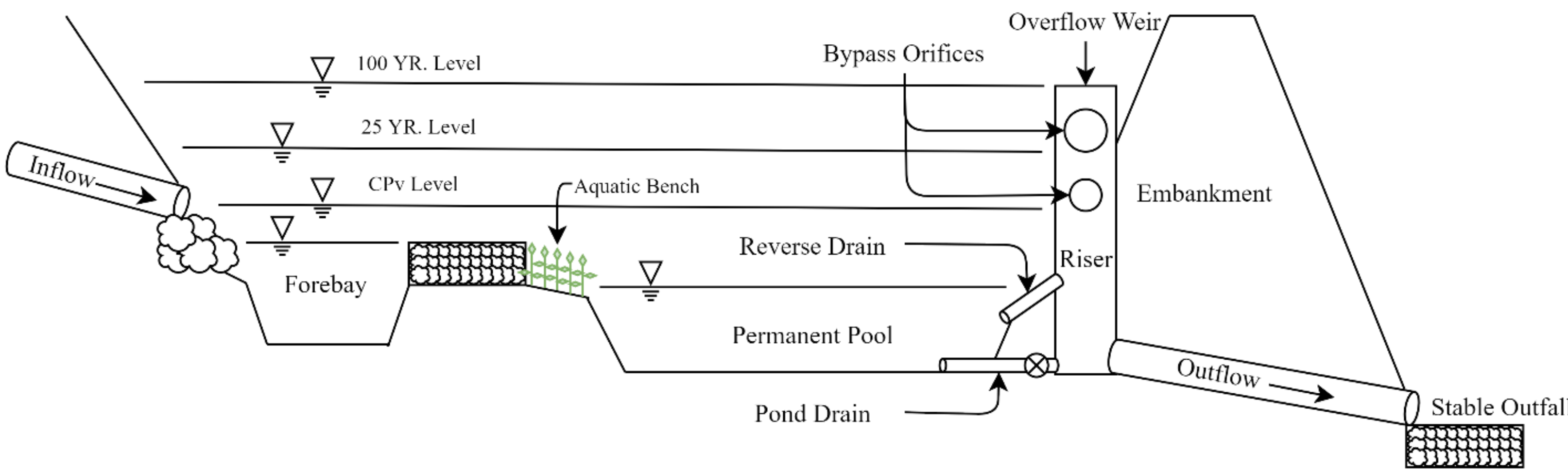

Figure 1.3. Profile view of a wet pond (adapted from Knox County, Tennessee Stormwater Management Manual 2008).

These practices provide considerably more pollutant removal than dry extended detention basins through settling of sediment and biological uptake in the permanent pool (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Additionally, these permanent pools create a more aesthetic design over dry extended detention basins which may lead to higher community acceptance (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). They also provide opportunities for wildlife habitat (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). While the permanent pool feature is the reason for these benefits, it does increase the overall volume, and in some cases surface area, required for this SCM to be installed.

1.3. Real-Time Control for Stormwater Management

Dry extended detention basins and wet ponds are able to provide numerous hydrologic and water quality benefits by mitigating the impacts of stormwater runoff. However, as noted above, they are unable to adapt to changing conditions such as alterations in watershed restoration needs, changes in watershed landcover, or more extreme rainfall patterns caused by climate change. Therefore, these practices represent a "static solution to a dynamic problem" that requires innovative technologies and methodologies to solve (Kerkez et al. 2016). Implementation of "smart" stormwater systems presents an opportunity to address these dynamic problems by leveraging low-cost sensors, controllers, and actuators in conjunction with innovative real-time control (RTC) strategies to transform a once static piece of infrastructure into an adaptive and responsive system (Kerkez et al. 2016). Typically, implementation of these systems occurs through retrofits by installing hydrologic sensors (precipitation, stage, etc.) and controllable outlets to change how the system responds to stormwater runoff (such as increasing detention times or limiting intra-storm discharges). Subsequent sections will examine how existing literature has shown that leveraging this technology has the ability to reduce the hydrologic and water quality impacts of both dry extended detention basins and wet ponds.

1.3.1. Solution for Hydrologic Impacts

Previous research (case studies and simulations) implementing RTC on dry extended detention basins and wet ponds have been successful in leveraging this technology to improve hydrologic conditions (such as a reduction in the exceedance of various flow thresholds in the receiving stream) primarily by preventing water release during rainfall, utilizing innovative control algorithms, and communicating with downstream flow conditions upon release to ensure that flow thresholds are not exceeded (Bilodeau et al. 2019; Boyle et al. 2016; Gaborit et al. 2013; Gaborit et al. 2016; Jacopin et al. 2001; Mullapudi et al. 2018). Reduction of intra-storm discharges and increases in the utilization of basin capacity were the primary hydrologic impacts observed when implementing RTC on dry extended detention basins. Jacopin et al. (2001) observed substantial improvements in the reduction of discharge at the cost of available storage in the basin, i.e. the dry extended detention basins utilized more of their capacity when limiting discharge. Similar results were observed by Bilodeau et al. (2019) with reductions in peak discharges averaging 46% when RTC was implemented. Even when the RTC strategy did not prioritize reducing hydrologic impacts (such as systems which prioritized water quality), reductions in the magnitude and duration of intra-storm and inter-storm discharges were observed (Gaborit et al. 2013; Gaborit et al. 2016; Muschalla et al. 2014).

This observed reduction in intra-storm discharges was observed in wet ponds as well (Boyle et al. 2016; Mullapudi et al. 2018). For example, Boyle et al. (2016) in their retrofit of an existing wet pond were able to reduce channel forming discharges by >25% by optimizing when discharge occurred, shifting the occurrence of ~15% of discharge from intra-storm to inter-storm. Mullapudi et al. (2018) concluded similar findings and was able to leverage RTC, wet ponds, and communication with downstream sensors to limit intra-storm discharge while attenuating inter-storm discharge to a set-point.

Review of the existing literature highlighted that the majority of previous studies have focused on the hydrologic impact of RTC on dry extended detention basins, with limited investigation of the unique advantages that wet ponds equipped with RTC may provide. Additionally, because this research area is novel, additional studies quantifying and contextualizing the hydrologic impact of these systems is necessary to inform future applications. These observations from literature highlight major gaps in the literature that need to be addressed.

1.3.2. Solution for Water Quality Impacts

Implementation of RTC on dry extended detention basins has been documented to improve and mitigate the water quality impacts of stormwater, especially when control strategies are developed to target specific pollutants (Gilpin and Barrett 2014; Gaborit et al. 2013; Gaborit et al. 2016; Jacopin et al. 2001; Middleton and Barrett 2008; Muschalla et al. 2014). RTC is able to accomplish these goals by augmenting the sediment settling process of dry extended detention basins, which is the primary process for pollutant removal in these systems (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). By limiting intra-storm discharge and artificially detaining stormwater within the basin, internal velocities are reduced which allow sediment settling and trapping rates to rise (Huffman et al.

2013). Therefore, implementation of RTC on dry extended detention basins should substantially improve the removal efficiency of sediment and any pollutants attached to these particles. In simulations of a dry extended detention basin near Québec City, Gaborit et al. (2013; 2016) and Muschalla et al. (2014) observed substantial improvements in TSS removal efficiency (60%-90%) when RTC was utilized when compared to a baseline uncontrolled (~40%). Field studies by Gilpin and Barrett (2014), Jacopin et al. (2001), and Middleton and Barrett (2008) validate these observations with RTC strategies able to achieve TSS removal efficiencies of 70-90%.

RTC for dry extended detention basins has also proven useful for addressing other water quality impairments besides TSS. For example, by exposing sediment and detained stormwater to sunlight over an extended period of time, these systems have displayed increased removal rates for bacteria. An 88% removal rate of *E. coli* was observed by Gilpin and Barrett (2014), a substantial improvement to the 39% removal rate of a nearby uncontrolled basin. However, this report only monitored one event and more studies are necessary before broader conclusions regarding bacteria removal rates can be determined. Additional pollutants that RTC is able to mitigate includes heavy metals, chemical oxygen demand, total nitrogen, and total phosphorous primarily through sediment settling processes (Gilpin and Barrett 2014; Middleton and Barrett 2008).

It can be concluded that the majority of the literature focuses on the impacts that RTC has on TSS, with limited investigation of other pollutants. Additionally, there are no studies which investigate the impact on other water quality parameters important to ecological health such as temperature, turbidity, or dissolved oxygen or the impact of other SCMs such as wet ponds. This constitutes a substantial gap in the literature that must be addressed for the field to advance.

1.3.3. Impact on Design Parameters

In their reexamination of RTC strategies for improving TSS removal efficiencies of a dry extended detention basin, Gaborit et al. (2016) investigated the efficiency of RTC strategies in scenarios where the total volume of their study's dry extended detention basin was altered. Specifically, the basin was altered in their simulations and examined at 100%, 32%, and 15% of existing capacity. The authors concluded that basin capacity could be significantly altered while still observing improvements to the TSS removal efficiency over existing conditions with the smallest basin capacity (15%) still achieving TSS removal efficiencies around 70% (Gaborit et al. 2016). While this represents a sharp decrease from the ~90% observed for the 100% capacity scenario, it still offers a significant improvement over passive situations (Gaborit et al. 2016). However, this reduction in volume (however desirable) came at the cost of substantially increased basin discharge and overflows which may lead to habitat degradation and significant erosion in the receiving water body (Gaborit et al. 2016). It is possible that the initial reductions in SCM volumes of this study were too extreme to mitigate hydrologic impacts and that smaller reductions in volume may be able to strike a balance. This theory was validated by Wong and Kerkez (2018) and Boyle et al. (2016) during their respective investigations of RTC. Wong and Kerkez (2018) concluded in a simulation study of watershed control strategies that they could reduce the volume of controlled SCMs in their network by over 50% and still achieve comparable performance in the watershed when compared to the uncontrolled baseline. Boyle et al. (2016) concluded similar results in their simulation of a wet pond and found that they could reduce the required volume of the pond by 30%-50% while still achieving desirable flow conditions. These investigations establish a pattern that RTC may be able to decrease the required volume of SCMs while still mitigating hydrologic and water quality impacts. The relationships between these improvements and SCM volume reduction will need to be further quantified in future studies as reductions in required volume, and the required surface area, could provide an economic incentive to land developers to implement RTC over traditional passive systems.

1.3.4. Watershed-Scale Control

The vast majority of literature has focused on the impact of RTC at the site-scale through investigations of individual dry extended detention basins or wet ponds to respond and adapt to their surroundings. Unfortunately, investigations solely performed on individual systems may limit our understanding of their contribution to watershed-scale problems or restoration objectives. Investigation of the barriers to watershed-scale control, or scenarios in which a series of SCMs are outfitted with RTC and connected to sensor networks within the receiving body of water, offers a solution for watershed-scale restoration objectives through coordinated responses to rainfall events. Mullapudi et al. (2018) demonstrated that coordination of discharges from two networked SCMs in response to downstream conditions could produce desirable hydrographs in the downstream waterbody to mitigate streambed erosion. Conversely, if their respective RTC strategies operated individually and were not networked to meet watershed-scale objectives, discharges from each may overlap leading to undesirable discharges in the receiving water body. Wong and Kerkez (2018) concluded similar findings in respect to the performance of networked SCMs while also investigating the necessity of wide-spread RTC adoption. Specifically, is it necessary to implement RTC on every available SCM in a watershed to achieve watershed-scale objectives or is similar performance achievable through targeted installations? For the authors' watershed the latter was confirmed, with comparable performance being achieved by implementing RTC on 30% of the available storage nodes in the watershed (Wong and Kerkez 2018). While each of these studies displays promising results and highlights the benefits of watershed-scale control strategies, more studies investigating the response and application of watershed-scale RTC strategies is recommended to expand the limited existing literature.

1.4. Knowledge Gaps and Contributions

While previous sections reviewed existing work on the application and impacts of outfitting dry extended detention basins and wet ponds with RTC, this section will now reiterate gaps in the literature and how they will be addressed in this dissertation. A diverse selection of case studies and simulations will be used to investigate each research question. In summary, this dissertation will make the following contributions to the existing literature:

- **Chapter 2:** This chapter explores the development, deployment, and validation of a low-cost, accurate stream gauging station capable of remotely sensing stream stage as an alternative to more traditional, but cost prohibitive, systems.
- **Chapter 3:** This chapter analyzes the performance of a RTC dry extended detention basin outfitted with a turbidity sensor in order to meet water quality objectives more consistently.
- **Chapter 4:** This chapter analyzes the in-stream hydrologic and water quality impact of a RTC dry extended detention basin when releasing water following an increased detention period.
- **Chapter 5:** This chapter analyzes the performance of a diverse selection of control strategies on dry extended detention basins and wet ponds.

To assist in the real-time data collection required to make data driven decisions regarding placement of SCMs outfitted with real-time control (RTC) (or to inform the control decisions of the RTC stormwater infrastructure itself), deployment of data acquisition systems to remotely monitor environmental parameters (such as stream stage and flow) is a necessity. Existing systems which remotely monitor stream stage and flow are cost and maintenance prohibitive to most municipalities which has left many waterways unmonitored (Normand 2019). Chapter 2: "Design and Application of a Low-Cost, Accurate Stream Gauging Station" addresses this issue by outlining the development, deployment, and validation of a novel stream gauging station designed to be low-cost, accurate, and easy to install to provide municipalities with a better alternative to cover gaps in their existing networks.

Previous research has concluded that dry extended detention basins outfitted with RTC observed improvements in water quality over traditional passive systems (Gilpin and Barrett 2014; Gaborit et al. 2013; Gaborit et al. 2016; Jacopin et al. 2001; Middleton and Barrett 2008; Muschalla et al. 2014). Typically, these control strategies base their decisions on hydrologic variables or predetermined water quality models, though there is evidence that utilizing real-time water quality data in the control decisions may be more beneficial for meeting water quality objectives (Sazzad et al. 2019). However, there are no case studies which validate these conclusions, with the only recorded use of incorporating real-time water quality data in the decision framework being in sewer systems to prevent combined sewer overflows or to redirect water to wastewater treatment plants (Hoppe et al. 2011). Chapter 3: "Turbidity Informed Real-Time Control of a Dry Extended Detention Basin: A Case Study" addresses this gap in the literature by analyzing the performance of a dry extended detention basin outfitted with RTC and a real-time water quality sensor where the decision framework incorporates this water quality data.

While most of the literature focuses on water quality improvements within dry extended detention basins, little is known about how these systems impact in-stream conditions once detained water is released. Specifically, how do these inter-storm discharges affect critical and not previously examined water quality parameters such as dissolved oxygen, temperature, and turbidity? Chapter 4: "Quantifying the In-Stream Hydrologic and Water Quality Impact of a Real-Time Controlled Dry Extended Detention Basin: A Case Study" addresses these inquiries and knowledge gaps through real-time hydrologic and water quality monitoring downstream of a dry extended detention basin outfitted with RTC.

The application of RTC for stormwater management is a relatively novel research area, which makes contextualization of the broader implications of a diverse set of RTC strategies necessary to corroborate existing studies and inform future work and applications. Compounding on this issue is that the majority of existing studies have focused on the impacts of RTC on dry extended detention basins, with limited investigation of how RTC can be uniquely leveraged with wet pond systems. Chapter 5: "Impact of Real-Time Control on the Hydrology and Design Parameters of Wet Ponds and Dry Extended Detention Basins" explores several diverse RTC strategies for both wet ponds and dry extended detention basins while contextualizing the advantages of each through their hydrologic (discharge and volume released) and design parameter (stage and storage) results. Unlike the previous chapters outlined in this dissertation, this chapter will consist of a robust simulation approach to accomplish its objectives.

References

Bilodeau, K., G. Pelletier, and S. Duchesne. 2019. "Real-time control of stormwater detention basins as an adaptation measure in mid-size cities." *Urban Water Journal*, 15 (9), 858-867. https://doi.org/10.1080/1573062X.2019.1574844.

Boyle, R., A. Poresky, O. Cadwalader, and S. Landers. 2016. "Stormwater Real Time Controls at the Watershed Scale: Evaluating the Business Case and Developing an Implementation Roadmap for an Oregon MS4." In *Proc., Water Environment Federation*, 750-755. New Orleans, LA: WEF. https://doi.org/10.2175/193864716819705997.

Clary, J., J. Jones, M. Leisenring, P. Hobson, and E. Strecker. 2020. "International Stormwater BMP Database: 2020 Summary Statistics." The Water Research Foundation. Accessed February 1st, 2020. https://www.waterrf.org/system/files/resource/2020-11/DRPT-4968_0.pdf.

Dunne, T. and L. B. Leopold. 1978. *Water in Environmental Planning*. San Francisco, CA: W.H. Freeman and Company.

Gaborit, E., D. Muschalla, B. Vallet, P. A. Vanrolleghem, and F. Antcil. 2013. "Improving the performance of stormwater detention basins by real-time control using rainfall forecasts." *Urban Water Journal*, 10 (4), 230-246. https://doi.org/10.1080/1573062X.2012.726229.

Gaborit, E., F. Antcil, G. Pelletier, and P. A. Vanrolleghem. 2016. "Exploring forecast-based management strategies for stormwater detention ponds." *Urban Water Journal*, 13 (8), 541-851. https://doi.org/10.1080/1573062X.2015.1057172.

Georgia Stormwater Management Manual. 2016. Atlanta Regional Commission.

Gilpin, A. and M. Barrett. 2014. "Interim Report on the Retrofit of an Existing Flood Control Facility to Improve Pollutant Removal in an Urban Watershed." In *World Environmental* *and Water Resources Congress 2014*, 65-74. Portland, Oregon: ASCE. https://doi.org/10.1061/9780784413548.009.

Hoppe, H., S. Messmann, A. Giga, and H. Gruening. 2011. "A real-time control strategy for separation of highly polluted storm water based on UV–Vis online measurements – from theory to operation." *Water Sci. Technol.*, 63 (10), 2287-2293. https://doi.org/10.2166/wst.2011.164.

Huffman, R. L., D. D. Fangmeier, W. J. Elliot, and S. R. Workman. 2013. *Soil and Water Conservation Engineering*. Seventh edition. St. Joseph, MI: ASABE.

Jacopin, C., E. Lucas, M. Desbordes, and P. Bourgogne. 2001. "Optimisation of Operational Management Practices for the Detention Basins." *Water Sci. Technol.,* 44 (2-3), 277−285. https://doi.org/10.2166/wst.2001.0780.

Kerkez, B., C. Gruden, M. Lewis, L. Montestruque, M. Quigley, B. Wong, A. Bedig, R. Kertesz, T. Braun, O. Cadwalader, A. Poresky, and C. Pak. 2016. "Smarter Stormwater Systems." *Environ. Sci. Technol.*, 50 (14), 7267-7273. https://doi.org/10.1021/acs.est.5b05870.

Knox County, Tennessee Stormwater Management Manual. 2008. Knox County Tennessee Department of Engineering and Public Works.

Middleton, J. R. and M. E. Barrett. 2008. "Water Quality Performance of a Batch-Type Stormwater Detention Basin." *Water Environ. Res.*, 80 (2), 172-178. https://doi.org/10.2175/106143007X220842.

Mullapudi, A., M. Bartos, B. Wong, and B. Kerkez. 2018. "Shaping Streamflow Using a Real-Time Stormwater Control Network." *Sensors*, 18 (2259), 1-11. https://doi.org/10.3390/s18072259.

Muschalla, D., B. Vallet, F. Antcil, P. Lessard, G. Pelletier, and P. A. Vanrolleghem. 2014. “Ecohydraulic-driven real-time control of stormwater basins.” *J. Hydrology*, 511 (2014), 82-91. https://doi.org/10.1016/j.jhydrol.2014.01.002.

Normand, A. E. 2019. “U.S. Geological Survey (USGS) Streamgaging Network: Overview and Issues for Congress.” *R45695*, Congressional Research Service, Washington, D.C.

Pyzoha, D. S. 1994. *Implementing a Stormwater Management Program*. Boca Raton, FL: Lewis Publishers.

Sazzad, S., W. McDonald, and A. J. Parolari. 2019. “Improved reliability of stormwater detention basin performance through water quality data-informed real-time control.” *J. Hydrol.*, 573 (2019), 422-431. https://doi.org/10.1016/j.jhydrol.2019.03.012.

The Federal Interagency Stream Restoration Working Group. 2001. *Stream Corridor Restoration: Principles, Processes, and Practices*. Washington, DC: U.S. Government Publishing Office.

Wong, B. P., and B. Kerkez. 2018. “Real-Time Control of Urban Headwater Catchments Through Linear Feedback: Performance, Analysis, and Site Selection.” *Water Resources Research*, 54 (10), 7309-7330. https://doi.org/10.1029/2018WR022657.

CHAPTER 2: DESIGN AND APPLICATION OF A LOW-COST, ACCURATE STREAM GAUGING STATION

2.1. Abstract

The threats of urbanization and climate change have created the need to reimagine watershed management and restoration objectives. Deployment of data acquisition systems to monitor environmental parameters, such as stream stage and flow, in high resolution would be invaluable information for informing future management or restoration objectives. Therefore, a novel stream gauging station was designed with the objective of being a low-cost, accurate, and easy to install alternative to traditional stream stage monitoring systems. This design used a custom circuit that would measure stream stage using an ultrasonic distance sensor and wirelessly upload the measurements to an online server for real-time data viewing. The total cost of the stream gauging station was less than $200.

Two stream gauging stations were assembled, installed, and allowed to operate for over a year, and it was concluded that both stations reported stage accurately with a MAE of 1.22 cm and 1.78 cm, respectively. Additionally, it was assessed if this uncertainty in stage had an effect on the derived discharge measurements for one of the monitoring locations. Though it was concluded the stage uncertainty had a significant effect on the derived discharge (p-value < 0.001), this only equated to a median uncertainty of 2.63% in the derived discharge. Therefore, it can be concluded that the uncertainty in stage measurements from these stations have no significant effect on the measured discharge. These results prove that this novel stream gauging station is an excellent alternative to traditional stream monitoring systems and should be deployed to cover gaps in existing coverage allowing local municipalities to make more informed, data driven decisions regarding watershed management.

2.2. Introduction

The threats of urbanization and climate change have created the need to reimagine watershed management and restoration objectives. Deployment of data acquisition systems to monitor environmental parameters, such as stream stage and flow, in high resolution (both temporal and spatial) would provide invaluable information for informing future management or restoration objectives (Streeter and Wylie 1985). Existing stream gauging stations, the majority of which are managed by the U.S. Geological Survey (USGS), are costly to install and manage. Each stream gauging station managed by the USGS costs $25,000 to $40,000 to install with an additional $16,500 to $30,000 each year for operation and maintenance (Normand 2019). While the USGS offers cheaper rapid deployment gauges (RDG) as temporary fixtures to measure stream stage, these stations are still quite expensive with an installation cost of $15,000 and an annual operation and maintenance cost of $3,500 (Normand 2019). This prohibitive cost has left many waterways unmonitored, especially in Tennessee, where only 101 federally funded stream gauging stations are in operation year-round (Normand 2019). Therefore, novel, low-cost, accurate, and easy to install stream gauging stations are necessary for local municipalities to make data driven decisions regarding watershed management.

2.2.1. Objective

The objective of this study was to design a low-cost, accurate, and easy to install stream gauging station and to investigate its practical application and effectiveness.

2.3. Materials and Methods

A stream gauging station was designed using low-cost, open-source technologies to monitor and wirelessly transmit the stage of a stream in real-time. The system consists of an ultrasonic distance sensor (HC-SR04) to measure stream stage (or water depth above a reference point), a lithium-ion battery to keep the station online, a solar panel to charge the battery, a custom control circuit (Figure 2.1), and a Particle Photon Wi-Fi development board to upload the measured data to an online server and save on data transmission costs. The custom control circuit (Figure 2.1) was designed to be simple and effective and includes a Particle Boron LTE development board to control the station and transmit data to the Particle Photon, Adafruit's Miniboost (AP3602A) to increase the output voltage of the Particle Boron to 5V to make it compatible with the ultrasonic distance sensor, two resistors which act as a voltage divider for signals returning from the ultrasonic distance sensor, and two switches that allow debugging modes to be enabled when the stream gauging station is being serviced.

Two stream gauging stations, referred to as "upstream" and "downstream" based on their relative positions, were assembled, and installed on Conner Creek, a tributary of the Clinch River in eastern Tennessee. Conner Creek has had no stream monitoring instrumentation installed by the U.S. Geological Survey in almost two decades with the most recent active station, 03535617, last reporting measurements in 2001 (U.S. Geological Survey 2021). To assemble the stream gauging stations the custom circuit was placed inside the weatherproof housing (Figure 2.1) and two holes were drilled into the base of the housing to allow the ultrasonic distance sensor to protrude out of the bottom to allow the ultrasonic transmitter and receiver to sense the surface of the water below. Since each of the stations were installed over an open channel, rather than on a bridge or culvert, structures were constructed to hold the stations above the stream using two metal u-posts set in concrete on either side of the channel bridged by pressure treated lumber. The stations were then installed in the center of these structures with the ultrasonic distance sensors facing down towards the water and with the solar panels attached and connected to each

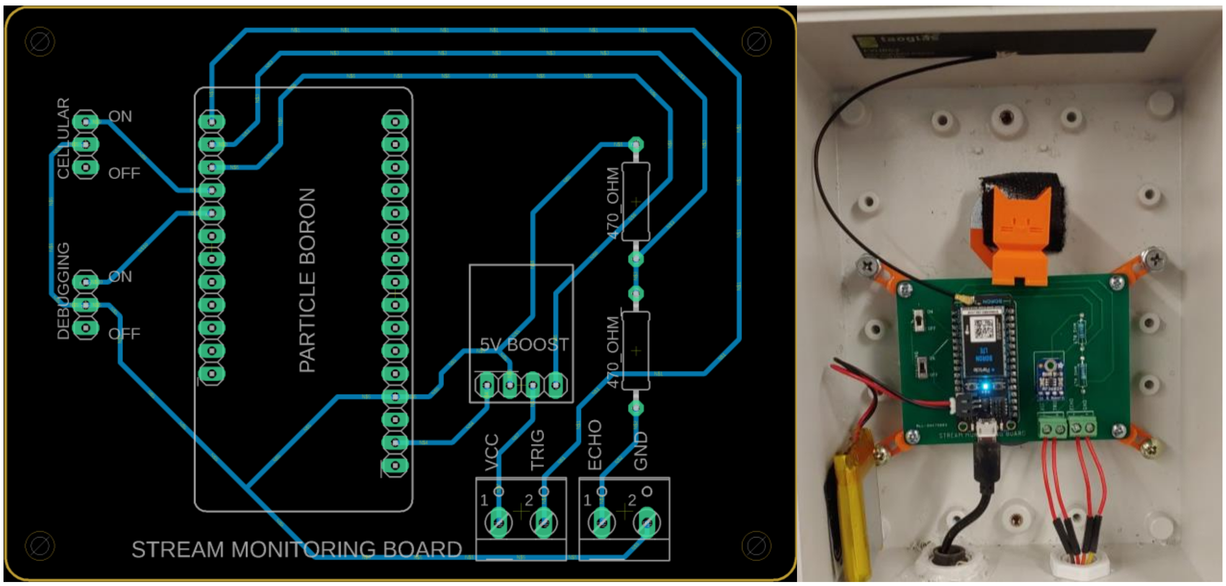

Figure 2.1. Stream gauging station circuit design (left) and assembled circuit board in weatherproof housing (right).

station (Figure 2.2). To provide a consistent reference for stage, paver stones were installed in the stream bed below each sensor. The total cost of each of these stream gauging stations, including the structures that hold the station above the open channel, was less than $200.

During normal operation, the stream gauging station first instructs the ultrasonic distance sensor to take a measurement to determine the distance between it and the water's surface. The sensor does so by transmitting a pulse of ultrasound which reflects off the closest surface, in this embodiment the water's surface, and listening for the reflected sound wave to return to the sensor (Scherz and Monk 2016). Using the time between when the ultrasound pulse was transmitted and its reflection sensed, the distance between the sensor and the nearest surface can be calculated (Scherz and Monk 2016). This distance measurement can then be used to calculate the current stage of the stream using the known constant distance from the sensor to the stage reference point (i.e. the paver stones).

The process of determining stage is repeated an additional four times, and the median of all five measurements is saved as the current stage measurement. The station then checks this current measurement against the previously transmitted stage measurement to ensure the change in the measurements is reasonable ($\leq \pm 50$ cm) and not due to an error in the ultrasonic sensor or the sensor being obscured. Additionally, the station checks if the stage measurement is within the acceptable range of possible stage measurements between the bed of the stream and the sensor itself. If the station still finds the stage measurement acceptable, and the debugging mode (explained below) is disabled, the station then transmits this stage measurement to the Particle Cloud using the Particle Boron's built-in cellular connectivity. Meanwhile, the Particle Photon is installed in a location with a strong Wi-Fi signal, such as a lab or office, and is set to subscribe to all data published by the stream gauging station. When data is uploaded to the Particle Cloud via

Figure 2.2. Stream gauging station installed at the upstream site during baseflow (top) and flooding (bottom) conditions.

the stream gauging station, the Particle Photon will pull this data, check that it is in the appropriate format, and then upload the data to an online server for real-time data viewing. The addition of the Particle Photon for uploading the data to the online server significantly saves on data transmission costs as data transmission over Wi-Fi using the Particle Photon is free while data transmission over a cellular connection using the Particle Boron is not. Additionally, data transmission to the Particle Cloud is optimized on all Particle devices to use less data which is why the stream gauging station does not upload data directly to the online server and first must send it to the Particle Cloud. The station repeats this entire process of determining stage and uploading this data approximately once every minute. An example hydrograph of this uploaded data can be seen below in Figure 2.3 with rainfall data being transmitted from a separate system.

Two additional modes, debugging and cellular control, were built into the station to increase its functionality and serviceability and can be accessed remotely or via the built-in switches on the control circuit. The first of these modes, debugging, allows the user to disable data transmission. When enabled the station will still continue to take stage measurements, which are viewable as exposed variables in the Particle console, but the data will not be uploaded. This allows the user to calibrate the station and ensure that it is reporting accurate measurements. The second mode, cellular control, controls if the station stays connected to the Particle Cloud via its cellular connection between data transmissions. Maintaining a cellular connection is one of the tasks which has a higher power consumption (Particle 2021). Therefore, in embodiments where the time between data uploads is increased, disabling the cellular connection between data uploads may conserve battery.

2.4. Results and Discussion

To ensure that the reported measurements from the stream gauging stations were

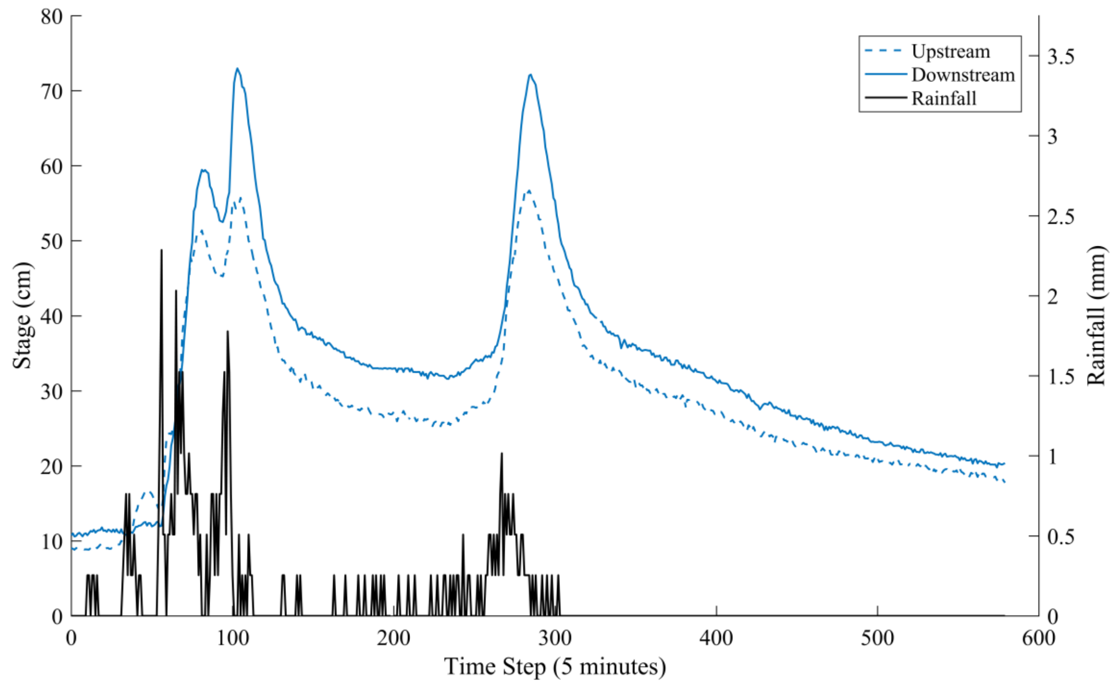

Figure 2.3. Example hydrograph of data wirelessly transmitted from stream gauging stations.

accurate, and that the stations were reliable over long periods of time, the measurements from the stations were periodically checked against the actual stage (measured in person) over a 19-month and 13-month period for the downstream and upstream stations, respectively. The stations rarely required maintenance over this time period with the most common issues being the occasional replacement of a drained battery (once every few weeks) or recalibration of the station itself (once every few months). The effect of seasonal temperature changes was likely the cause for the sensor drift that required the station to be recalibrated every few months as temperature and humidity may slightly change the speed at which the ultrasound pulse transmitted by the sensor travels (Scherz and Monk 2016). To solve this problem, stations would likely need to be equipped with a low-cost humidity and temperature sensor to correct stage measurements in real-time as conditions change. A comparison of stage measured by the stream gauging stations and actual stage for both stations can be seen below in Figure 2.4 along with an idealized reference line. This reference line is an idealized scenario where the measured stage and actual stage are equal to one another. An analysis of covariance (ANCOVA) was used to determine if the slopes and intercepts between the idealized reference line and the regression line formed by the actual measurements were significantly different ($\alpha = 0.05$). The downstream station performed very well with no significant difference between the measurement comparisons and the idealized reference line (p-value = 0.45 for slopes; p-value = 0.78 for intercepts) while having a low mean absolute error (MAE) of 1.22 cm. In comparison, the upstream station still performed extremely well but was significantly different from the idealized reference line (p-value $<$ 0.0001 for slopes; p-value = 0.0054 for intercepts) and tended to slightly under report values at lower stage heights while slightly over reporting values at higher stage heights. Even with these tendencies, the upstream station still had a low MAE of 1.78 cm.

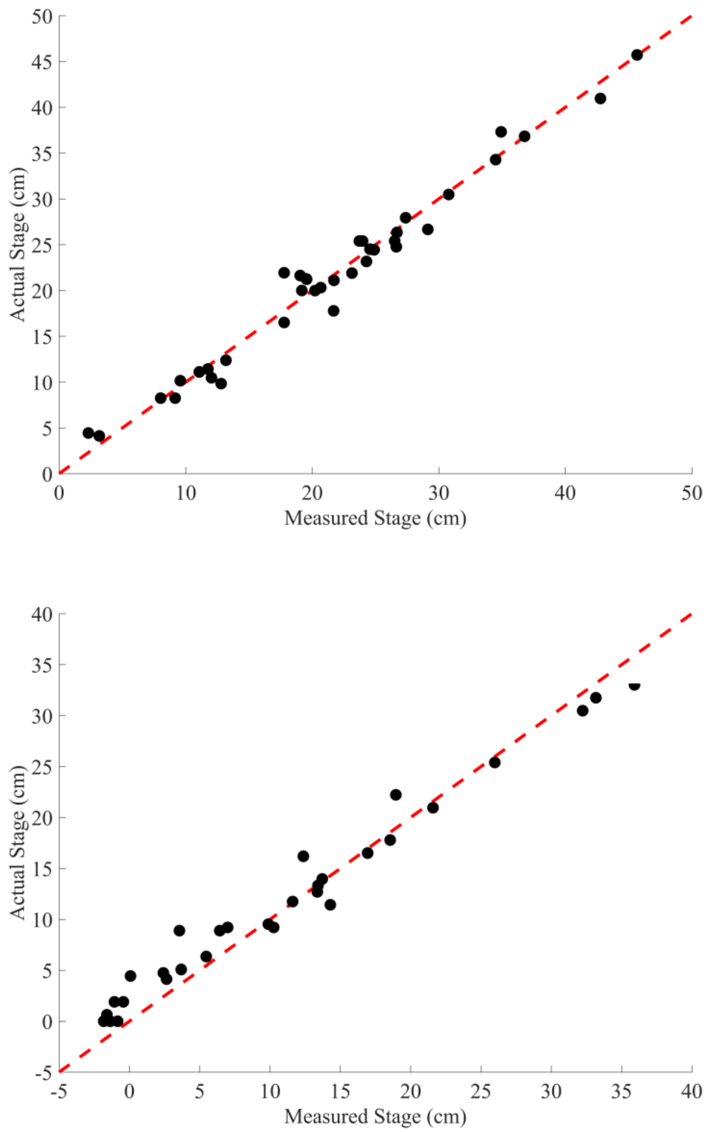

Figure 2.4. Comparison of stage measured by the stream gauging stations and actual stage for the downstream (top) and upstream (bottom) stations along with an idealized reference line.

While these low MAE values of stage from the stream gauging stations ensure that they are accurate, stage is not the only parameter of interest when monitoring streams. Discharge, or flow, of a stream is a vitally important parameter for watershed monitoring and management (Streeter and Wylie 1985). Therefore, it is important to investigate how the measurement uncertainty of stage effects discharge measurements. In open channels, discharge is generally derived as a function of stage through the development of a stage-discharge curve (Streeter and Wylie 1985). An established stage-discharge curve for the downstream station was already available and used for this analysis. The existing curve, represented by the dashed line in Figure 2.5, is surrounded by a shaded area of uncertainty. The upper and lower bounds of this uncertainty were derived using the MAE value (1.22 cm) from the stage measurements, i.e. the lower bound was calculated as if stage had been under reported by the MAE value while the upper bound was calculated as if stage had been over reported by the MAE value. ANCOVA ($\alpha = 0.05$) was used to determine if the upper and lower bounds of uncertainty were significantly different from the existing curve. While it was concluded that the slopes of some of the regression terms and intercepts were significantly different from the existing curve, this only equated to a median uncertainty of 2.63% in the derived discharge. Therefore, it can be concluded that the uncertainty in stage measurements has no significant effect on the derived discharge for this station.

2.5. Conclusions

A novel stream gauging station was designed that is low-cost (< \$200), accurate (MAE < 1.78 cm), and easy to install that will measure stream stage and wirelessly upload measurements to an online server for real-time data viewing. Two of these stations were assembled, installed, and allowed to operate for over a year, and it was concluded that both stations reported stage

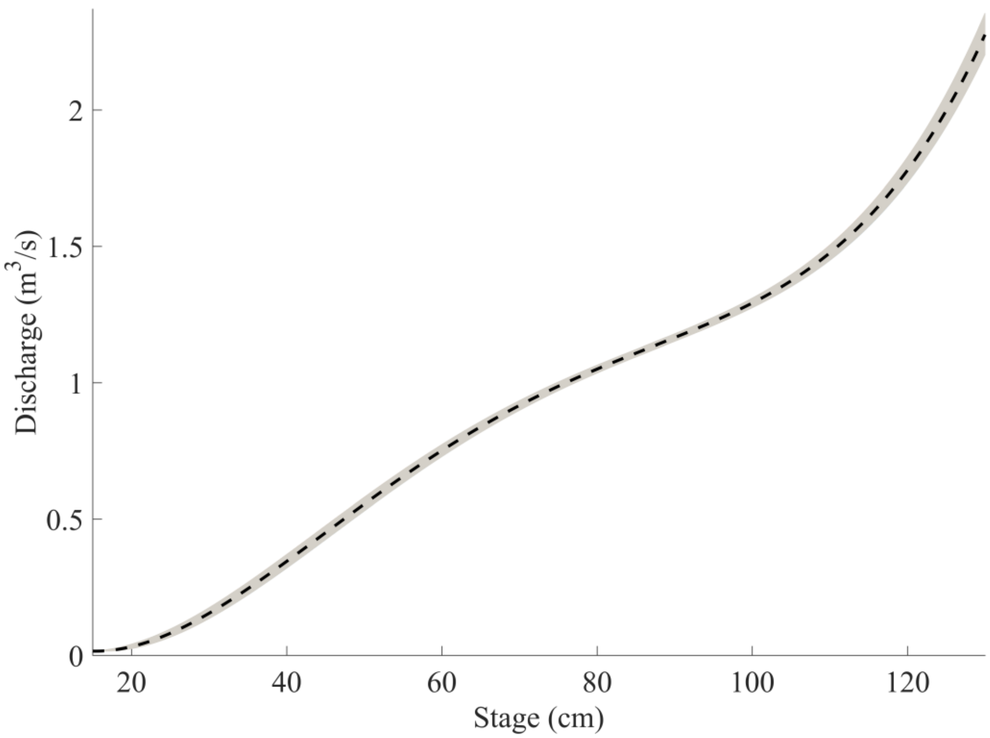

Figure 2.5. Stage-discharge curve for the downstream station (dashed line) and the effect of stage measurement uncertainty on measured discharge (shaded area around curve).

accurately (MAE of 1.22 cm and 1.78 cm, respectively). It was also assessed if the observed uncertainty in stage measurements had a significant effect on the derived discharge measurements for one of the monitoring locations. It was concluded that this uncertainty in stage only equated to a median uncertainty of 2.63% in the derived discharge and was therefore not significant. These results prove that this novel stream gauging station is an excellent alternative to traditional stream monitoring systems and should be deployed to cover gaps in existing coverage allowing local municipalities to make more informed, data driven decisions regarding watershed management.

References

Normand, A. E. 2019. "U.S. Geological Survey (USGS) Streamgaging Network: Overview and Issues for Congress." *R45695*, Congressional Research Service, Washington, D.C.

Particle. 2021. "Boron Datasheet." *Particle Docs*. Accessed January 13, 2021. https://docs.particle.io/datasheets/boron/boron-datasheet/.

Scherz, P. and S. Monk. 2016. *Practical Electronics for Inventors*. New York, NY: McGraw-Hill Education.

Streeter, V. L. and E. B. Wylie. 1985. *Fluid Mechanics*. New York, NY: McGraw-Hill.

U.S. Geological Survey. 2021. "USGS 03535617 CONNER CREEK AT STEEL RD. NEAR SOLWAY, TN." *National Water Information System: Web Interface*. Accessed January 12, 2021. https://nwis.waterdata.usgs.gov/nwis/inventory/?site_no=03535617.

CHAPTER 3: TURBIDITY INFORMED REAL-TIME CONTROL OF A DRY EXTENDED DETENTION BASIN: A CASE STUDY

3.1. Abstract

Dry extended detention basins are static stormwater infrastructure, unable to adapt to shifts in water quality caused by their contributing watersheds becoming increasingly urbanized or long-term changes in rainfall patterns. As a potential solution to these problems, this research investigated the impact and use of real-time water quality data on a dry extended detention basin retrofitted with a controllable valve and a turbidity sensor with the goal being to meet water quality objectives more consistently. Turbidity was selected for this study as it is an important parameter for judging stream health, can act as a surrogate for other pollutants, and can be measured reliably with commercially available sensors (unlike many other water quality parameters). When rainfall was detected, the basin's valve would close and detain all water until either a maximum allowable detention time was reached, or turbidity values fell below a predetermined threshold. This method was shown to produce highly variable detention times after rainfall events with 63% of events meeting the turbidity threshold before the maximum detention time with a median turbidity of 24.7 FNU at release for all events in this study. Even events that did not meet the criteria for release before the maximum detention time still experienced improvements in water quality with a median decrease of 7.9 FNU (22% reduction) during the detention period. This diversity in system response highlights the advantages an adaptive system has over a traditional static system or one which uses predetermined detention times to meet water quality objectives. To determine if turbidity-based controls could operate effectively in the future if the turbidity sensor were to be removed, an advantage for economical resource allocation, several modeling approaches were evaluated to estimate the detention time of the system based on observed basin stage and precipitation data. Two of these models, a logistic regression model and a Long Short-Term Memory (LSTM) model, proved accurate in

determining detention time of the system with MAE's of 8.49 and 5.16 hours, respectively. With this system's ability to meet water quality objectives more consistently when real-time water quality data was integrated into the decision framework, this study should lay the groundwork for other applications targeting additional water quality parameters.

3.2. Introduction

The majority of stormwater infrastructure is static, unable to adapt as watershed restoration needs are altered or rainfall patterns change. This includes stormwater control measures such as dry extended detention basins. Dry extended detention basins are storage facilities which are installed within drainage networks to temporarily store stormwater runoff (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Their primary purpose is to provide channel and flood protection for the receiving stream or river by attenuating flows to match pre-development conditions (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008).

Recent studies have begun to investigate the impact of retrofitting such systems with real-time control (RTC) by installing a controllable valve on the outlet to increase or change detention times during rainfall events (Gaborit et al. 2013; Gaborit et al. 2016; Gilpin and Barrett 2014; Jacopin et al. 2001; Middleton and Barrett 2008; Mullapudi et al. 2018; Muschalla et al. 2014). Typically, these detention times are predetermined, and thus don't account for changing conditions between and during rainfall events such as shifts in water quality. Thus, they are still treated as a "static solution to a dynamic problem" (Kerkez et al. 2016). Although there is evidence that utilizing real-time water quality data in the control decisions of stormwater infrastructure is beneficial for meeting water quality objectives (Sazzad et al. 2019), there are limited case studies in literature. Of those studies that have been performed, the primary focus was using this technology to prevent combined sewer overflows or to redirect water to wastewater treatment plants (Hoppe et al. 2011). Additional studies are needed to investigate the impact and efficiency of adaptable stormwater systems which integrate real-time water quality data into the decision framework for stormwater controls.

3.2.1. Impact and Measurement of Turbidity

Turbidity, which can cause water bodies to appear murky or cloudy, is an optical quality of water and a measurement of the scattering and absorption of light (U.S. EPA 2009). It is elevated primarily by the presence of suspended sediment but also by organic matter and microscopic organisms (Anderson 2005). Turbidity is considered an indicator of the ecological health of a water body (Anderson 2005). For example, elevated turbidity levels can result in negative impacts to aquatic life and stream ecology by reducing photosynthetic activity, reducing food availability to fish and aquatic life, degrading aquatic habitats, and directly harming organisms by impairing respiration and digestive processes (U.S. EPA 2009).

There are numerous standards and techniques for measuring turbidity, but most use a light source and detector to measure the optical scatter of a water sample (Anderson 2005). This diversity of instrumentation and measurement techniques have resulted in numerous designations for the units of a turbidity measurement. For the purposes of this study, turbidity measurements were reported in Formazin Nephelometric Units (FNU) which corresponds to an instrument that measures turbidity by analyzing the sidescatter (90° to incident beam) from a single illumination beam light source using near infrared wavelengths (Anderson 2005). Another common turbidity unit is Nephelometric Turbidity Units (NTU) which replaces the near infrared light source of the

FNU measurement technique with a white light source (Anderson 2005). Some instrumentation manufacturers have continued to report turbidity measurements in NTU as a generic turbidity unit though it may not be the correct designation (Anderson 2005). While frequent calibration of modern instruments is not generally required (unlike sensors for other water quality parameters), maintenance and installation of these sensors can be quite time consuming. Maintenance issues generally arise when sediment or biologic fouling occurs and obscures the sensor. To alleviate this issue, many sensors come equipped with cleaning protocols that physically wipe/remove any obscurities from the sensor's lens, though the addition of this feature makes the sensor considerably more expensive. However, these cleaning protocols are not equipped to handle the sensor being obscured by larger debris (such as vegetation) blocking the sensor's view of the water column; alleviation of these issues would require physical removal of the object(s) from in front of the sensor.

To reduce the turbidity of stormwater entering a stream or river, thereby improving the ecological health of the system, stormwater controls such as dry extended detention basins are used. Dry extended detention basins are able to reduce the impact of turbidity primarily through gravitational settling and trapping of suspended particles found in stormwater (Anderson 2005; Gaborit et al. 2013; Gaborit et al. 2016; Georgia Stormwater Management Manual 2016; Gilpin and Barrett 2014; Knox County, Tennessee Stormwater Management Manual 2008; Muschalla et al. 2014). By attenuating flows and increasing the hydraulic residence time, these settling and trapping processes have more time to occur which results in removal rates of 40-70% for suspended sediment (Gaborit et al. 2013; Gaborit et al. 2016; Georgia Stormwater Management Manual 2016; Gilpin and Barrett 2014; Knox County, Tennessee Stormwater Management Manual 2008; Muschalla et al. 2014). RTC has been able to enhance these processes and substantially improve the removal efficiency of suspended sediment to 70-90% by increasing the hydraulic residence time (Gaborit et al. 2013; Gaborit et al. 2016; Gilpin and Barrett 2014; Middleton and Barrett 2008; Muschalla et al. 2014). However, none of these studies incorporated real-time water quality data to control this hydraulic residence time. This may prove to be a better alternative for targeting specific water quality objectives by adjusting the hydraulic residence time as shifts in water quality occur.

3.2.2. Objectives

Although RTC is increasingly being viewed as a way to bolster the performance of stormwater infrastructure, there are numerous applications yet to be explored. To the authors' knowledge there are no case studies utilizing real-time water quality data in the decision framework of dry extended detention basins, or other stormwater control measures, retrofitted with active controls. Based on the understanding that effluent turbidity levels may improve when detention times within stormwater facilities are increased, RTC may offer an avenue to achieve better outcomes than static systems. Furthermore, integration of real-time turbidity data is an excellent starting point for proving that water quality informed RTC can be leveraged to achieve water quality objectives more consistently. Thus, the results of this study should encourage novel research into other applications of RTC integrated with real-time water quality. Therefore, the objectives of this study were to: (1) investigate the impact and use of real-time water quality data on a dry extended detention basin retrofitted with a controllable valve and a turbidity sensor as a novel methodology for more consistently meeting water quality objectives, and (2) see if predictive models can be generated that can alleviate the need for the turbidity sensor long-term which would be an advantage for economical resource allocation during widespread adoption by reducing the number of necessary sensors and required maintenance.

3.3. Materials and Methods

3.3.1. Site Description

A dry extended detention basin in the Conner Creek watershed of Eastern Tennessee was chosen for this study (Figure 3.1). The dry extended detention basin collects runoff from the impervious areas (such as roofs and parking lots) and practice fields of a local high school and elementary school. The contributing drainage area is 19.7 ha and the landcover is 86% impervious. The basin can detain approximately 14,760 m^3 of water at a maximum stage of 3.05 m before water overtops the outlet riser of the basin.

To convert this static stormwater infrastructure into an adaptable system, the outlet structure (Figure 3.2; left) was retrofitted with a 150 mm (6”) diameter butterfly valve (Valworx 564548) and matching electric actuator (Valworx 561877A). An ultrasonic depth sensor was installed above the basin (Grove Ultrasonic Ranger), and a dual sidescatter/backscatter turbidity sensor (Campbell Scientific OBS501) was installed directly next to the basin’s outlet to ensure that all turbidity measurements were reflective of the basin’s effluent conditions. A custom control circuit was developed and powered by a Particle Boron LTE development board to which the actuator and sensors were connected. Additionally, a tipping bucket rain gauge was integrated into the system to record rainfall and assist in the control decisions made by the system. While this system allowed for variable control of the valve (could be set anywhere between 100% fully open and 0% fully closed), binary control (fully closed or fully open) was

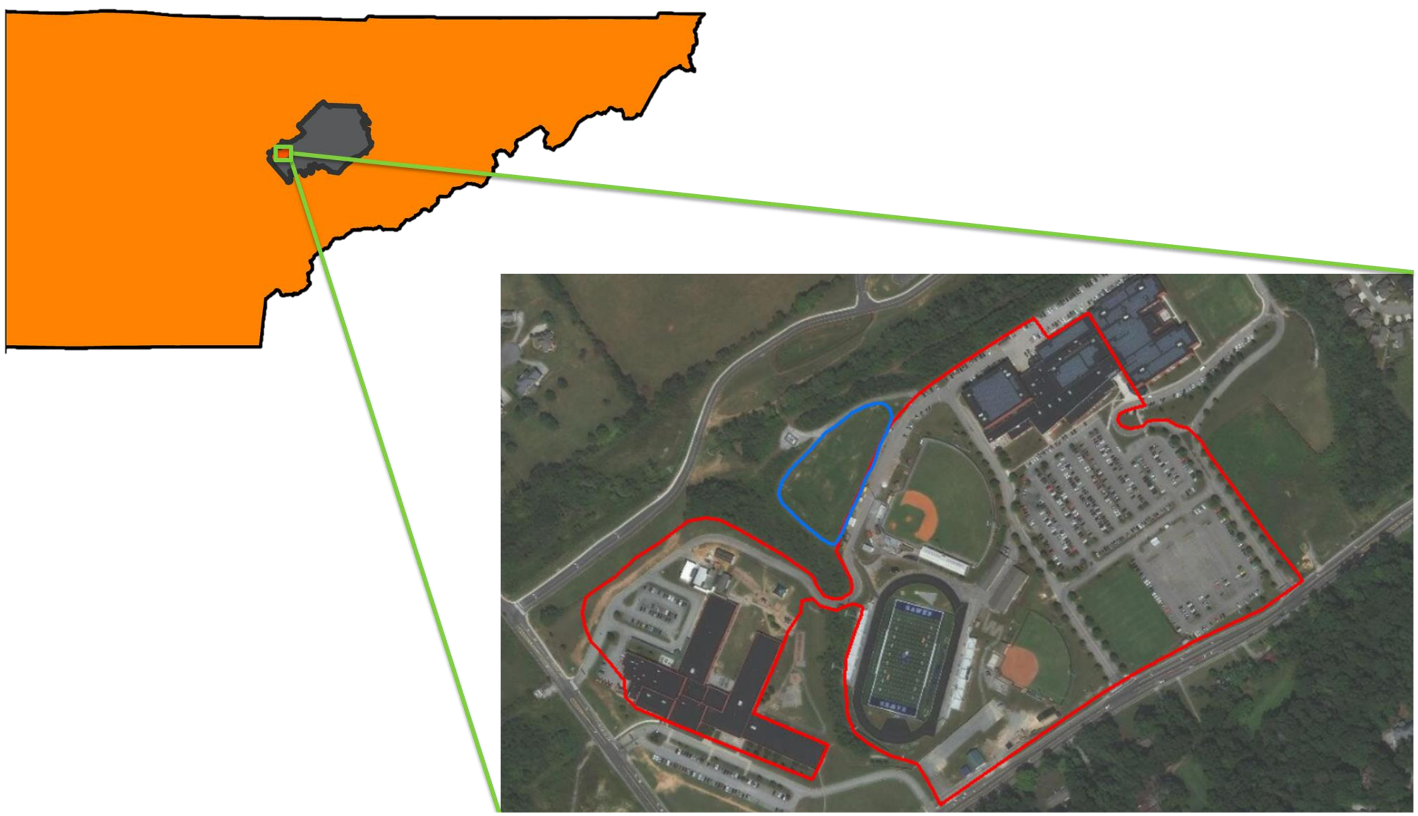

Figure 3.1. Study location in the Conner Creek watershed of Eastern Tennessee with the subcatchment of the dry extended detention basin outlined in red and the footprint of the basin outlined in blue.

Figure 3.2. Dry extended detention basin outlet riser (left) outfitted with controllable valve, water depth sensor, and turbidity sensor and (right) the basin following a rainfall event.

used in this study. To utilize the full capacity of the basin, the bypass orifice (used to attenuate flows not able to be conveyed by the 150 mm low flow orifice) on the outlet riser was sealed with a circular metal plate and gasket to prohibit any discharge (as seen in the center of the left figure in Figure 3.2).

3.3.2. Water Quality Informed RTC Strategy

Turbidity was selected for this study as it is an important parameter for judging stream health, can act as a surrogate for other pollutants, and can be measured reliably with commercially available sensors (unlike many other water quality parameters). To investigate how real-time turbidity data may allow improved system performance for water quality, a set of control rules for the system were established. When rainfall was detected, the basin's valve would close and detain all water (Figure 3.2; right) for a minimum of 24 hours following the end of a rainfall event. The valve would remain closed until either a maximum detention time of 72 hours was reached, or turbidity values fell below a predetermined threshold of 25 FNU determined via the turbidity sensor's sidescatter measurements (justification for these thresholds is provided below).

To ensure that a series of insignificant rainfall events did not detain water within the basin indefinitely, additional advanced control rules were added. These rules would require that the initial rainfall or any additional rainfall (≥6 hours post the end of initial rainfall) must meet a minimum threshold (2.54 mm) equal to the initial abstraction of the watershed within a 6-hour duration for the rainfall to be included in control decisions. For example, if 12 hours after the end of initial rainfall a secondary storm passed through the watershed and rained 5 mm within 3 hours, the system would recognize this as the new end of rainfall, thus resetting the countdown for the 24-hour minimum detention time. If that rainfall threshold was not met, or was not met within the time limit (6 hours), the countdown to the minimum detention time would remain unchanged. Safety precautions were also included in these additional control rules to prevent overtopping of the outlet riser. If the water depth of the basin exceeded 2.51 m (~80% of maximum water depth; ~75% of maximum volume) the valve would open and release water until the water depth fell below 2.44 m. This control rule was designed to override all others and was only enacted by the system once during the study when cumulative rainfall exceeded 130 mm.

The sidescatter turbidity measurements were chosen for this study as they have the advantage of being more accurate in clean water compared to backscatter measurements which are useful for measuring higher levels of turbidity (≤4000 FNU) (Campbell Scientific 2017). The minimum and maximum detention times were adopted from regional design and operation guidance on dry extended detention basins (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Additionally, since Tennessee does not have any explicit regulations regarding turbidity in surface waters, guidance for the turbidity threshold came from regulations for ponds, reservoirs, and streams from 8 states' water quality standards: Arizona, Hawaii, Iowa, Louisiana, Minnesota, North Carolina, Oklahoma, and Vermont (U.S. EPA 2009).

3.3.3. Modeling Analysis

Following the data collection period of this study, several modeling approaches were examined to determine if they could accurately estimate the detention time of the system necessary to meet the turbidity threshold (within the minimum and maximum detention times of this study). The purpose of this modeling investigation was to determine if the system could operate effectively in the future if the turbidity sensor were to be removed. This would allow organizations implementing this system to save on maintenance and overhead costs associated with keeping the turbidity sensor clean and functional while also reducing the quantity of turbidity sensors required for the operation of multiple systems. The models evaluated consisted of a diverse selection of traditional statistical models and machine learning techniques which were validated to determine if system performance using this approach would remain comparable to decisions made using real-time turbidity measurements. Available predictors for these models consisted of data that could be derived without the need of a turbidity sensor and included: initial water depth (m), maximum water depth during the initial 24 hours after a rainfall event (m), cumulative rainfall (mm), rainfall duration (h), maximum 5-minute rainfall intensity (mm/h), antecedent dry time (h), and time between storms (h). Each of these models predicted the detention time (h) required to meet the turbidity threshold within the minimum and maximum detention time constraints outlined previously.

The traditional statistical models analyzed ranged from simple to complex and included logistic, linear, multiple, and polynomial regression models and were chosen to represent a diverse selection of regression models and predictors. The logistic regression model was created by analyzing predictors iteratively for potential sigmoidal relationships. Once predictors displaying sigmoidal relationships were identified, each was analyzed using a diverse set of starting functions. The model with the lowest RMSE (root mean square error) value was selected as the optimal logistic regression model. The linear regression model was created by testing all possible subsets of predictors and selecting the model with the lowest RMSE. Similarly, the multiple regression model was created by testing all possible subsets of predictors and selecting a model with the lowest RMSE while also ensuring that the chosen model was free of multicollinearity. The polynomial regression model was derived using the same process used for deriving the multiple regression model with the addition of squared predictors. Each of these models were validated using 10-fold cross-validation.

A random forest model was the first machine learning technique that was explored as a viable option for predicting detention time of the system. Random forest models consist of a number of randomly generated decision trees, grouped together as a “forest”, which ask binary questions of predictors in order to arrive at a conclusion (Genuer and Poggi 2020). The random forest model developed in this study consisted of 500 trees in its “forest” using a variety of predictors as the model’s independent variables. The number of trees used in the creation of this random forest model was fixed at 500 trees due to restrictions with the software package. However, while the number of trees was fixed, this package exposed additional tuning parameters absent in other packages that were observed to be more beneficial during the model’s creation. These additional tuning parameters included the number of randomly selected parameters at each node, target node size, and enacted splitting rule. The optimal random forest model was chosen by assessing the importance of each available predictor, altering the tuning parameters (number of randomly selected parameters, target node size, and splitting rule) using a tuning grid to assess all available combinations, and assessing model performance. The combination which resulted in the lowest RMSE for 10-fold cross-validation was chosen.

Finally, a more advanced machine learning model was created and analyzed to determine if additional complexity would result in improved model performance. This model consisted of a Long Short-Term Memory (LSTM) network which is a type of recurrent neural network used for time series prediction that has the ability to learn from short-term and long-term trends in data to predict an output (Ganegedara 2018). This ability to learn from both long and short-term data trends makes it an ideal candidate for modeling scenarios that may be temporally dependent, such as this study. Since LSTM models use time series data (as opposed to tabular data) as their input to predict an output at each modeled time step, the LSTM model developed for this study used observed basin stage (m) and rainfall (mm) time series data at 15-minute time steps to predict turbidity as a binary output (1 for turbidity < 25 FNU, 0 for turbidity ≥ 25 FNU). To simulate real world conditions, the output data (turbidity) was shifted 12 hours so that any prediction made by the LSTM model was always 12 hours in the future (i.e. basin stage and rainfall at any time *t* would predict turbidity at time *t* + 12 hours). In a production setting, this would allow enough time for the model to iterate every few hours (as the computational time for this model is significantly higher than others developed within this study) with updated time series data and form a prediction before a control decision would actually need to be made. This time shift would not be necessary for other models within this study as they are able to form a decision with data collected during and immediately following rainfall. The LSTM model used a 10-fold cross-validation process in which 90% of the time series data were used for training while the remaining 10% were used for validation on each iteration. As a reminder, for the other models explored within this study, the split between training and validation was based on the total number of events. The predicted turbidity at each 15-minute time step from each of these validation iterations were then combined and fed through the control rules outlined above to determine the valve position of the dry extended detention basin (1 for open, 0 for closed). From the predicted valve position and observed rainfall, detention time was then estimated.

3.4. Results and Discussion

3.4.1. Observed Performance of System

A total of 21 events were collected from October 19th, 2019, through March 18th, 2020, with an event being defined as the time between when rainfall is initially detected at the site and when the system makes the control decision to release water from the dry extended detention basin. No events were recorded between December 5th, 2019, and January 13th, 2020, as the turbidity sensor was uninstalled due to ambient temperatures routinely falling below its operating temperature range (Campbell Scientific 2017). A summary of each of these events can be found below in Table 3.1. Events 3 and 12 were removed from any further analysis in this study as they were deemed not representative. Event 3 was removed as debris covered the outlet and obscured the turbidity sensor's measurements, while event 12 was removed due to the extremely high rainfall (134.87 mm) that occurred and flooded the basin/watershed as the control rules were limited in their ability to attenuate turbidity conditions under these extreme circumstances.

Overall, 63% of events (12 of 19) met the 25 FNU turbidity threshold for water release before the maximum detention time, and the median turbidity value for all events in the study at release was 24.7 FNU. Although the turbidity threshold was not met for 37% (7 of 19) of events, events in this category still saw a median decrease of 7.9 FNU (22% reduction) during the 24 to 72 hours following the end of the rainfall event with a median turbidity value of 35.0 FNU at release. The majority of events resulted in turbidity trends comparable to that of Figure 3.3. Specifically, turbidity initially increases during and following rainfall before steadily decreasing over the next few days. Though similar trends in turbidity occurred, overall detention times were highly variable due to differences in initial turbidity magnitudes, the rate at which readings fell

Table 3.1. Summary of events collected in study.

Event	Start Time	Rainfall Duration (h)	Rainfall (mm)	Initial Water Depth (m)	Maximum* Water Depth (m)	Maximum* Turbidity (FNU)	Turbidity at Release (FNU)	Detention Time (h)
1	10/19/2019 17:35	9.42	6.60	0.51	0.62	40.5	24.8	24.33
2	10/21/2019 20:35	8.42	27.43	0.00	1.16	100.2	58.7	72.17
3	10/25/2019 16:40	33.00	45.72	0.81	1.71	74.5	495.1	72.17
4	10/30/2019 08:40	30.08	47.50	1.29	2.12	615.0	24.0	46.50
5	11/07/2019 10:30	10.00	10.41	0.82	0.96	28.0	9.7	24.42
6	11/22/2019 06:45	32.92	53.85	0.00	1.86	148.4	32.9	72.17
7	11/26/2019 22:55	9.67	21.08	1.06	1.52	324.7	24.7	30.50
8	11/30/2019 14:30	15.92	55.37	0.00	2.02	100.6	35.0	72.17
9	01/14/2020 01:10	112.92	41.91	0.00	1.52	148.6	28.5	72.17
10	01/23/2020 21:55	15.75	30.48	0.00	1.23	39.9	24.9	52.42
11	01/27/2020 04:05	6.50	3.05	0.84	0.92	82.4	24.1	24.25
12	02/04/2020 06:00	56.50	134.87	0.00	3.23	100.7	27.6	72.33
13	02/10/2020 03:55	30.33	50.29	1.09	2.17	25.1	20.8	24.08
14	02/12/2020 13:00	20.58	30.99	1.81	2.37	58.5	28.4	72.25
15	02/18/2020 05:30	17.33	22.61	0.00	1.12	412.1	24.5	33.67
16	02/20/2020 09:15	6.58	6.89	1.10	1.25	34.4	19.2	24.17
17	02/24/2020 06:50	58.25	22.86	0.00	1.12	71.0	35.4	72.25
18	03/02/2020 06:50	26.67	40.13	0.00	1.59	143.4	84.6	72.25
19	03/10/2020 05:35	14.92	10.67	0.00	0.63	187.3	22.3	24.17
20	03/13/2020 00:20	53.75	13.72	0.00	0.78	238.9	19.9	24.92
21	03/16/2020 23:40	12.42	11.18	0.70	1.09	32.2	19.8	24.25
Median for All Events		15.92	22.86	0.00	1.23	100.2	24.7	24.7
St. Dev for All Events		25.06	16.77	0.57	0.52	150.6	16.1	16.1

Note: Median and St. Dev do not include Events 3 and 12 as they were removed from any analysis.

***Maximum during time period between when rainfall begins and 24 hours following the end of rainfall has elapsed.**

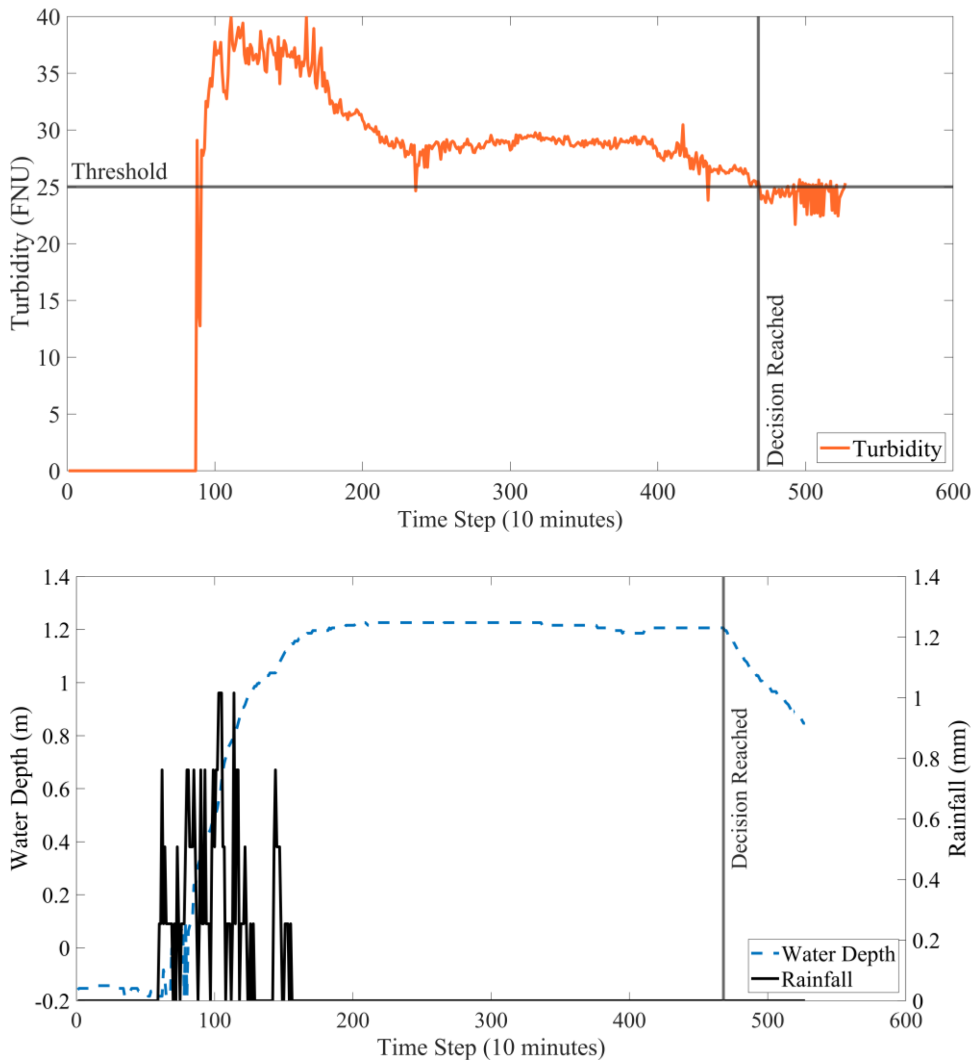

Figure 3.3. Turbidity measurements (upper) and dry extended detention basin hydrograph (lower) for event 10.

(settling rate of suspended particles), or resuspension of sediment due to biologic activity. These observations highlight one of the many advantages an adaptive RTC strategy (that incorporates real-time water quality data) has over other control strategies as it is able to adapt to these diverse conditions.

3.4.2. Comparison to an Uncontrolled Basin

While performance metrics and water quality data for an uncontrolled baseline were not collected in this study, a comparison in performance between this adaptive RTC strategy and an uncontrolled basin can be inferred by comparing their hydraulic residence times. Multiple studies have observed a positive relationship between water quality and hydraulic residence time in which an increase in the latter leads to an improvement in the former (Gaborit et al. 2013; Gaborit et al. 2016; Gilpin and Barrett 2014; Huffman et al. 2013; Middleton and Barrett 2008; Muschalla et al. 2014). This observed relationship occurs because sediment settling and nutrient uptake mechanisms have more time to process. For example, Gaborit et al. (2013; 2016) and Muschalla et al. (2014), during their simulations of a dry extended detention basin, observed substantial improvements in TSS removal efficiency (60%-90%) when RTC was utilized and compared to an uncontrolled baseline (~40%). However, the baseline uncontrolled in these studies may have been underperforming as these systems generally remove approximately 66% of TSS (Clary et al. 2020). Field studies by Gilpin and Barrett (2014), Jacopin et al. (2001), and Middleton and Barrett (2008) validate these observations with RTC strategies which extend hydraulic residence times able to achieve TSS removal efficiencies of 70-90%.

Simulations using the Personal Computer Stormwater Management Model (PCSWMM; Computational Hydraulics International; version 7.3.3095) and collected rainfall data were used to determine the hydraulic residence times for each event in an uncontrolled scenario (both the bypass orifice and valve of the basin are left open). This PCSWMM model of the study site was calibrated and validated in a separate study (Chapter 5). Table 3.2 (below) displays these results with the maximum uncontrolled residence time (beginning of rainfall until the basin is drained), the minimum residence time of the system using RTC (beginning of rainfall until when the valve was opened), and the minimum increase in residence time between the uncontrolled and RTC equipped basin. Equipping the basin with water quality informed RTC led to a median minimum increase in the hydraulic residence time of 82%. From this significant increase in hydraulic residence time, it can be inferred that the water quality informed RTC strategy can provide substantial improvements in water quality when compared to existing/baseline conditions.

3.4.3. Comparison to Predetermined Detention Time RTC Strategy

To determine if the turbidity threshold would have been met by a system using a predetermined detention time, the turbidity values of each event at a variety of pre-determined detention times (12, 24, 48, and 72 hours) were extracted from the observed data set. In instances where the predetermined detention time was longer than the water quality informed detention time, the turbidity value at release was used. This conservative assumption was allowed because the majority of events experienced declining trends in turbidity with increased detention time (as previously explored). Analysis of the efficiency of using predetermined detention times and how this strategy compared to the water quality informed RTC strategy can be found below in Table 3.3. A substantially higher number of events were observed to meet the turbidity threshold for the water quality informed RTC (63%; 12 of 19 events) in comparison to predetermined detention times of 12 (21%; 4 of 19 events), 24 (42%; 8 of 19 events), and 48 (58%; 11 of 19

Table 3.2. Comparison of hydraulic residence times between water quality informed RTC and uncontrolled scenarios.

Event	Uncontrolled Residence Time (h)	RTC Residence Time (h)	Increase in Residence Time (%)
1	18.58	33.75	82
2	31.75	80.59	154
4	50.67	76.58	51
5	24.50	34.42	41
6	56.75*	105.09	85
7	29.42	40.17	37
8	43.83	88.09	100
9	73.45*	185.09	152
10	31.58	68.17	116
11	18.42	30.75	67
13	52.92	54.41	3
14	38.83	92.83	139
15	34.50	51.00	48
16	21.08	30.75	46
17	48.50*	130.5	169
18	47.33	98.92	109
19	26.42	39.09	48
20	42.00*	78.67	87
21	26.00	36.67	41
Median for All Events	34.50	68.17	82
St. Dev for All Events	14.35	39.23	46

Note: Uncontrolled residence times denoted by an * are the cumulative residence times for instances where the basin fully drained during an event and was refilled by later rainfall.

Table 3.3. Analysis of results investigating if the turbidity threshold would be met using predetermined detention times (red indicates turbidity ≥25 FNU at release; green indicates turbidity <25 FNU at release).

			Turbidity (FNU) at Release if Predetermined Detention Time Used *			
Event	RTC Detention Time (h)	Turbidity at Release (FNU)	12 Hours	24 Hours	48 Hours	72 Hours
1	24.33	24.76	**28.4**	**25.6**	**24.8**	**24.8**
2	72.17	58.69	**51.1**	**98.5**	**64.2**	**58.7**
4	46.50	23.99	**39.4**	**34.6**	**24.0**	**24.0**
5	24.42	9.67	**15.6**	**9.9**	**9.7**	**9.7**
6	72.17	32.94	**44.9**	**66.3**	**49.9**	**32.9**
7	30.50	24.73	**35.9**	**34.5**	**24.7**	**24.7**
8	72.17	35.02	**55.3**	**38.6**	**34.3**	**35.0**
9	72.17	28.48	**39.7**	**36.4**	**31.6**	**28.5**
10	52.42	24.91	**29.1**	**29.2**	**26.2**	**24.9**
11	24.25	24.11	**27.6**	**26.1**	**24.2**	**24.3**
13	24.08	20.78	**21.5**	**20.7**	**20.8**	**20.8**
14	72.25	28.36	**52.8**	**34.1**	**30.2**	**28.4**
15	33.67	24.54	**101.0**	**30.1**	**24.5**	**24.5**
16	24.17	19.15	**25.4**	**19.2**	**19.2**	**19.2**
17	72.25	35.40	**49.8**	**40.3**	**47.1**	**35.4**
18	72.25	84.57	**91.0**	**113.3**	**95.8**	**84.6**
19	24.17	22.27	**57.9**	**22.6**	**22.6**	**22.6**
20	24.92	19.92	**31.8**	**19.9**	**19.9**	**19.9**
21	24.25	19.81	**12.8**	**19.8**	**19.8**	**19.8**
Median Turbidity at Release			**39.4**	**30.1**	**24.7**	**24.7**
St. Dev at Release			**22.4**	**26.1**	**19.4**	**16.1**
Efficiency of Predetermined Detention Time			**21%**	**42%**	**58%**	**63%**

***Note: Turbidity threshold was initially met within ± 2 hours of predetermined detention time.**

events) hours. While no considerable increase in the number of events which would have met the turbidity threshold occurred between the 48 and 72 hour predetermined detention times, there was a substantial reduction in turbidity between these two detention times. Events that fell into this category (events 2, 6, 8, 9, 14, 17, and 18) experienced a median decrease of 5.48 FNU (~10%) during that additional 24 hours. In short, a system utilizing predetermined detention times would need to use the maximum detention time of 72 hours to match the efficiency of the water quality informed RTC strategy. While this is feasible to implement, a system utilizing a predetermined detention time strategy would not provide numerous hydrologic advantages such as not detaining water longer than necessary and therefore ensuring capacity in the system for any subsequent rainfall. Therefore, it can be concluded that the water quality informed RTC strategy shows greater potential as an alternative for meeting water quality objectives.

3.4.4. Modeling Results

3.4.4.1 Regression Models

As noted above, a variety of models were developed using predictors that could be derived independently of the turbidity sensor. The form of each of these models, including coefficients and independent variables, can be found below in Table 3.4. Variables of significant value for explaining the data and predicting *DT* (detention time in h) included *Rainfall* (cumulative rainfall in mm), D_0 (basin's initial water depth in m), and D_M (basin's maximum water depth during the initial 24 hours following a rainfall event in m). Cumulative rainfall as an important predictor was expected as it is directly responsible for higher rates of runoff that carry sediment/pollutants and contribute to higher levels of turbidity (Huffman et al. 2013; Pyzoha 1994; U.S. EPA 2009). Maximum water depth as a predictor appears to represent hydrologic

Table 3.4. Analyzed regression models and their form.

Model	Form
Logistic Regression	$DT = 25.038 + 37.851 / \left(1 + e^{-17.704(Rainfall) - 22.663)}\right)$
Linear Regression	$DT = 22.497 + 0.859(Rainfall)$
Multiple Regression	$DT = 12.335 - 24.943(D_0) + 33.015(D_M)$
Polynomial Regression	$DT = 26.877 - 62.695(D_0) + 30.378\left({D_0}^2\right) + 23.425(D_M)$

processes similar to rainfall, as determined by the high multicollinearity observed between this predictor and rainfall. Initial water depth also appears to play a vital role in how quickly the turbidity threshold is reached primarily through its impact on resuspension processes. Through investigation of the observed data, it is hypothesized that when the basin still contains a portion of the previous event when a new event begins, the erosive energy of the incoming water is diminished, thus reducing resuspension of trapped particles in the basin. This would allow the dry extended detention basin to mimic the function of a wet pond (stormwater control measure which contains a permanent pool) which has been documented to have increased removal rates of suspended particles (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008).

3.4.4.1 Random Forest Model

The random forest model consisted of 500 trees in its "forest" (for reasons previously discussed) and used cumulative rainfall (mm) and initial water depth (m) of the basin as the model's independent variables. The model also applied the following tuning parameters: using both parameters at each node, using a target node size of 1, and enacting an "extratrees" splitting rule. An example of a decision tree that may appear in this random forest model can be found below in Figure 3.4. Similar to the regression models, it appears that predictors which describe the resuspension (initial depth) and hydrologic (rainfall) processes of the basin are those which most substantially impact the required detention time to meet the turbidity threshold.

3.4.4.2 Long Short-Term Memory Model

Overall, the LSTM model performed well (Figure 3.5). The MAE for this model using 17 of the 19 available events and 10-fold cross-validation was 5.16 hours with a median absolute error of less than half an hour. The model was unable to reach a prediction for the detention

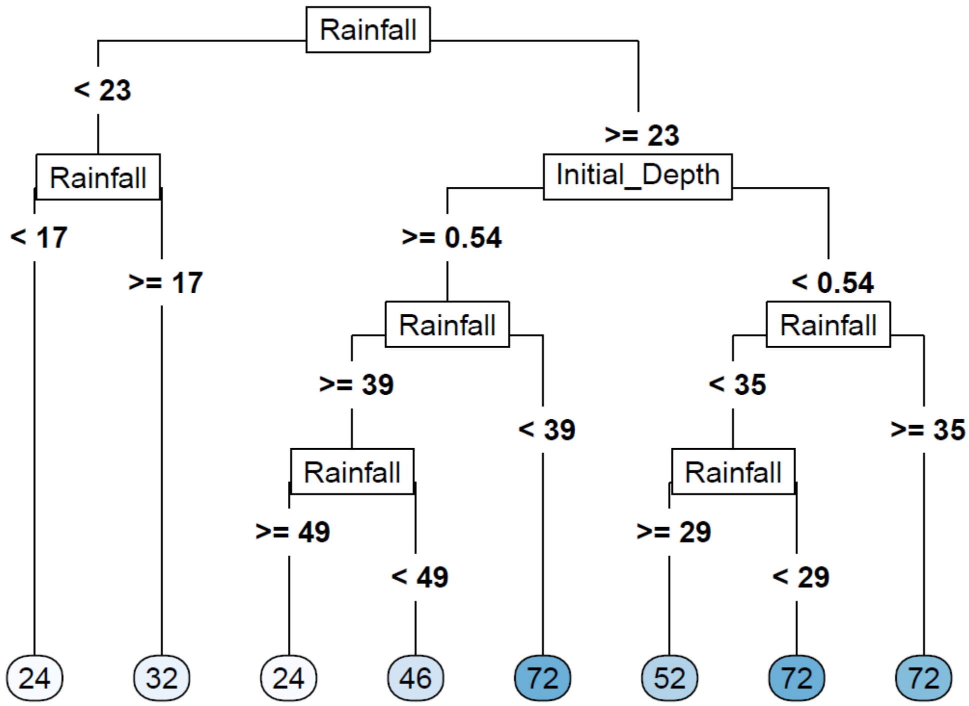

Figure 3.4. Example decision tree that may appear in the random forest model.

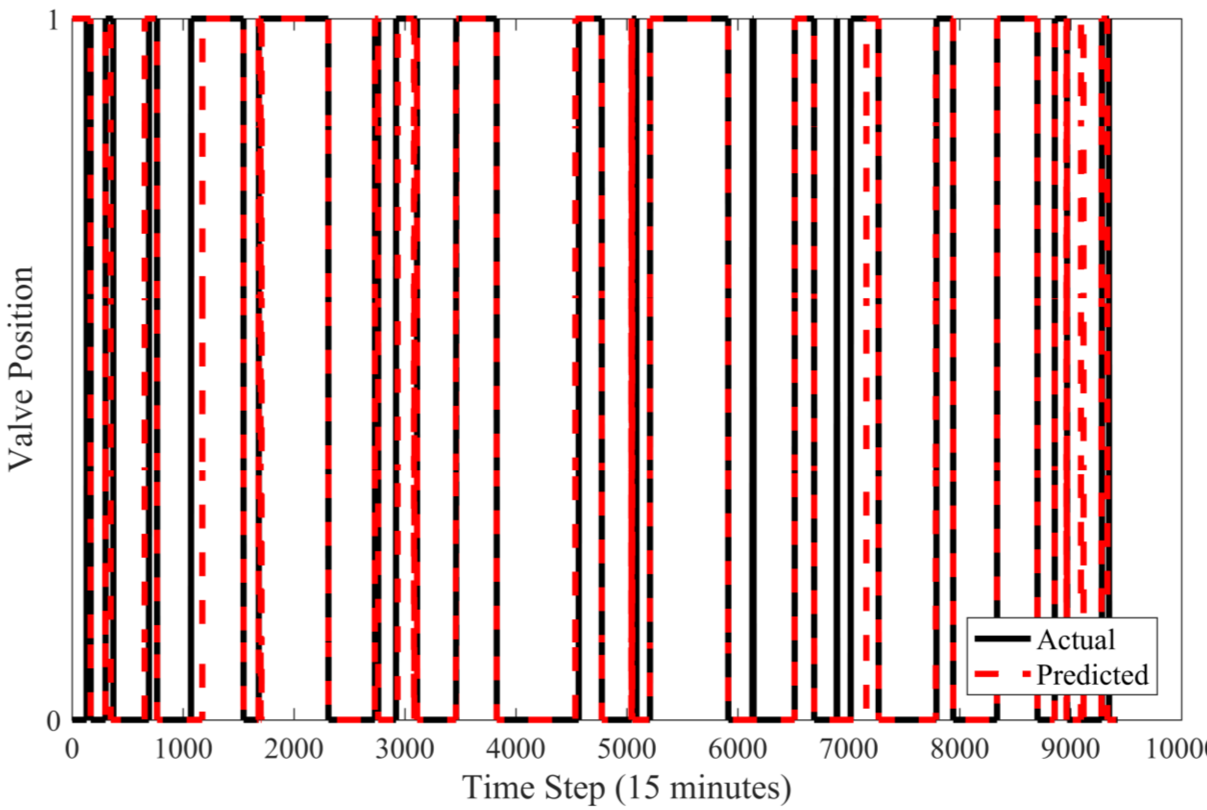

Figure 3.5. LSTM modeling results (1 represents fully open; 0 represents fully closed).

times for events 13 and 15 due to the short period of time between when the system actually made the decision to open and when a new rainfall event began (~2.5 and ~0.75 hours, respectively). It should be noted that LSTM models are variable and dependent on layers added to the model. Thus, it is possible that a different, yet to be determined combination could outperform the current iteration. However, the LSTM model analyzed in this study was the optimal model derived from 50 iterations of testing different layers/layer types and tuning parameters.

3.4.4.3 Model Comparison

The fit statistics for the full models and the results of validation using 10-fold cross-validation can be found below in Table 3.5. The LSTM model outperformed all other models with a significantly lower mean absolute error (MAE). This MAE equates to the model predicting detention times with an error of ±5.16 hours (10-fold cross-validation). Therefore, if a model were implemented as the primary control of the system, one could possibly counteract performance error by instructing the system to increase the predicted detention time by adding the MAE to ensure that the turbidity threshold is always met (for detention times ≤72 hours) or that comparable performance to the water quality informed RTC is achieved (for detention times >72 hours) before water is released from the system.

3.4.5. Future Work

While the water quality informed RTC strategy successfully improved the ability of a dry extended detention basin to meet water quality objectives, future work is necessary to investigate the impact of this system more broadly beyond the scope of this study site. It is recommended that this RTC strategy be implemented on dry extended detention basins across a diverse

Table 3.5. Model fit statistics and validation using 10-fold cross-validation.

	Full Model			10-Fold Cross-Validation
Model	**MAE**	**R^2**	**Adjusted R^2**	**MAE**
Logistic Regression	7.56	0.72	0.70	8.49
Linear Regression	12.37	0.44	0.41	13.52
Multiple Regression	10.17	0.60	0.55	11.96
Polynomial Regression	8.77	0.71	0.66	12.44
Random Forest	N/A	0.51 [1]	N/A	10.04
LSTM Network	N/A	N/A	N/A	5.16 [2]

[1] **OOB Error**

[2] **Time series data**

selection of regions, designs, and watershed characteristics as site specific features may play a significant role in the hydrologic and settling processes that affect turbidity. For example, if the soil of a basin's watershed consists of more fine particles than those herein, then it can be expected that initial turbidity magnitudes may increase while overall system performance decreases due to additional suspended particles. Conversely, soils with larger particles may lead to an improved ability of this system to meet turbidity objectives. Changes in the design of the basin (such as differences in orifice diameter or basin capacity) may also substantially affect the ability of the system to meet water quality objectives due to their influence on hydrologic processes. Finally, the chosen turbidity threshold for this study may not be what is required by local regulations. Assuming similar pond function as observed herein (initial turbidity magnitudes and rate at which turbidity readings fall), then systems which utilize a higher turbidity threshold (based on local guidance) will experience shorter detention times, while systems which use a lower turbidity threshold will experience much longer detention times.

3.5. Conclusions

The purpose of this study was to investigate the impact and use of real-time water quality data on a dry extended detention basin retrofitted with a controllable valve and a turbidity sensor. Such an assembly was theorized to be an advancement over static systems by allowing additional detention time during which sedimentation of particles could occur. The results showed highly variable detention times with 42% of storms reaching the turbidity threshold approximately 24 hours after the end of a rainfall event (minimum detention time) and 37% of events reaching the maximum detention time of 72 hours without reaching the required turbidity threshold. These highly variable detention times were the direct result of differences in initial turbidity magnitudes and the rate at which levels fell based on rainfall amounts and initial basin water depth conditions (as indicated by which variables were identified as consistently important during the modeling investigation). Overall, 63% of events met the 25 FNU turbidity threshold for water release before the maximum detention time, and the median turbidity value for all events in the study at release was 24.7 FNU. The water quality informed RTC strategy experienced a median minimum increase of 82% in hydraulic residence time when compared to the uncontrolled scenario using static infrastructure. Further, it was concluded that a system utilizing predetermined detention times would need to use the maximum detention time of 72 hours to match the efficiency of the water quality informed RTC strategy. While this is feasible to implement, it does not provide the numerous hydrologic benefits or adaptability of the water quality informed RTC. These combined results support the conclusion that the adaptive system integrated with real-time water quality data was effective in meeting water quality objectives that may not have been met with traditional systems, or those that rely on a predetermined detention time.

Several modeling approaches were investigated to determine if they could accurately estimate the detention time of the system (thereby negating the need for continued deployment of a turbidity sensor). The best performing models consisted of a logistic regression model using cumulative rainfall (mm) to predict detention time as well as a more advanced LSTM model which analyzed the time series data for rainfall and water depth of the basin to predict if turbidity was above or below the predetermined threshold (from which predicted detention time was determined). While the LSTM model outperformed the logistic regression model (MAE of 5.16 and 8.49 hours, respectively), the complexity and computational expense of generating a decision from the LSTM model may lead future users to abandon this for the simplicity of the logistic regression model. Overall, the results from this modeling investigation conclude that either the LSTM model or logistic regression model estimations for the detention time of the basin are comparable to those detention times determined using real-time water quality data. This indicates that after a period of data collection using a turbidity sensor, the sensor may be removed in favor of the basin being controlled by its site-specific model. This would assist municipalities in the widespread adoption of this technology as it would reduce the number of sensors necessary for multiple basins (economic resource allocation) as well as reduce the time and cost of sensor maintenance.

Future work is necessary to investigate and quantify the impact of this water quality informed RTC strategy beyond this study site. It is recommended that this system should be implemented on a diverse selection of dry extended detention basins (varying watershed and design characteristics) in order to corroborate the conclusions of this study and ensure that this system is broadly applicable. However, the results of this study, both field and modeling in origination, substantially advance the literature and should assist future studies investigating the use of water quality data to make real-time control decisions for stormwater infrastructure.

References

Anderson, C. W. 2005. "Chapter A6. Section 6.7. Turbidity." In *Techniques of Water-Resources Investigations*. Reston, VA: U.S. Geological Survey.

Campbell Scientific. 2017. "OBS501 Smart Turbidity Meter with ClearSensor Technology". Accessed December 16th, 2020. https://s.campbellsci.com/documents/us/manuals/obs501.pdf.

Clary, J., J. Jones, M. Leisenring, P. Hobson, and E. Strecker. 2020. "International Stormwater BMP Database: 2020 Summary Statistics." The Water Research Foundation. Accessed February 1st, 2020. https://www.waterrf.org/system/files/resource/2020-11/DRPT-4968_0.pdf.

Ganegedara, T. 2018. "Long Short-Term Memory Networks." In *Natural Language Processing with TensorFlow : Teach Language to Machines Using Python's Deep Learning Library*. Birmingham, UK: Packt Publishing Ltd., 201-228.

Genuer, R. and J. Poggi. 2020. *Random Forests with R*. Cham, Switzerland: Springer International Publishing.

Georgia Stormwater Management Manual. 2016. Atlanta Regional Commission.

Gilpin, A. and M. Barrett. 2014. "Interim Report on the Retrofit of an Existing Flood Control Facility to Improve Pollutant Removal in an Urban Watershed." In *World Environmental and Water Resources Congress 2014*, 65-74. Portland, Oregon: ASCE.

Hoppe, H., S. Messmann, A. Giga, and H. Gruening. 2011. "A real-time control strategy for separation of highly polluted storm water based on UV–Vis online measurements – from theory to operation." *Water Sci. Technol.*, 63 (10), 2287-2293. https://doi.org/10.2166/wst.2011.164.

Huffman, R. L., D. D. Fangmeier, W. J. Elliot, and S. R. Workman. 2013. *Soil and Water Conservation Engineering*. Seventh edition. St. Joseph, MI: ASABE.

Jacopin, C., E. Lucas, M. Desbordes, and P. Bourgogne. 2001. “Optimisation of Operational Management Practices for the Detention Basins.” *Water Sci. Technol.,* 44 (2-3), 277−285. https://doi.org/10.2166/wst.2001.0780.

Kerkez, B., C. Gruden, M. Lewis, L. Montestruque, M. Quigley, B. Wong, A. Bedig, R. Kertesz, T. Braun, O. Cadwalader, A. Poresky, and C. Pak. 2016. “Smarter Stormwater Systems.” *Environ. Sci. Technol.*, 50 (14), 7267-7273. https://doi.org/10.1021/acs.est.5b05870.

Knox County, Tennessee Stormwater Management Manual. 2008. Knox County Tennessee Department of Engineering and Public Works.

Middleton, J. R. and M. E. Barrett. 2008. “Water Quality Performance of a Batch-Type Stormwater Detention Basin.” *Water Environ. Res.*, 80 (2), 172-178. https://doi.org/10.2175/106143007X220842.

Mullapudi, A., M. Bartos, B. Wong, and B. Kerkez. 2018. “Shaping Streamflow Using a Real-Time Stormwater Control Network.” *Sensors*, 18 (2259), 1-11. https://doi.org/10.3390/s18072259.

Pyzoha, D. S. 1994. *Implementing a Stormwater Management Program*. Boca Raton, FL: Lewis Publishers.

Sazzad, S., W. McDonald, and A. J. Parolari. 2019. “Improved reliability of stormwater detention basin performance through water quality data-informed real-time control.” *J. Hydrol.*, 573 (2019), 422-431. https://doi.org/10.1016/j.jhydrol.2019.03.012.

U.S. Environmental Protection Agency. 2009. “Environmental Impact and Benefits Assessment for Final Effluent Guidelines and Standards for the Construction and Development

Category.” Accessed December 16th, 2020.
https://www.epa.gov/sites/production/files/2015-06/documents/cd_envir-benefits-assessment_2009.pdf.

CHAPTER 4: QUANTIFYING THE IN-STREAM HYDROLOGIC AND WATER QUALITY IMPACT OF A REAL-TIME CONTROLLED DRY EXTENDED DETENTION BASIN: A CASE STUDY

4.1. Abstract

Retrofitting the outlets of static stormwater infrastructure, such as dry extended detention basins, with controllable valves to increase or change detention times has been investigated as a solution for mitigating the effects of urbanization, climate change, and degraded infrastructure. While the hydrologic benefits of these retrofits have begun to be examined, no case studies exist which quantify the impact to a receiving stream's water quality following water release from an actively controlled detention period. The purpose of this case study was to investigate the hydrologic and water quality impact that a real-time controlled dry extended detention basin has on a receiving stream when water is released following a long period of detention. A dry extended detention basin in Knox County, Tennessee, was retrofitted with a controllable valve, and water quality and flow instrumentation was installed in the receiving stream downstream of the basin. When rainfall was detected, the basin's valve would close and detain all water for 72 hours following the end of rainfall. After this detention period the valve was opened, and the impact of the released water was quantified using real-time continuous measurement of stage, discharge, dissolved oxygen, temperature, and turbidity. A total of ten events were analyzed between August 15, 2020, and November 21, 2020, over the transition from summer into autumn. A SARIMA model was used to forecast future in-stream conditions (as if the basin's valve was not open) using the previous 48-hours of observed data from which the in-stream impact was quantified via any deviation beyond the 95% confidence interval for this forecast. Overall, the basin discharge caused median increases in the stream in stage (5.81 cm), discharge (0.02 m^3/s), temperature (0.60 °C), and turbidity (2.30 FNU). Conversely, no change in dissolved oxygen (0.00 mg/L) was observed, though the time of day the basin discharged appeared to affect dissolved oxygen trends. Additional case studies are recommended to further quantify

these impacts and better understand the implications of real-time control of stormwater infrastructure beyond the site scale.

4.2. Introduction

As the urban environment expands, larger fractions of precipitation are converted into stormwater runoff which flows across the landscape and collects in receiving streams and rivers (Pyzoha 1994; The Federal Interagency Stream Restoration Working Group 2001). Though stormwater runoff generation is a natural hydrologic process, these changes in landcover have exacerbated this process creating an increased intensity and volume of stormwater runoff which rapidly accumulates in receiving streams causing flooding and erosion (Dunne and Leopold 1978; Huffman et al. 2013). Compounding on these hydrologic issues are the pollutants (nutrients, bacteria, heavy metals, sediment, etc.) that stormwater runoff washes off and carries to receiving waterbodies that are detrimental to the aquatic life and the ecological health of the system (Huffman et al. 2013; Pyzoha 1994). Stormwater control measures (SCMs) are installed in watersheds to mitigate these impacts by attenuating flows and intercepting pollutants (Dunne and Leopold 1978). While SCMs are diverse in their design and objectives, this study will explore the use and impact of one common practice, dry extended detention basins, as a solution for stormwater management in urban watersheds.

Dry extended detention basins are surface storage facilities whose primary purpose is to attenuate flows coming from stormwater runoff to provide channel and flood protection for the receiving stream (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). These SCMs accomplish these objectives by temporarily detaining runoff during rainfall and slowly releasing water over the next 1 to 5 days (dependent on local guidance), while remaining dry between rainfall events (Georgia Stormwater

Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008; NCDEQ Stormwater BMP Manual 2017). While the primary benefit of these systems is peak flow attenuation and volume capture, by extending the time water is detained within the basin, pollutant removal and improvement in water quality is possible through trapping and settling of suspended sediment (Clary et at. 2020; Gaborit et al. 2013; Gaborit et al. 2016; Georgia Stormwater Management Manual 2016; Gilpin and Barrett 2014; Knox County, Tennessee Stormwater Management Manual 2008; Muschalla et al. 2014).

Even with the benefits of dry extended detention basins quantified, they are still static infrastructure, unable to adapt to changing rainfall patterns caused by climate change, its contributing watershed becoming increasingly urbanized, or re-evaluation of watershed restoration objectives. This is because these practices were designed to attenuate flows to pre-development conditions as determined by calculated peak flow using historical rainfall, and once these SCMs are installed it is very difficult to modify their performance or function (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Therefore, more adaptable solutions are required to solve these dynamic problems (Kerkez et al. 2016). Retrofitting static stormwater infrastructure with controllable outlets to increase or change detention times has been investigated as a dynamic and adaptable solution for urbanization, climate change, and degraded infrastructure (Boyle et al. 2016; Gaborit et al. 2013; Gaborit et al. 2016; Gilpin and Barrett 2014; Jacopin et al. 2001; Kerkez et al. 2016; Middleton and Barrett 2008; Mullapudi et al. 2018; Muschalla et al. 2014; Xu et al. 2020). Several of these studies have been able to leverage this technology to improve hydrologic conditions (such as a reduction in the exceedance of flow thresholds) in the receiving stream primarily by preventing water release during rainfall, utilizing innovative control algorithms, and/or communicating with downstream flow conditions (by integrating systems such as the stream gauging station presented in Chapter 2) upon release to ensure that flow thresholds are not exceeded (Boyle et al. 2016; Jacopin et al. 2001; Mullapudi et al. 2018). Additionally, these systems have been proven to increase pollutant removal efficiencies in the basin for TSS, bacteria, and nitrate/nitrite over their static infrastructure counterpart by extending the hydraulic residence time of the system (Gaborit et al. 2013; Gaborit et al. 2016; Gilpin and Barret 2014; Jacopin et al. 2001; Middleton and Barrett 2008; Muschalla et al. 2014). While these improvements in water quality are impressive, it should be noted that no case studies exist (to the authors' knowledge) which investigate how or if these improvements in the basin translate to in-stream conditions once the basin begins discharging, or how additional critical in-stream parameters (such as dissolved oxygen, temperature, and turbidity) are affected.

The hydrologic and water quality parameters of stage (stream depth), discharge, dissolved oxygen, temperature, and turbidity are a few parameters that can directly impact a receiving stream. Specifically, increases in stage, discharge, temperature, and turbidity as well as decreases in dissolved oxygen should be avoided whenever possible due to the potential effects described below (Swenson and Baldwin 1965; U.S. Environmental Protection Agency 2009). Significant increases in turbidity (a measurement of the scattering and absorption of light primarily elevated by suspended sediment) in a stream can negatively affect aquatic life by reducing photosynthetic activity, reducing food availability to fish and aquatic life, burying habitat, or by harming organisms directly by impacting respiration and digestive processes (U.S. Environmental Protection Agency 2009). Increases in temperature will influence water chemistry, primarily by decreasing the availability of dissolved oxygen (Swenson and Baldwin 1965). Extreme temperature fluctuations outside of natural cycles will impact aquatic organisms directly by influencing biological activity and the degree to which pollution affects aquatic life (Swenson and Baldwin 1965). Decreases in dissolved oxygen (a measure of oxygen availability in water) can negatively affect aquatic life as adequate levels are necessary for the majority of aquatic life to survive, with most aquatic life unable to tolerate levels below 3-5 mg/L (Swenson and Baldwin 1965). Meanwhile, increases in stage and discharge will primarily affect a receiving stream's channel and bed via erosion processes if maximum allowable thresholds are exceeded (Huffman et al. 2013).

4.2.1. Objective

While the hydrologic benefits to a receiving stream provided by real-time controlled dry extended detention basins have begun to be explored, no case studies (to the author's knowledge) exist which quantify the impact to a receiving stream's water quality following release of runoff that has been detained for an extended period. This constitutes a substantial gap in the literature as improvement of hydrologic conditions should not be at the expense of water quality. Therefore, the purpose of this case study was to investigate and quantify the hydrologic and water quality impact that a real-time controlled dry extended detention basin has on a receiving stream when releasing water following a period of extended detention.

4.3. Materials and Methods

4.3.1. Site Description

A dry extended detention basin in the Conner Creek watershed of Eastern Tennessee was retrofitted with a controllable valve (150 mm orifice), water depth sensor, and rain gauge to allow active management of the system (Figure 4.1, top). The contributing drainage area was 19.68 ha (86% impervious; SCS curve number of 94.70) and the basin could detain

Figure 4.1. Dry extended detention basin (top) retrofitted with a controllable valve, water depth sensor, and rain gauge following a rainfall event and (bottom) the downstream monitoring location outfitted with a custom stream gauging station and water quality instrumentation.

approximately 14,760 m^3 of water at a maximum stage of 3.05 m before water overtopped the outlet riser of the basin. When the valve was opened, water was discharged through the outlet riser and traveled approximately 60 m through a rock-lined channel before reaching Conner Creek. Water quality and flow instrumentation was installed on Conner Creek approximately 90 m downstream from where the basin's water met Conner Creek (Figure 4.1, bottom).

4.3.2. Monitoring Design

Flow instrumentation in Conner Creek consisted of a custom stream gauging station (presented in Chapter 2) which would continuously upload stage (±1.22 cm) measurements at a 1-minute frequency. From these stage measurements, discharge (m^3/s) was derived using an existing stage-discharge curve for the site. Water quality instrumentation consisted of YSI's EXO2 Multiparameter Water Quality Sonde which was connected to a custom control circuit that would wirelessly upload dissolved oxygen (±0.10 mg/L), temperature (±0.20 °C), and turbidity (±0.30 FNU) measurements at a < 10-minute frequency (YSI 2020). To protect this sensitive water quality instrumentation from harm or theft, it was placed in a flow cell in a secure box and water was pumped to it. A peristaltic pump was used to pump water to the EXO2's flow cell at a rate of approximately 1×10^{-5} m^3/s, which is within the recommended guidance for the instrumentation (YSI 2020). The entirety of the water quality setup was powered by three 100W solar panels charging two deep-cycle batteries (Figure 4.2).

4.3.3. Real-Time Control Strategy

A set of simple control rules for the dry extended detention basin were established. When rainfall was detected, the basin's valve would close and detain all water for 72 hours following the end of rainfall. This detention time was based on guidance for dry extended detention basins

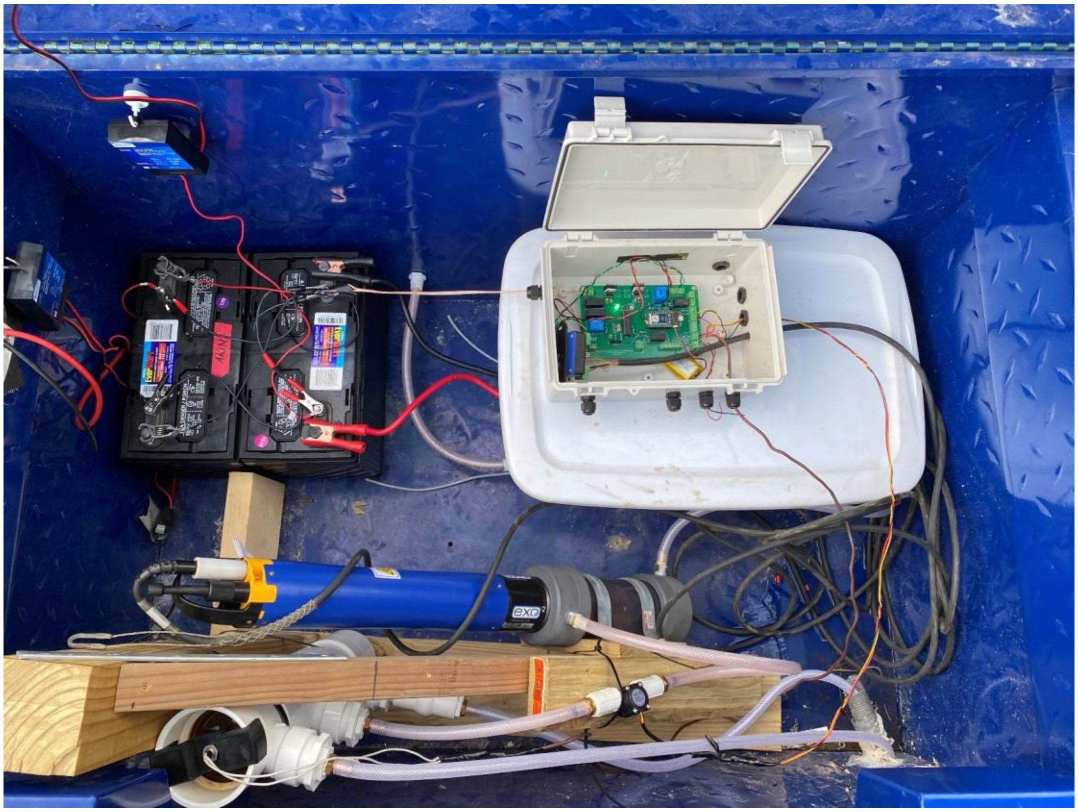

Figure 4.2. Top-down view of water quality instrumentation including EXO2 in flow cell (bottom center), custom control circuit for wirelessly uploading data (top right), peristaltic pump (top right - inside white tub), and deep-cycle batteries for power (top left).

for Georgia, North Carolina, and Knox County, TN (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008; NCDEQ Stormwater BMP Manual 2017). To ensure that insignificant rainfall events were not detained by the system, a minimum threshold of 6.35 mm of rainfall within 6 hours was required for the basin to detain a storm and be counted as an event within the study period. Additionally, secondary rainfall (rainfall which occurred >6 hours since the end of initial rainfall) also needed to meet the 6.35 mm threshold within 6 hours to reset the end of rainfall time used for determining when the 72-hour detention time had elapsed.

4.3.4. Data Analysis

After the detention period, the valve was opened (per the control rules) and the impact of the released water was observed. Specifically, the observed measurements were compared to those that were forecasted using Seasonal Auto Regressive Integrated Moving Average (SARIMA) models. SARIMA models fit autoregressive, differencing, moving average, and seasonal trends to time series data in order to describe the observed data and forecast future conditions (Cryer and Chan 2008). By focusing on the past temporal trends and the observed diurnal nature of these parameters, it is possible for these models to forecast in-stream conditions if no significant change in the system were to take place, i.e. if the basin was not discharging (Cryer and Chan 2008). Each model used the previous 48 hours of observed measurements prior to each instance of the basin discharging to forecast each parameter. This 48-hour window was chosen as it would allow the maximum time to determine temporal trends in the observed data without the rainfall event (which ended 72 hours prior to the basin discharging) substantially impacting these trends (shorter or longer observation windows resulted in reduced model performance). Through iterative investigation it was determined that the optimal SARIMA model for this study was one which used 0th order for the autoregressive, differencing, and moving average terms for the trend aspect of the model; 1st order for the autoregressive term, 0th order for the differencing and moving average terms, and 144th (24 hours) order for the seasonal aspects. This model was chosen as the form which consistently reported low Akaike Information Criterion (AIC) values in addition to qualitative analysis via observation. The effect of the basin discharging was quantified as any change in the measured parameter outside of the forecasted 95% confidence interval for every 10-minute time step while the basin was discharging that would negatively impact the system (i.e. negative impacts were defined as increases in stage, discharge, temperature, and turbidity or decreases in dissolved oxygen). Once the basin stopped discharging (either from the basin fully draining or the valve closing) the analysis was complete. An example of one of these SARIMA models can be seen in Figure 4.3, where the impact of the basin discharging can be seen by the sharp increase in temperature outside of the forecasted 95% confidence interval.

4.4. Results and Discussion

4.4.1. Summary of Collected Events

A total of 10 events were observed from August 15th, 2020, through November 21st, 2020, with an event being defined as the time between when rainfall begins and when the basin finishes discharging after the 72-hour detention time (either because the basin has been emptied or new rainfall was detected in which case the valve would close). No events were recorded after November 21st, 2020, because ambient temperatures routinely fell below the operating

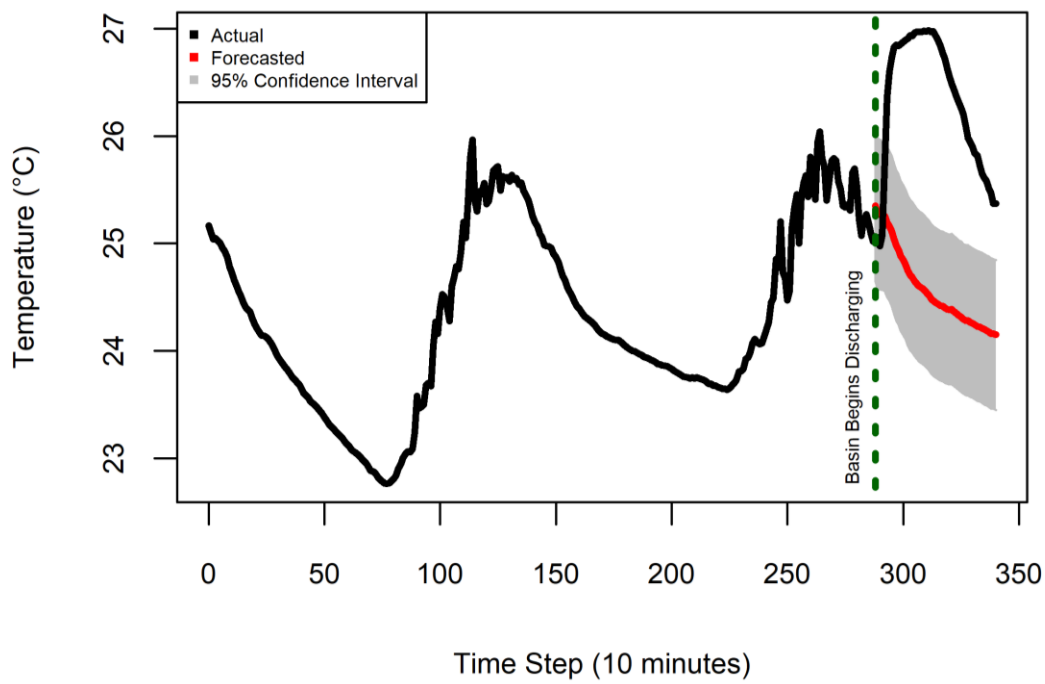

Figure 4.3. SARIMA model created to forecast temperature for event 2. Forecast begins when the basin begins discharging (valve opens) and continues until the basin is no longer discharging (valve closed or basin is fully drained).

temperature threshold for the water quality instrumentation (YSI 2020). A summary of the basin's conditions for each event can be found below in Table 4.1. To protect sensitive instrumentation in the basin from freezing conditions, event 10 had a significantly increased detention time of 207 hours to keep sensors in the basin below the water level (eliminating exposure to freezing temperatures). If an event experienced a >0.00 m initial basin stage (as was observed for events 3, 4, 5, and 6) this was caused by the basin not having enough time to fully drain the previously detained rainfall event before new rainfall was detected and the basin's valve closed (per the control strategy outlined above). A diversity of rainfall occurred between all of the events in this study with cumulative totals ranging from 8.13 to 64.52 mm (median of 27.43 mm).

4.4.2. Observed In-Stream Impact

Figure 4.4, below, is an example of the SARIMA forecasts and analysis for event 1. As noted above, the previous 48 hours of observed data was used in the creation of the in-stream forecast (with 95% confidence interval) for each parameter that begins when the basin's valve initially opens. While all other forecasts (and analysis) ended when the basin stopped discharging, this forecast was extended to demonstrate that the chosen SARIMA model was effective in forecasting each parameter over an extended time period. For this particular event two distinct peaks in the majority of the parameters are clearly visible. This was caused by the basin's valve clogging and requiring maintenance with the second peak occurring when the debris was removed, and the basin began discharging again. This also occurred during event 4. However, as with all other events, analysis and quantification of the in-stream impact only occurred while the basin was discharging. These in-stream responses for this event are

Table 4.1. Summary of basin conditions for each event collected in study.

Event	Start Time	Rainfall (mm)	Initial Basin Stage (m)	Maximum Basin Stage (m)	Valve Opened	Detention Time (h)
1	08/15/2020 17:30	9.65	0.00	0.69	08/18/2020 18:10	72
2	08/23/2020 08:40	32.00	0.00	1.03	08/28/2020 18:00	72
3	08/29/2020 02:40	18.80	0.91	1.18	09/03/2020 03:00	72
4	09/03/2020 14:40	8.13	1.04	1.86	09/06/2020 15:00	72
5	09/24/2020 15:20	45.97	0.01	1.60	09/28/2020 11:50	72
6	09/28/2020 19:10	22.10	0.85	1.31	10/02/2020 03:10	72
7	10/10/2020 02:30	50.04	0.00	1.49	10/14/2020 22:50	72
8	10/24/2020 02:20	22.86	0.00	1.03	10/27/2020 07:40	72
9	10/28/2020 08:20	64.52	0.00	2.24	11/01/2020 07:50	72
10	11/11/2020 13:00	38.61	0.00	1.26	11/20/2020 13:10	207
Median for All Events		27.43	0.00	1.29		
St. Dev for All Events		17.44	0.43	0.43		

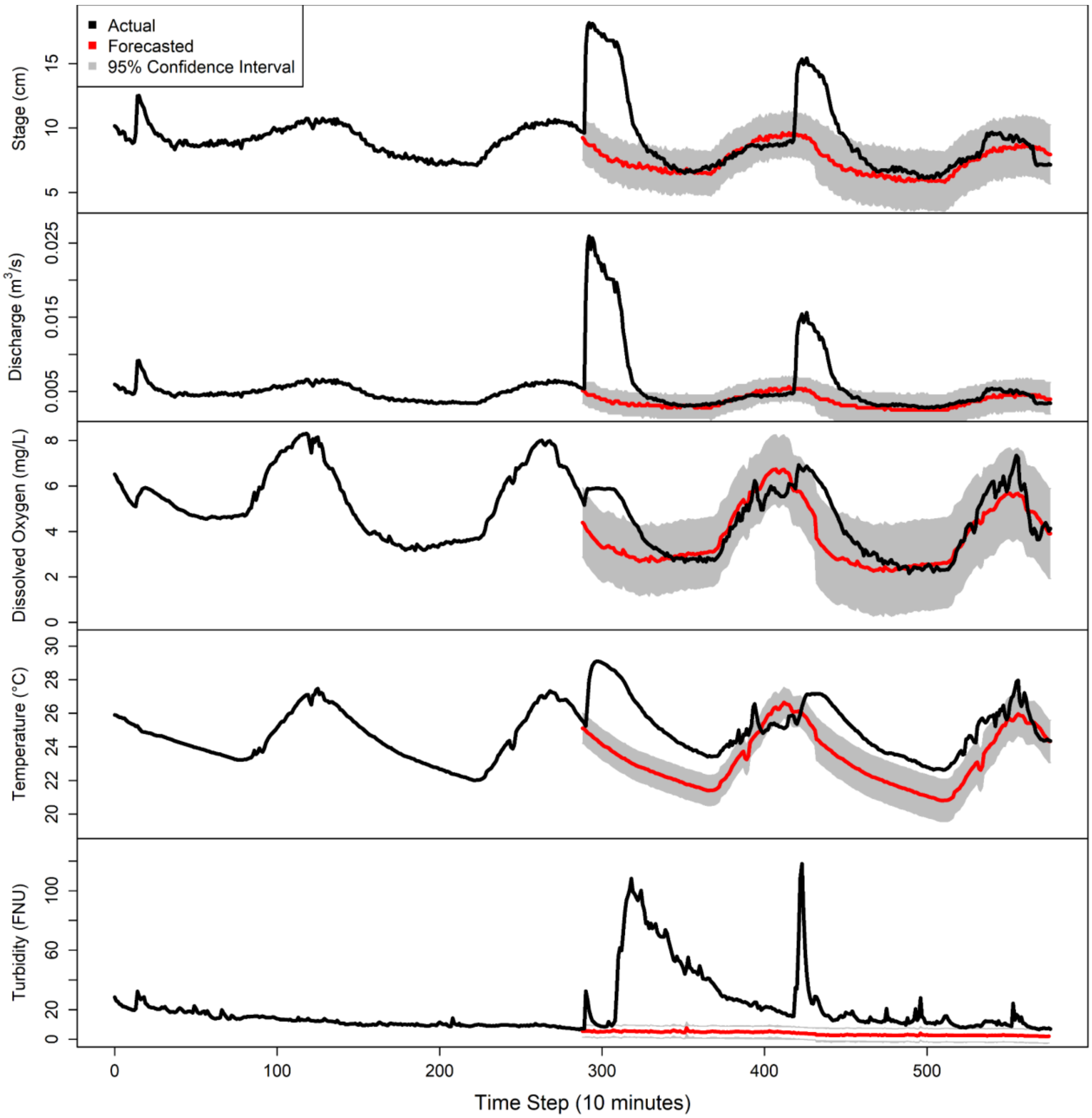

Figure 4.4. SARIMA forecasts and analysis for event 1. Forecasts began when the basin's valve initially opened and continued past when the basin finished discharging to demonstrate the effectiveness of this model to forecast each parameter over an extended time period.

representative of the majority of other events in this study in which stage and discharge were only elevated while the basin was discharging, dissolved oxygen experienced limited change, temperature substantially increased with a lasting effect, and turbidity spiked before quickly subsiding or substantially increased with a lasting effect (both are visible in Figure 4.4).

Table 4.2, below, summarizes the impact that the basin discharging had on every parameter for every event in the study as well as a summary of all 10 events. Impacts were defined and quantified as a deviation in the observed data from the forecasted 95% confidence interval that would negatively impact in-stream conditions (elevating stage, discharge, temperature, and turbidity or reducing dissolved oxygen) at each 10-minute time step while the basin was discharging. Metrics for quantifying these impacts included median change, maximum change, duration of the impact, and how long these impacts occurred relative to the duration of the basin discharging (% of basin discharging; Table 4.2). The full water quality impact of event 3 is not known as the monitoring instrumentation lost power for the first 6 hours of the basin discharging. Additionally, no hydrologic data is available for event 10 as that monitoring instrumentation lost power during the entirety of the basin discharging. The significantly higher turbidity impacts of event 3 (Table 4.2), was presumed to have been caused by excess sediment building up on the sensor while power was out. Overall, the basin discharging caused noticeable impacts (median change; % of basin discharging) in the stream in stage (5.81 cm; 98%), discharge (0.02 m^3/s; 98%), temperature (0.60 °C; 59%), and turbidity (2.30 FNU; 64%) and caused no change in dissolved oxygen (0.00 mg/L; 6%).

4.4.3. Significance of Observed In-Stream Impacts

While noticeable impacts in hydrologic and water quality parameters (except for

Table 4.2. In-stream impact to hydrologic and water quality parameters while basin was discharging.

Event (cumulative rainfall; maximum basin stage)	Impact Metrics	Hydrologic and Water Quality Parameters				
		Stage (cm)	Discharge (m^3/s)	Dissolved Oxygen (mg/L)	Temperature (°C)	Turbidity (FNU)
1	Median Change	4.39	0.009	0.00	1.68	9.99
(9.65 mm; 0.69 m)	Maximum Change	7.8	0.02	0.00	4.00	110.04
	Duration of Impact (h)	7.17	7.17	0.00	6.00	6.33
	% of Basin Discharging	93	93	0	78	83
2	Median Change	3.49	0.005	0.00	1.25	16.52
(32.00 mm; 1.03 m)	Maximum Change	5.77	0.012	0.00	1.81	109.37
	Duration of Impact (h)	8.5	8.33	0.00	8.00	8.50
	% of Basin Discharging	96	94	0	91	96
3	Median Change	2.42	0.003	0.00	0.61	100.43
(18.80 mm; 1.18 m)	Maximum Change	5.71	0.015	0.00	1.79	506.00
	Duration of Impact (h)	11.67	11.67	0.00	4.67	5.50
	% of Basin Discharging	99	99	0	85	100
4	Median Change	6.64	0.019	0.00	2.92	0.48
(8.13 mm; 1.86 m)	Maximum Change	7.87	0.023	0.00	4.81	74.71
	Duration of Impact (h)	15.33	15.33	0.00	14.67	8.67
	% of Basin Discharging	98	98	0	94	55
5	Median Change	7.48	0.029	0.00	0.00	1.96
(45.97 mm; 1.60 m)	Maximum Change	8.34	0.035	0.00	0.78	54.13
	Duration of Impact (h)	7.33	7.33	0.00	3.33	6.17
	% of Basin Discharging	98	98	0	44	82

Table 4.2 continued. In-stream impact to hydrologic and water quality parameters while basin was discharging.

Event (cumulative rainfall; maximum basin stage)	Impact Metrics	Hydrologic and Water Quality Parameters				
		Stage (cm)	**Discharge (m^3/s)**	**Dissolved Oxygen (mg/L)**	**Temperature (°C)**	**Turbidity (FNU)**
6	Median Change	5.49	0.018	0.00	0.00	0.00
(22.10 mm; 1.31 m)	Maximum Change	7.81	0.021	0.00	0.08	26.00
	Duration of Impact (h)	16.33	16.33	0.00	1.00	3.00
	% of Basin Discharging	98	98	0	6	18
7	Median Change	6.39	0.051	0.00	2.11	8.05
(50.04 mm; 1.49 m)	Maximum Change	7.43	0.073	-0.55	3.04	10.54
	Duration of Impact (h)	16.67	16.67	6.83	16.33	16.83
	% of Basin Discharging	99	99	41	97	100
8	Median Change	12.51	0.07	0.00	0.84	2.14
(22.86 mm; 1.03 m)	Maximum Change	13.28	0.085	0.00	1.80	26.69
	Duration of Impact (h)	12.17	12.17	0.00	8.17	12.17
	% of Impact	97	97	0	65	97
9	Median Change	3.98	0.04	0.00	0.00	0.00
(64.52 mm; 2.24 m)	Maximum Change	6.02	0.056	0.00	0.54	111.03
	Duration of Impact (h)	15.17	15.17	0.00	0.17	0.67
	% of Basin Discharging	99	99	0	1	4
10	Median Change	N/A	N/A	0.00	0.72	2.77
(38.61 mm; 1.26 m)	Maximum Change	N/A	N/A	-0.16	1.13	34.41
	Duration of Impact (h)	N/A	N/A	3.17	12.83	12.50
	% of Basin Discharging	N/A	N/A	24.00	99	96
Overall	Median Change	**5.81**	**0.019**	**0.00**	**0.60**	**2.30**
	Maximum Change	**13.28**	**0.085**	**-0.55**	**4.81**	**506.00**
	% of Basin Discharging	**98**	**98**	**6**	**59**	**64**

dissolved oxygen) were consistently observed throughout this study while the basin was discharging, these changes may not be substantial. To investigate if the observed impact to a parameter was substantial for a given event, each parameter was analyzed to discern if the observed changes occurred outside the natural diurnal cycle of the stream. This was accomplished by creating boundaries for the diurnal fluctuations of each parameter using the minimum and maximum daily values of what was forecasted and what was observed during the previous 48 hours. The actual measurements when the basin was discharging were then compared to these boundaries to see if any were outside this range. An example of this can be seen below in Figure 4.5 where the observed increase in temperature was significant enough to extend outside the natural diurnal cycle. This trend was identified for the vast majority of events and parameters.

The substantial increase and duration (98% of the time while the basin discharges) in the hydrologic parameters were expected due to the rate at which the basin discharges and are a function of physical properties of the basin such as orifice size and stage in the basin (i.e. flow rate based on driving head). If these increases were to rise to levels where erosion or in-stream habitat degradation started to occur, then the hydrologic impact of the real-time controlled dry extended detention basin would be considered detrimental to the ecological health of the system. However, for this case study this is unlikely as stage and discharge routinely (during rainfall events) rose above the thresholds observed when the basin discharged. The increases in turbidity and temperature (impacts from both occurred at a similar frequency; Table 4.2) are likely linked more directly to internal processes of the basin. The increase in temperature is presumably due to the stagnant water of the basin being heated via solar radiation while the turbidity increase is either caused by sediment being discharged from the basin or resuspension of settled sediment in

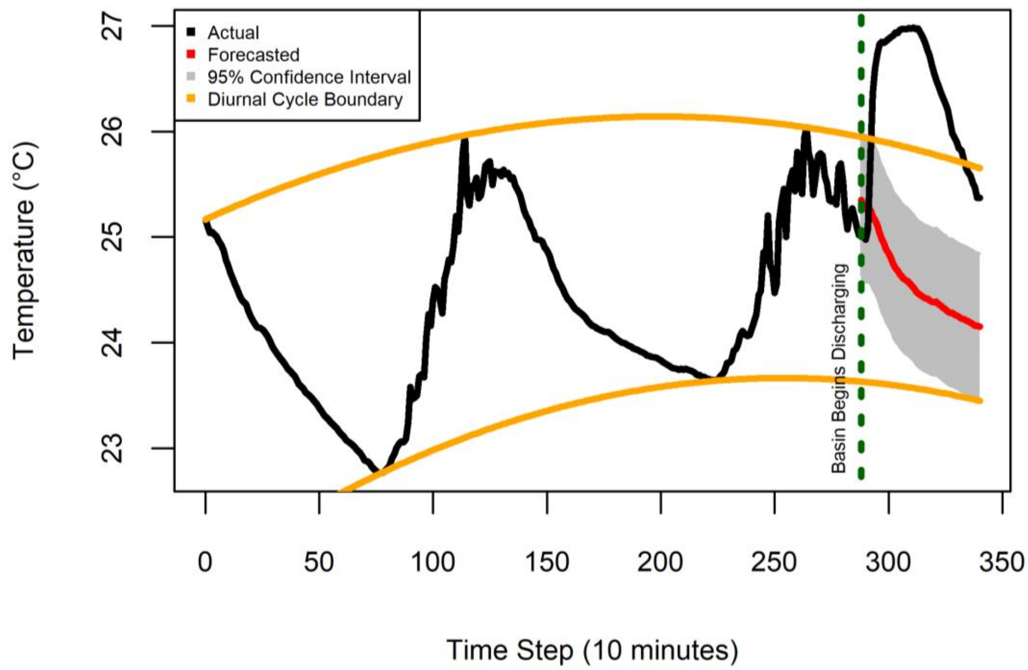

Figure 4.5. Analysis of the observed increase in temperature while the basin was discharging for event 2 concluded that it occurred outside of the natural diurnal cycle.

the stream itself when discharge increases (Eder et al. 2014). However, it can be inferred that the impact of turbidity directly linked to sediment being discharged from the basin was likely reduced due to the increased hydraulic residence time of the system (a topic previously explored; Chapter 3). Additionally, the increase in temperature due to the basin discharging during warm weather events (events 1, 2, and 4) exceeded the state of Tennessee's maximum rate of change and, while none exceeded the overall temperature threshold of 30.5 °C, events 1 and 3 were within ~2 °C showing a maximum deviation of ~1.6°C from the 95% confidence interval for forecasted temperature if the basin had not been discharging (U.S. Environmental Protection Agency 2019). Thus, there is evidence to suggest that the basin discharging may be a concern for stream temperatures during warm weather events, and, to limit these thermal impacts, it may be necessary to reduce the detention time of the system provided that this change does not significantly worsen other parameters. Future work is necessary to analyze the impact these observed changes (especially turbidity and temperature) have on aquatic ecology to determine if it is significantly affected or if these changes can be ignored from a regulatory perspective.

While it was originally concluded that no (or limited) negative impacts to dissolved oxygen occurred while the basin was discharging (i.e. reduction in in-stream dissolved oxygen), it appears that time of day when the basin discharges seems to play a vital role in the in-stream response. It was observed that substantial improvements in dissolved oxygen occurred when the basin began discharging in the evening, with events that discharged in the evening during warm weather (events 1, 2, and 4) decreasing the time the stream spent below the state of Tennessee's threshold of 5 mg/L for fish and aquatic life (U.S. Environmental Protection Agency 2019). An example of this phenomenon can be seen below in Figure 4.6. Therefore, it may be possible to

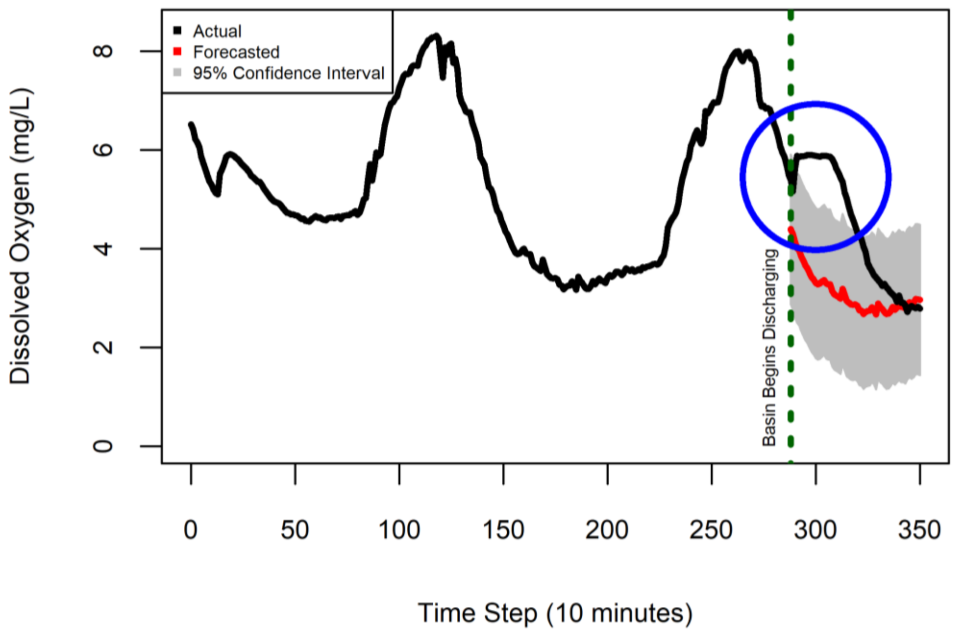

Figure 4.6. Observed increase in dissolved oxygen during event 1 when basin initially discharges.

leverage real-time controlled SCMs to reduce the occurrence of dissolved oxygen levels falling below thresholds harmful to aquatic life. The efficacy of this method may increase with additional SCMs being controlled (i.e. through system-level control algorithms) as the system-wide storage would increase. However, it is unknown how much storage and release would be needed to make a noticeable improvement over multiple days and weeks. Future studies analyzing this phenomenon and how it may be leveraged for ecological gain are recommended.

4.5. Conclusions

The purpose of this case study was to investigate the hydrologic and water quality impact that discharge from a real-time controlled dry extended detention basin has on a receiving stream. A dry extended detention basin was retrofitted with a controllable outlet while water quality and flow instrumentation were installed in the receiving stream downstream of the basin outfall. When rainfall was detected, the basin's valve would close and detain all water for 72 hours following the end of rainfall. After this detention period the valve was opened, and the impact of the released water was quantified by comparing the real-time continuous measurement of turbidity, dissolved oxygen, temperature, stage, and discharge to what was forecasted if the basin did not discharge.

A total of ten events were analyzed between August 15, 2020, and November 21, 2020, which included the transition from summer into autumn. The majority of events experienced similar impacts to in-stream conditions in which stage and discharge were elevated as a function of the basin stage (driving head), dissolved oxygen experienced limited change, and temperature and turbidity were substantially increased though not for the entire time the basin was discharging. Overall, the basin discharging resulted in the following changes in-stream (median change; % of basin discharging): stage (5.81 cm; 98%), discharge (0.02 m^3/s; 98%), temperature (0.60 °C; 59%), turbidity (2.30 FNU; 64%), and dissolved oxygen (0.00 mg/L; 6%).

Further analysis into these noticeable changes determined that these changes are substantial enough to occur outside of the natural diurnal cycle (except for dissolved oxygen), though the impact to aquatic life and ecological health of the stream is unknown and requires additional study. It is unlikely that the observed changes in the hydrologic conditions (stage and discharge) were substantial enough in this case study to be detrimental to aquatic life as more extreme changes were routinely observed during rainfall events. However, concerning impacts to in-stream temperature and turbidity were observed during this study that should be further studied. For example, during warm weather events, the rapid rise in in-stream temperature when the basin was opened exceeded local regulations with two of these events approaching the maximum water temperature threshold (within ~2 °C). Additionally, the change in initial turbidity was extreme once the valve opened, and while the majority of events quickly subsided, several events experienced lasting effects (i.e. elevated turbidity levels). Lastly, while it was concluded that dissolved oxygen experienced no change while the basin was discharging, time of day when the basin discharges has a substantial effect on the significance of this impact. Specifically, events which discharged in the evening during warm weather improved in-stream dissolved oxygen and decreased the time the stream spent below the threshold harmful to aquatic life. Therefore, it may be possible to leverage real-time controlled SCMs in conjunction with in-stream dissolved oxygen sensors to time basin discharges such that dissolved oxygen levels are prevented from falling below thresholds harmful to aquatic life. The results of this study should assist future research investigating the in-stream impact of real-time controlled stormwater infrastructure.

References

Boyle, R., A. Poresky, O. Cadwalader, and S. Landers. 2016. “Stormwater Real Time Controls at the Watershed Scale: Evaluating the Business Case and Developing an Implementation Roadmap for an Oregon MS4.” In *Proc., Water Environment Federation*, 750-755. New Orleans, LA: WEF. https://doi.org/10.2175/193864716819705997.

Clary, J., J. Jones, M. Leisenring, P. Hobson, and E. Strecker. 2020. “International Stormwater BMP Database: 2020 Summary Statistics.” The Water Research Foundation. Accessed February 1st, 2020. https://www.waterrf.org/system/files/resource/2020-11/DRPT-4968_0.pdf.

Cryer, J., and K. Chan. 2008. *Time Series Analysis With Applications in R*. Second Edition. New York, NY: Springer Science+Business Media, LLC.

Dunne, T. and L. B. Leopold. 1978. *Water in Environmental Planning*. San Francisco, CA: W.H. Freeman and Company.

Eder, A., M. Exner-Kittridge, P. Strauss, and G. Blöschl. 2014. “Re-suspension of bed sediment in a small stream – results from two flushing experiments.” *Hydrology and Earth Science Systems*, 18, 1043-1052. https://doi.org/10.5194/hess-18-1043-2014.

Gaborit, E., D. Muschalla, B. Vallet, P. A. Vanrolleghem, and F. Antcil. 2013. “Improving the performance of stormwater detention basins by real-time control using rainfall forecasts.” *Urban Water Journal*, 10 (4), 230-246. https://doi.org/10.1080/1573062X.2012.726229.

Gaborit, E., F. Antcil, G. Pelletier, and P. A. Vanrolleghem. 2016. “Exploring forecast-based management strategies for stormwater detention ponds.” *Urban Water Journal*, 13 (8), 541-851. https://doi.org/10.1080/1573062X.2015.1057172.

Georgia Stormwater Management Manual. 2016. Atlanta Regional Commission.

Gilpin, A. and M. Barrett. 2014. "Interim Report on the Retrofit of an Existing Flood Control Facility to Improve Pollutant Removal in an Urban Watershed." In *World Environmental and Water Resources Congress 2014*, 65-74. Portland, Oregon: ASCE. https://doi.org/10.1061/9780784413548.009.

Huffman, R. L., D. D. Fangmeier, W. J. Elliot, and S. R. Workman. 2013. *Soil and Water Conservation Engineering*. Seventh edition. St. Joseph, MI: ASABE.

Jacopin, C., E. Lucas, M. Desbordes, and P. Bourgogne. 2001. "Optimisation of Operational Management Practices for the Detention Basins." *Water Sci. Technol.*, 44 (2-3), 277−285. https://doi.org/10.2166/wst.2001.0780.

Kerkez, B., C. Gruden, M. Lewis, L. Montestruque, M. Quigley, B. Wong, A. Bedig, R. Kertesz, T. Braun, O. Cadwalader, A. Poresky, and C. Pak. 2016. "Smarter Stormwater Systems." *Environ. Sci. Technol.*, 50 (14), 7267-7273. https://doi.org/10.1021/acs.est.5b05870.

Knox County, Tennessee Stormwater Management Manual. 2008. Knox County Tennessee Department of Engineering and Public Works.

Middleton, J. R. and M. E. Barrett. 2008. "Water Quality Performance of a Batch-Type Stormwater Detention Basin." *Water Environ. Res.*, 80 (2), 172-178. https://doi.org/10.2175/106143007X220842.

Mullapudi, A., M. Bartos, B. Wong, and B. Kerkez. 2018. "Shaping Streamflow Using a Real-Time Stormwater Control Network." *Sensors*, 18 (2259), 1-11. https://doi.org/10.3390/s18072259.

Muschalla, D., B. Vallet, F. Antcil, P. Lessard, G. Pelletier, and P. A. Vanrolleghem. 2014. "Ecohydraulic-driven real-time control of stormwater basins." *J. Hydrology*, 511 (2014), 82-91. https://doi.org/10.1016/j.jhydrol.2014.01.002.

NCDEQ Stormwater BMP Manual. 2017. North Carolina Department of Environmental Quality.

Pyzoha, D. S. 1994. *Implementing a Stormwater Management Program*. Boca Raton, FL: Lewis Publishers.

Strassler, E., J. Pritts, and K. Strellec. 1999. "Description and Performance of Storm Water Best Management Practices." In *Preliminary Data Summary of Urban Stormwater Best Management Practices*. Washington, DC: U.S. Environmental Protection Agency.

Swenson, H. A., and H. L. Baldwin. 1965. "A primer on water quality". In *General Interest Publication*. Washington, DC: U.S. Government Printing Office. https://doi.org/10.3133/7000057.

The Federal Interagency Stream Restoration Working Group. 2001. *Stream Corridor Restoration: Principles, Processes, and Practices*. Washington, DC: U.S. Government Publishing Office.

U.S. Environmental Protection Agency. 2019. "Chapter 0400-40-03 General Water Quality Criteria." In *Rules of the Tennessee Department of Environment and Conservation*. https://www.epa.gov/sites/production/files/2014-12/documents/tn-chapter1200-4-3.pdf.

U.S. Environmental Protection Agency. 2009. "Environmental Impact and Benefits Assessment for Final Effluent Guidelines and Standards for the Construction and Development Category." Accessed December 16th, 2020. https://www.epa.gov/sites/production/files/2015-06/documents/cd_envir-benefits-assessment_2009.pdf.

Xu, W. D., M. J. Burns, F. Cherqui, and T. D. Fletcher. 2021. "Enhancing stormwater control measures using real-time control technology: a review." *Urban Water J.*, 18 (2), 101-114. https://doi.org/10.1080/1573062X.2020.1857797.

YSI. 2020. “EXO User Manual.” Accessed February 1st, 2020.
https://www.ysi.com/File%20Library/Documents/Manuals/EXO-User-Manual-Web.pdf.

CHAPTER 5: IMPACT OF REAL-TIME CONTROL ON THE HYDROLOGY AND DESIGN PARAMETERS OF WET PONDS AND DRY EXTENDED DETENTION BASINS

5.1. Abstract

The purpose of this study was to investigate the impact that various real-time control strategies have on the hydrology and design parameters of wet ponds and dry extended detention basins. Two dry extended detention basins (one large and one small) retrofitted with real-time controllable infrastructure were modeled in PCSWMM. Following calibration (NSE = 0.82 for the large basin; NSE = 0.92 for the small basin) and validation, each model was modified to simulate a wet pond by incorporating a permanent pool. Four control strategies for the wet pond scenarios and three control strategies for the dry extended detention basin scenarios were analyzed in this study and represented a diverse selection of RTC methodology. The results of this study found that RTC has the potential to improve or attenuate SCM discharge to the receiving stream with control strategies which integrated rainfall forecasts into the decision framework able to meet this objective more consistently (up to a 43% reduction in intra-storm discharge as compared to the 33% possible with reactive strategies). Wet ponds equipped with RTC showed the most promise during this investigation, with control strategies which proactively drew down a portion of the wet pond's permanent pool before a rainfall event able to (in some cases) completely mitigate stormwater runoff. Due to this reason, RTC seems to impact the design parameters (such as required storage volume) of wet ponds more than dry extended detention basins. Specifically, control strategies which targeted reducing usage of the wet pond's temporary storage zone only required 14-62% (dependent on site-specific factors) of the temporary storage zone to achieve similar (or improved) performance to that of a static system. Therefore, it may be possible to reduce the overall volume of wet ponds integrated with RTC by 19-65%, which would be a benefit to economic resource allocation or would provide an incentive to land developers to install RTC stormwater infrastructure in lieu of traditional, static

systems. While each control strategy explored in this study successfully met their respective objectives and improved system performance beyond existing conditions, special care should be taken to ensure that implementation of RTC does not exacerbate existing conditions such as increasing the frequency of outlet overtopping.

5.2. Introduction

5.2.1. Dry Extended Detention Basins

Dry extended detention basins are surface storage facilities whose primary purpose is to attenuate flows coming from stormwater runoff to provide channel and flood protection for the receiving stream (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). These stormwater control measures accomplish these objectives by temporarily detaining runoff during rainfall and slowly releasing it over the next 1 to 3 days (dependent on local guidance) while remaining dry between rainfall events (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Stormwater management is achieved by sizing the basin's outlet structures appropriately so that the peak flow is attenuated to match pre-development conditions (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). However, once these practices are installed, they are unable to adapt to changing rainfall or landcover conditions.

5.2.2. Wet Ponds

Similar to dry extended detention basins, wet ponds (also referred to as retention ponds or stormwater ponds) are surface storage facilities for stormwater runoff but include a permanent pool for retention in addition to a temporary storage zone for runoff quantity control (Georgia

Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). During rainfall events, stormwater runoff up to the site's water quality volume is detained within the permanent pool through displacement of existing water, with anything greater detained above in the temporary storage zone (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Similar to dry extended detention basins, channel and flood protection for the receiving stream is provided by sizing the wet pond's outlet structure for appropriate peak flow attenuation to match pre-development conditions (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Also as is the case with dry extended detention basins, once this practice is installed it is unable to adapt to changing rainfall or landcover conditions. These practices provide considerably more pollutant removal than dry extended detention basins through settling of sediment and biological uptake in the permanent pool (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). Additional advantages of wet ponds over dry extended detention basins include more aesthetic designs which lead to higher community acceptance as well as opportunities for wildlife habitat (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). While the permanent pool feature is the primary cause of these benefits, it does increase the overall volume, and in some cases surface area, required for this practice to be installed.

5.2.3. Real-time Control for Stormwater Infrastructure

Both wet ponds and dry extended detention basins qualify as static stormwater infrastructure, or infrastructure that is unable to adapt to changing conditions such as rainfall increasing in magnitude and frequency due to climate change, its contributing watershed becoming increasingly urbanized, or re-evaluation of watershed restoration objectives. Retrofits of these practices with controllable outlets to change detention times or increase flow attenuation have been explored as a more dynamic and adaptable solution (Boyle et al. 2016; Gaborit et al. 2013; Gaborit et al. 2016; Gilpin and Barrett 2014; Jacopin et al. 2001; Kerkez et al. 2016; Mullapudi et al. 2018; Muschalla et al. 2014; Wong and Kerkez 2018; Xu et al. 2020). Several of these studies have been able to leverage this technology to improve hydrologic conditions (such as a reduction in the exceedance of flow thresholds) in the receiving stream primarily by preventing water release during rainfall, utilizing innovative control algorithms, and communicating with downstream flow conditions upon release to ensure that flow thresholds are not exceeded (Boyle et al. 2016; Jacopin et al. 2001; Mullapudi et al. 2018; Wong and Kerkez 2018). Additionally, there is evidence to suggest that implementation of these retrofits in certain situations can actually decrease the required volume of the system by up to 50% and still achieve adequate performance (Boyle et al. 2016; Wong and Kerkez 2018).

5.2.4. Objective

The application of real-time control (RTC) for stormwater management is a relatively novel research area, which makes contextualization of the broader implications of a diverse set of RTC strategies necessary to corroborate existing studies and inform future work and applications. Compounding on this issue is that the majority of existing studies have focused on the impacts of RTC on dry extended detention basins, with limited investigation of how RTC can be uniquely leveraged with wet pond systems. The purpose of this study was to investigate the impact that a diverse selection of RTC strategies has on the hydrology and design parameters of wet ponds and dry extended detention basins and to contextualize the unique advantages of each strategy explored.

5.3. Materials and Methods

5.3.1. Site Description

Two dry extended detention basins (approximately 100 m apart) in the Conner Creek watershed of Eastern Tennessee detain and attenuate stormwater runoff generated by nearby schools, parking lots, and practice fields. These two basins will be referred to as “Large Basin” and “Small Basin” throughout the remainder of this study due to their relative size as compared to one another. The contributing drainage area of the large basin is 20 ha as compared to 4 ha for the small basin, including their surface area. During rainfall events, stormwater runoff is generated and routed to the basins. The large basin can detain approximately 14,760 m^3 of water at a maximum stage of 3.13 m while the small basin can detain approximately 760 m^3 of water at a maximum stage of 1.24 m before water overtops each basin’s respective outlet structure (Figure 5.1). The outlet structure of each basin is also equipped with one or more passive bypass orifices which helps to attenuate larger flows to pre-developed conditions (Figure 5.1). To make full use of the available storage of each system when implementing RTC, and to further attenuate discharge leaving the system, the bypass orifices were plugged to prevent any discharge (note: they were left open during uncontrolled modeling scenarios as described in subsequent sections). Once passive pieces of stormwater infrastructure, these basins have since been retrofitted with controllable valves (0.15 m orifice for the large basin; 0.05 m for the small basin), stage (or water depth above a reference) sensors, and a rain gauge to transform them into real-time controllable, or “smart”, stormwater infrastructure. The large basin has been online since

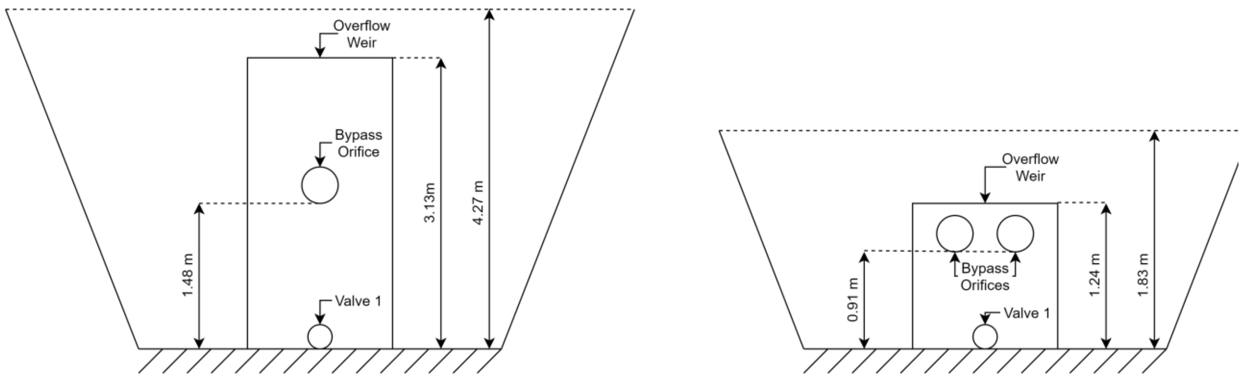

Figure 5.1. Diagram of dry extended detention basin outlet structures for the large basin (left) and small basin (right) detailing placement of valves, orifices, and overflow weirs (not to scale).

October of 2019 and the small basin has been online since January of 2020 and each system continuously reports stage, rainfall, and the state of their valve (percent open). Data is wirelessly uploaded for real-time data viewing and analysis at a < 10-minute interval.

5.3.2. Models Implemented in Study

5.3.2.1 Dry Extended Detention Basin Models

Models of the existing dry extended detention basins' watersheds and drainage networks were created using the Personal Computer Storm Water Management Model (PCSWMM; Computational Hydraulics International; version 7.3.3095) for use in the evaluation of real-time control strategies and scenarios (Figure 5.2). Data for the drainage networks (pipe properties, delineation of subcatchments, etc.) were derived from construction and planning documents and data provided by Knoxville GIS, while soil data (texture, infiltration properties, etc.) were obtained from the Natural Resources Conservation Service's Web Soil Survey (Natural Resources Conservation Service 2021). The models implemented a modified Green-Ampt model for subcatchment infiltration, dynamic wave routing at 5 second intervals, and 10-minute reporting steps. Additionally, for reasons that will be discussed further, variable time steps and skipping of steady flow periods were disabled.

PCSWMM's Sensitivity-based Radio Tuning Calibration (SRTC) tool was used to calibrate the models as the tool allows for the quick assessment and tuning of model parameters and calibration to an observed data set (CHI Support 2021). The observed data set used for calibration of the large basin's model was a month-long period of stage data starting in December of 2019 which included 7 rainfall events for a cumulative rainfall total of 227.33 mm. Meanwhile, the observed data set used for calibration of the small basin's model was a 2-week

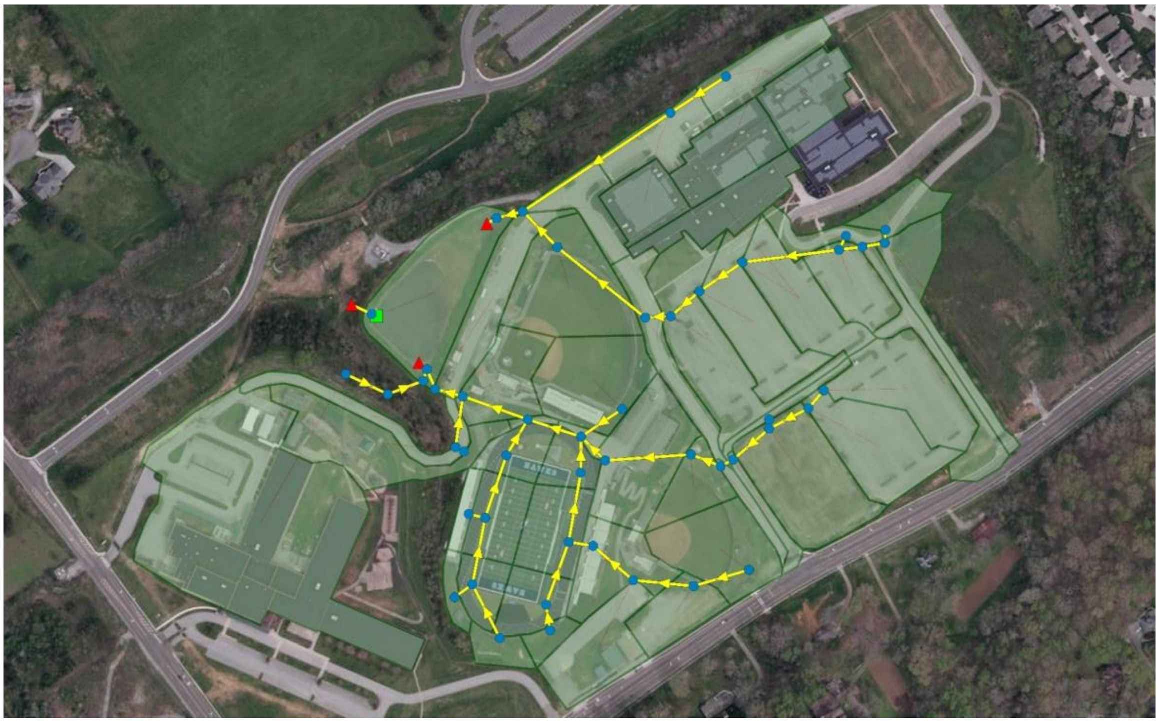

Figure 5.2. Map of the large basin's watershed overlayed with PCSWMM's representation of the drainage network.

period of stage data starting in February of 2020 which included 5 rainfall events for a cumulative rainfall total of 220.22 mm. In both observed time series used for calibration, no manipulation of the basin's valve occurred (left fully open). The calibration process (analyzed for the duration of the calibration period at 10-minute time steps) resulted in models with Nash-Sutcliffe Efficiencies of 0.82 and 0.92 for the large and small basins, respectively. Removal of periods where both simulated and observed data was zero (only accounting for when the basin was detaining water) decreased these values to 0.79 and 0.90, respectively (Table 5.1). A series of five validation events for each basin were then modeled. These validation events represented a diverse selection of cumulative rainfall to ensure that the calibrated models were applicable in a wide range of scenarios and had not been overfitted. While the observed data used for validation of the large basin included manipulation of the valve via RTC, no validation events for the small basin model utilized RTC as no data for this scenario was available. Overall, validation events for the large basin which utilized RTC outperformed the baseline calibration with Nash-Sutcliffe Efficiencies reaching as high as 0.98 for the entire simulation and 0.97 for non-zero periods (Table 5.1). These results indicate that the models will accurately predict conditions in each basin during rainfall events, especially for the larger basin in scenarios where RTC is utilized. A summary of the model calibration and validation results can be seen below in Table 5.1.

5.3.2.1 Wet Pond Models

Each calibrated dry extended detention basin model was manipulated to simulate the conditions of a wet pond. This was achieved by creating additional storage (wet pond permanent pool storage) below the existing detention basin bottom (wet pond temporary storage) in each model. The dimensions and storage volumes of each permanent pool were designed to capture the entirety of the water quality volume for each site and followed all local technical guidance

Table 5.1. Summary of model calibration and validation results.

Model	Event	Simulation Start	Simulation End	Cumulative Rainfall (mm)	RTC Used?	NSE of Stage: Entire Simulation	NSE of Stage: Non-Zero Periods
Large Basin	Calibration	12-07-2019 21:20	01-13-2020 10:50	227.33	No	0.82	0.79
	Validation #1	06-20-2020 03:10	06-25-2020 04:10	36.58	No	0.82	0.79
	Validation #2	07-30-2020 14:10	07-31-2020 15:30	23.11	No	0.46	0.42
	Validation #3	12-11-2020 13:40	12-23-2020 12:30	41.66	Yes	0.98	0.97
	Validation #4	10-09-2020 03:40	10-19-2020 03:30	52.07	Yes	0.98	0.95
	Validation #5	10-28-2020 02:40	11-08-2020 04:10	64.52	Yes	0.91	0.86
Small Basin	Calibration	02-03-2020 00:00	02-17-2020 00:00	220.22	No	0.92	0.90
	Validation #1	05-03-2021 08:00	05-08-2021 00:00	78.23	No	0.87	0.86
	Validation #2	04-12-2020 00:00	04-16-2020 00:00	69.09	No	0.96	0.95
	Validation #3	03-25-2021 00:00	04-03-2021 00:00	147.83	No	0.88	0.87
	Validation #4	02-17-2021 20:00	02-20-2021 00:00	24.64	No	0.64	0.62
	Validation #5	01-23-2020 11:20	01-26-2020 11:40	30.48	No	0.68	0.60

(Knox County, Tennessee Stormwater Management Manual 2008). No changes were made to the dimensions of the temporary storage zones (dry extended detention basins) as they already met the design standards for each wet pond (Knox County, Tennessee Stormwater Management Manual 2008). The designed permanent pools for both scenarios (large and small basin) have a maximum stage of 1.52 m with total storage volumes of 4461 m^3 and 786 m^3 for the large basin and small basin, respectively. To access this additional available storage during simulations or manipulate stage of the permanent pool, a controllable valve (Valve 2 in Figure 5.3) was added to each model at the base of the permanent pool and, similar to Valve 1, was assigned a diameter of 0.15 m for the large basin and 0.05 m for the small basin.

5.3.2.2 Predicting Stormwater Runoff

The calibrated models' runoff properties were then analyzed to determine the relationships and factors required for estimating stormwater runoff (necessary for several of the control strategies outlined in subsequent sections). The Soil Conservation Service's curve number method was chosen as the method to estimate runoff as it provides a simple and efficient procedure for determining runoff from a particular rainfall event. The cornerstone of this method, curve numbers (CN), are coefficients that describe landcover, hydrologic soil groups, and other properties important for determining runoff (Soil Conservation Service 1986). Generally, these values are determined by matching watershed landcover, condition, and soil type to corresponding curve numbers, but this method also allows for the creation of customized curve numbers for situations where existing values do not apply. Customized curve numbers were estimated for each basin's watershed using the impervious area percentages from the calibrated models and identification of the dominant hydrologic soil group following the process outlined by the Soil Conservation Service (1986). This process determined that the CNs for the

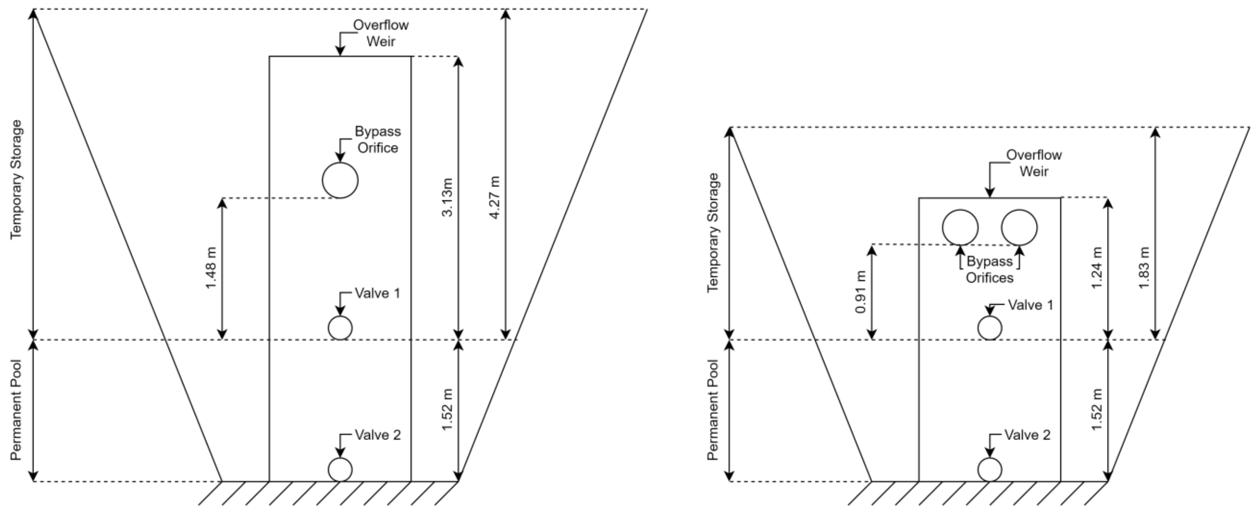

Figure 5.3. Diagram of outlet structures for the large basin (left) and small basin (right) for the wet pond scenario detailing placement of valves, orifices, overflow weirs, and storage zones (not to scale).

calibrated models were 94.70 for the large basin and 88.53 for the small basin. With the CNs known, an estimation of direct runoff depths for predicted events was possible using Equations 1 - 3 below:

$$S = \frac{25400}{CN} - 254 \tag{1}$$

$$I_a = 0.2 * S \tag{2}$$

$$Q^* = \begin{Bmatrix} 0\ for\ P \le I_a \\ \dfrac{(P - I_a)^2}{P - I_a + S}\ for\ P > I_a \end{Bmatrix} \tag{3}$$

where: S is the potential maximum retention (mm), CN is the curve number for the watershed, I_a is the initial abstraction amount (mm), P is the precipitation depth (mm), and Q^* is the direct runoff depth (mm) (Soil Conservation Service 1986).

5.3.2.3 Implementation of Pystorms

While implementation of control strategies is possible in PCSWMM, they are difficult to deploy and are quite limited in their complexity. Therefore, to overcome these limitations the models for both the wet pond and dry extended detention basin scenarios were imported into Pystorms. Pystorms is an open-source python extension and simulation sandbox that allows users to implement and evaluate complex control strategies for PCSWMM models (Rimer et al. 2019). This makes it an ideal tool for analyzing the control strategies investigated in this study. It is important to note that before importation of a model occurs, variable time steps and skipping of steady flow periods in the PCSWMM simulation options must be disabled, otherwise modeled time steps in Pystorms will not be consistent with chosen routing intervals.

5.3.3. Real-Time Control Strategies

Five sets of control strategies were developed and analyzed throughout this study, with three applied to the dry extended detention basin models (both large and small basin) and four applied to the wet pond models (both large and small basin): “Uncontrolled” (all scenarios), “Reactive” (all scenarios), “Dry Proactive” (dry extended detention basin scenarios only), “Wet Proactive” (wet pond scenarios only), and “Wet Ideal” (wet pond scenarios only).

5.3.3.1 Uncontrolled

Each control strategy besides the baseline “Uncontrolled” strategy used real-time rainfall and modeled stage data for each site to accomplish varying goals by manipulating a valve (or two in the case of the wet pond scenarios) on each system’s outlet to control discharge leaving each site and to detain runoff. The “Uncontrolled” control strategy was analyzed for both the wet pond and dry extended detention basin scenarios and acted as a control/comparison for all other control strategies implemented throughout this study. In scenarios implementing this control strategy the systems mimicked pre-RTC installation in which Valve 1 and the Bypass Orifice(s) were left fully open (all scenarios) while Valve 2 was left fully closed (wet pond scenarios only).

5.3.3.2 Reactive

The “Reactive” control strategy was designed as an RTC strategy which would react to changing conditions such as rainfall and prioritized detention of runoff and reduction of intra-storm discharges. Limitation of intra-storm discharges may prove useful in limiting the exceedance of erosive flows in the receiving stream as was observed in previous studies (Jacopin et al. 2001; Mullapudi et al. 2018; Wong and Kerkez 2018). This control strategy was implemented on both the dry extended detention basin and wet pond scenarios and included manipulating Valve 1 (Valve 2 of the wet pond scenarios is left closed) and keeping the Bypass

Orifice(s) closed to make full use of the available storage and to decrease discharge leaving the system during rainfall. This control strategy adhered to the following control rules:

(R1) If rainfall is detected, Valve 1 is closed to detain all runoff.

(R2) If cumulative rainfall meets or exceeds the site's initial abstraction amount (2.84 mm for the large basin; 6.58 mm for the small basin) determined via the curve number method (Eq. 3) within 6 hours from the beginning of rainfall, then runoff would be detained for 24 hours following the end of rainfall. This end of rainfall is determined using the last known rainfall once 6 hours of dry weather have occurred.

(R3) If the conditions of rule (R2) are not met, then Valve 1 would be fully opened, and the detained water would be released. If new rainfall is detected, rule (R1) starts the cycle anew.

(R4) If rainfall is detected after the end of rainfall has been determined (6 hours post initial rainfall; rule (R2)), this new rainfall must meet or exceed the site's initial abstraction amount (2.84 mm for the large basin; 6.58 mm for the small basin) within 6 hours to be considered in the decision framework. If the conditions are met, then a new end of rainfall would be determined similar to rule (R2), and runoff would be detained 24 hours following this new end of rainfall.

(R5) If volume detained in the wet pond's temporary storage (wet pond scenarios) or dry extended detention basin (dry extended detention basin scenarios) exceeds ~75% of its total storage capacity (10,680 m^3 for the large basin; 570 m^3 for the small basin), then Valve 1 is fully opened. This exceedance equates to a stage of 2.59 m for the large basin and 1.08 m for the small basin. To prevent rapid manipulation of the valve, Valve 1 will remain fully opened until stage decreases at least 0.08 m below each respective threshold (2.51 m for the large basin; 1.00 m for the small basin). This control rule supersedes all others.

(R6) Once the system has determined that 24 hours since the end of rainfall has passed, Valve 1 is fully opened, and the system is drained. If new rainfall is detected, rule (R1) starts the cycle anew.

The purpose of rule (R5) is to prevent overtopping of the overflow weir in each scenario, a process which will substantially increase discharge during the rainfall event. The minimum rainfall thresholds found in rules (R2) and (R4) force the system to ignore smaller, insignificant events which may not generate substantial levels of runoff. Additionally, these rules help ensure that the system does not detain runoff indefinitely if small, but frequent rainfall keeps occurring. The detention times found in this control strategy and all others were based on local technical guidance (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008).

5.3.3.3 Dry Proactive

The "Dry Proactive" control strategy reacts to current conditions similarly to the "Reactive" control strategy but incorporates rainfall forecasts into the decision framework. Through the inclusion of rainfall forecasts, this strategy not only prioritizes reducing discharges during rainfall and detaining runoff but is able to further attenuate flows leaving the system once water is released and anticipate the system reaching the maximum allowable volume (rule (R5)). Rainfall forecasts were derived using the National Oceanic and Atmospheric Administration's (NOAA) National Digital Forecast Database (NDFD) which provides quantitative precipitation forecasts in 6-hour blocks up to 72 hours from when the forecast is made (National Oceanic and Atmospheric Administration (b) 2021). Preprocessing of this data occurred prior to each simulation which utilized rainfall forecasts in the decision framework and included identifying cumulative rainfall for each 6-hour forecast block, finding when the forecast was created, filling empty values, and processing the available data into a continuous hourly time series. All control strategies which utilized forecasted rainfall data only used the first 48 hours of the complete forecast.

This control strategy also introduced the ability to set a valve to a specified percent open, unlike the "Reactive" control strategy which would only fully close or open a valve. This allows the control strategy to meet its objective of additional flow attenuation whenever possible. The opening percentage was a continuous variable ranging from 0.0 (fully closed) to 1.0 (fully open) and was evaluated at each reporting step (10-minute time steps) the valve was open. To determine the opening percentage, an estimate of the desired discharge (discharge required to drain the detained volume within a drawdown period) is required and was determined using the current detained volume as well as the drawdown time. This drawdown time is constantly reevaluated and represents the minimum between the time until the next forecasted rainfall (via forecast data) or the time left to drain in a 48-hour window from when the valve was initially opened. The objective of this condition was to both completely drain the system before new rainfall occurred while attenuating discharges over the available drawdown time. The maximum drawdown time of 48-hours follows local technical guidance for the time to completely drain the system following rainfall (Georgia Stormwater Management Manual 2016; Knox County, Tennessee Stormwater Management Manual 2008). The desired discharge is then divided by the estimated discharge of the valve if it were to be fully opened to determine the discharge fraction, or fraction of flow area that needs to be opened to generate the desired discharge. The discharge fraction is then converted to an opening percentage using derived equations for circular segments since the PCSWMM's control of the valve assumes opening percentages to be a function of flow height and not area. For example, a discharge fraction of 0.20 would equate to an opening percentage of approximately 0.25 as seen below in Figure 5.4. The process of determining opening percentage outlined above follows equations 4-6 below:

$$\bar{Q} = \frac{V}{t_{drawdown}} \tag{4}$$

$$DF = \frac{\bar{Q}}{0.65 * A * \sqrt{2 * g * Stage}} \tag{5}$$

$$OP = 4.996(DF)^5 - 12.489(DF)^4 + 11.936(DF)^3 - 5.416(DF)^2 + 1.966(DF) + 0.004 \tag{6}$$

where: $\bar{Q}$ is the desired discharge (m^3/s), *V* is the current detained volume of water (m^3), $t_{drawdown}$ is the drawdown time (s), *DF* is the discharge fraction (dimensionless), *A* is the cross-sectional area of the valve (m^2), *g* is the gravitational acceleration constant (m/s^2), *Stage* is the stage above the valve (m), and *OP* is the opening percentage of the valve (dimensionless). These relationships hold true for determining opening percentage except in the following scenarios:

- If drawdown time is equal to or less than 0, drawdown time is overwritten as 900 seconds (15 minutes).
- If the discharge fraction is greater than or equal to 1, opening percentage is set to 1.

This control strategy was implemented only on the dry extended detention basin scenarios and included keeping the Bypass Orifice(s) fully closed (for reasons previously explained) and manipulating Valve 1. This control strategy adhered to control rules (R1) through (R5) from the

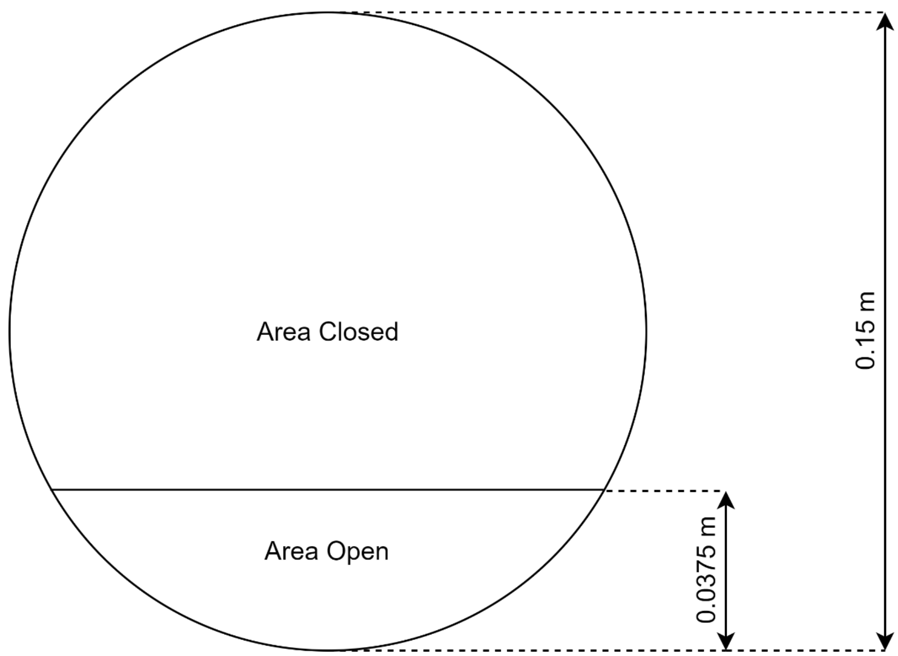

Figure 5.4. Visualization of how PCSWMM handles opening percentages as a function of flow height through the valve (opening percentage of 0.25 shown in figure).

"Reactive" control strategy with the addition of the following control rules:

(DP6) If forecasted rainfall (cumulative total for the next 48 hours) meets or exceeds the initial abstraction amount (2.84 mm for the large basin; 6.58 mm for the small basin), the forecasted runoff depth would be calculated following equations 1-3 and multiplied by the watershed area to estimate runoff volume. If the forecasted runoff volume exceeds the available storage of the basin (defined as the current detained volume in the basin subtracted from the 75% storage threshold from rule (R5)), then Valve 1 is set to fully open (1.0). Valve 1 stays fully open until forecasted runoff volume no longer exceeds available storage. This rule, similar to rule (R5), supersedes all others.

(DP7) Once the system initially determines that 24 hours since the end of rainfall has passed, Valve 1 is opened at a calculated opening percentage. This opening percentage is determined via the processes described above in equations 4-6 and attempts to drain the basin within either 48 hours or before new rainfall is forecasted to occur. Additionally, the time the valve initially opens is logged for use in rule (DP8). If new rainfall is detected, rule (R1) starts the cycle anew.

(DP8) Once rule (DP7) has been triggered (valve initially opened), the opening percentage of the valve is reevaluated at each subsequent time step following the process outlined in rule (DP7) with the drawdown time being revaluated as either the time until forecasted rainfall or the time left to drain within a 48-hour window from when the valve initially opens. If the stage of the basin is less than 0.03 m above the invert of the valve, then Valve 1 is set to fully open. If new rainfall is detected, rule (R1) starts the cycle anew.

5.3.3.4 Wet Proactive

The “Wet Proactive” control strategy reacts similarly to the “Dry Proactive” control strategy with the additional control of the permanent pool storage of the wet pond scenarios. This strategy prioritized reducing discharge during rainfall, anticipated if the maximum allowable stage of the temporary storage would be exceeded (rule (R5)), attenuated flows leaving the system following rainfall, and proactively drew down the permanent pool to create storage for incoming rainfall. This strategy was implemented only on the wet pond scenarios and included keeping the Bypass Orifice(s) fully closed (for reasons previously explained) and manipulating Valve 1 and 2. This control strategy adhered to control rules (R1) through (R5) from the “Reactive” control strategy with an exception to rule (R1) to ensure that both Valve 1 and 2 are closed when rainfall begins. Additionally, the following control rules apply:

(WP6) If forecasted rainfall meets or exceeds the initial abstraction amount (2.84 mm for the large basin; 6.58 mm for the small basin), the forecasted runoff volume is calculated following equations 1-3 and multiplying the runoff depth by the watershed area. If the forecasted runoff volume exceeds the available storage of both the permanent pool and temporary storage (up to the 75% threshold, rule (R5)) combined, then Valve 1 is set to fully open (1.0). Valve 1 stays fully open until forecasted runoff volume no longer exceeds available storage. This rule, similar to rule (R5), supersedes all others.

(WP7) If stage of the temporary storage zone is less than 0.08 m and more than 24 hours have passed since the end of rainfall, proactive drawdown of the pond’s permanent pool is allowed to occur. If forecasted runoff volume exceeds the available storage of the permanent pool, then Valve 2 is set to an opening percentage following the process outlined in equations 4-6. Valve 2 remains open until forecasted runoff volume no longer exceeds available storage with the opening percentage being reevaluated at every time step where the conditions apply. The exception to this rule occurs if the opening percentage is less than 0.10, in which case Valve 2 is set to fully closed.

(WP8) Once the system initially determines that 24 hours since the end of rainfall has passed, Valve 1 is opened at a calculated opening percentage. This opening percentage is determined via the processes described above in equations 4-6 with the exception that the forecasted runoff volume is added to the total volume to be drained. This process attempts to drain the basin within either 48 hours or before new rainfall is forecasted to occur. Additionally, the time the valve initially opens is logged for use in rule (WP9). If new rainfall is detected, rule (R1) starts the cycle anew.

(WP9) Once rule (WP8) has been triggered (Valve 1 initially opened), the opening percentage of Valve 1 is reevaluated at each subsequent time step following the process outlined in rule (WP8) with the drawdown time being revaluated as either the time until forecasted rainfall or the time left to drain within a 48-hour window from when Valve 1 initially opens. If new rainfall is detected, rule (R1) starts the cycle anew.

The purpose of the addition of forecasted runoff volume to the volume to be drained in rules (WP8) and (WP9) was to assist the system in drawing down the temporary storage zone with enough time to create additional storage in the permanent pool before a new rainfall event occurred. Valve 2 was not utilized for this purpose as it created substantially higher flow patterns during the drawdown period of the temporary storage zone due to the increased hydraulic head.

5.3.3.5 Wet Ideal

Unlike previous control strategies, the "Wet Ideal" control strategy does not prioritize reducing intra-storm discharge but instead prioritizes reducing usage of the temporary storage zone. However, this control strategy has the greatest potential out of all those analyzed in this study for reducing the necessary size and volume required for the temporary storage zone of the wet pond scenarios. It accomplishes this by manipulating Valve 2 and leaving Valve 1 and the Bypass Orifice(s) completely open in an attempt to keep stage at or below the maximum stage of the permanent pool. This control strategy was implemented on the wet pond scenarios and adhered to two control rules:

(WI1) If forecasted rainfall meets or exceeds the initial abstraction amount (2.84 mm for the large basin; 6.58 mm for the small basin), the forecasted runoff volume would be calculated following equations 1-3 and multiplying the runoff depth by the watershed area. If the forecasted runoff volume exceeds the available storage of the permanent pool, then Valve 2 is opened at an opening percentage consistent with equations 4-6. Valve 2 stays open until forecasted runoff volume no longer exceeds available storage.

(WI2) If stage of the wet pond exceeds the maximum stage of the permanent pool and rainfall has occurred within the last 6 hours, then Valve 2 is fully opened. Valve 2 stays fully opened until either the maximum stage of the permanent pool is no longer exceeded, or it has been greater than 6 hours since rainfall has occurred.

5.3.4. Simulations

5.3.4.1 Long-term Simulations

Long-term simulations were conducted for both the wet pond and dry extended detention basin scenarios utilizing all applicable control strategies. These long-term simulations utilized continuous 5-minute rainfall data from the site beginning on January 1^{st}, 2020 and continuing through December 31^{st}, 2020. If rainfall data from the rain gauge at the site was unavailable or corrupted (as was the case from April 15^{th} through June 1^{st}), these time steps were supplemented with a nearby (<2 km away) rain gauge's data. This time period was not only chosen due to the availability of rainfall data for the site but also due to the high cumulative rainfall that occurred during the year. The yearly rainfall total for the site was 1620.77 mm, making it both an above average yearly rainfall total (yearly average: 1215.64 mm) and the 4^{th} wettest year on record when compared to nearby Knoxville, TN (City of Knoxville Stormwater Engineering Division 2021; National Oceanic and Atmospheric Administration (a) 2021).

5.3.4.2 Simulation of Historical 24-Hour Events

In addition to long-term simulations, simulations of rainfall events that met standards for historical events with 24-hour durations at varying recurrence intervals were also conducted. The recurrence interval and duration of each event represent the historical probability (recurrence interval) that a rainfall event will meet or exceed a cumulative total within a specified time period (duration) (Huffman et al. 2013). The purpose of these simulations was to investigate how each control strategy would respond to rainfall events of varying magnitudes and frequency.

To avoid design storms with theoretical rainfall distributions, real storm events meeting the desired size and duration were located in the rainfall record. Since the availability of rainfall data from the site was limited to the year 2020, nearby rain gauges with longer data availability periods were required to find events with higher recurrence intervals. Rainfall data from a nearby (<3.5 km) U.S. Geological Survey (USGS) stream gauging station was available with a period of record beginning in 2007 (U.S. Geological Survey 2021). The available rainfall data was supplemented with what was available from the USGS stream gauging station and rainfall events (with corresponding rainfall forecasts) that met the 24-hour duration criteria for Knoxville, TN, were found. A summary of these events and how they compare to historical rainfall can be found below in Table 5.2 (National Oceanic and Atmospheric Administration (c) 2021). Additionally, the distribution of each of these events can be found below in Figure 5.5.

To accommodate the pre-event drawdown of the "Wet Proactive" and "Wet Ideal" control strategies, as well as the post storm drawdown time required for all of the active control strategies, these simulations were a week in length. Specifically, rainfall began exactly two days into the simulation as this is the maximum forecast window of the control strategies and to allow adequate time for proactive drawdown of the wet pond's permanent pool to occur. To isolate the events from the effect of any previous rainfall, rainfall forecasts were edited by removing data that corresponded to rainfall that occurred prior to the 24-hour period of interest.

5.4. Results and Discussion

5.4.1. Overview of Long-term Simulations

Plots displaying the input and output data from the first 10-days of the long-term simulation for the large basin can be found below in Figure 5.6. During this timeframe two rainfall events occurred (one large: 84.84 mm and one small: 10.92 mm) from which the effect of the majority of the established control rules can be observed. The only control rule which was not triggered in this timeframe was rule (R5) since the stage of the dry extended detention basin

Table 5.2. Summary of events that meet criteria for 24-hour rainfall totals at different recurrence intervals.

Event (Recurrence Interval, Duration)	Event Start	Cumulative Rainfall (mm)	Historical Rainfall (mm) (90% Confidence Interval)
100-year, 24-hour	02-23-2019 03:20	147.07	161 (146-175)
50-year, 24-hour	02-23-2019 04:00	139.95	144 (132-156)
25-year, 24-hour	11-29-2016 23:00	123.19	128 (118-138)
10-year, 24-hour	04-22-2017 16:00	105.41	108 (100-117)
5-year, 24-hour	11-30-2016 01:30	94.49	94 (87-102)
2-year, 24-hour	07-06-2013 14:30	75.69	77 (72-83)
1-year, 24-hour	04-12-2020 06:40	69.09	65 (60-70)

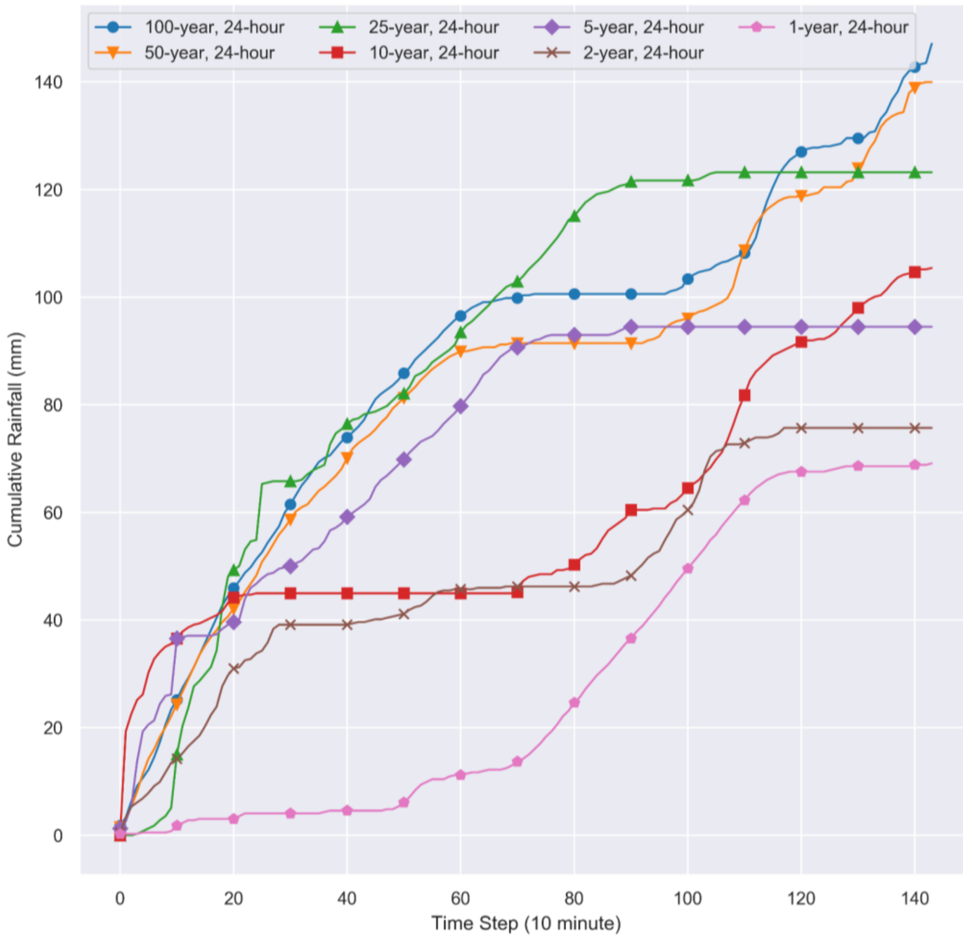

Figure 5.5. Rainfall distribution of events that meet criteria for 24-hour rainfall totals at different recurrence intervals.

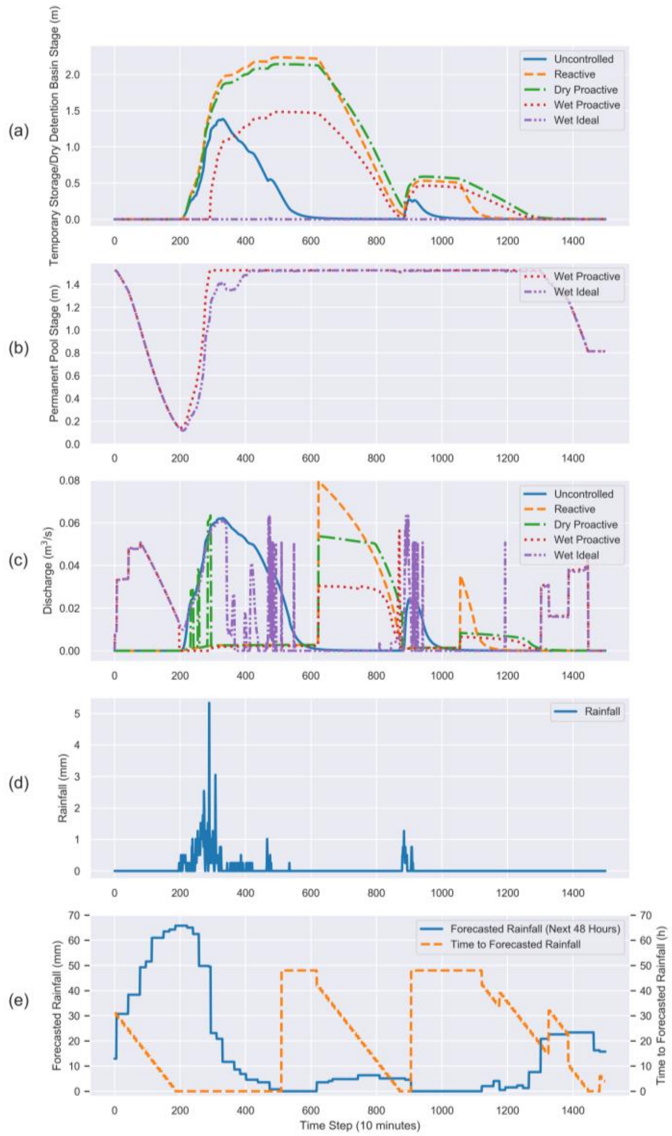

Figure 5.6. Plots displaying the large basin's simulation output and input data for the first 10 days of the long-term simulation for all control strategies analyzed in this study. (a) depicts the stage (m) of the temporary storage zone (wet pond scenario) and basin stage (dry extended detention basin scenario). (b) depicts the stage (m) of the permanent pool (wet pond scenario) for control strategies which manipulated the storage of the permanent pool. (c) depicts system discharge (m^3/s). (d) depicts rainfall (mm) while (e) depicts cumulative forecasted rainfall for the next 48 hours as well as the time until when this rainfall is forecasted to begin.

or temporary storage zone did not exceed 2.59 m. However, this rule was triggered several times during the rest of the large and small basin simulations. Pre-event drawdown of the permanent pool for the “Wet Proactive” and “Wet Ideal” control strategies (rules (WP7) and (WI1); wet pond scenario only) can be observed by the declining stage of the permanent pool (Figure 5.6b) and increased discharge from the system (Figure 5.6c) prior to the event beginning. Additionally, this pre-event drawdown occurred at a much higher rate during the first rainfall event than the second as this rate was determined as a function of current stage of the permanent pool (Figure 5.6b), forecasted cumulative rainfall for the next 48 hours (Figure 5.6e), and time until the forecasted rainfall is expected to begin (Figure 5.6e). Attenuation of discharge leaving the system following the 24-hour detention time, as was the objective of both the “Dry Proactive” and “Wet Proactive” control strategies (rules (DP7), (DP8), (WP8), and (WP9)), can be observed by comparing the discharge (Figure 5.6c) of these two control strategies to that of the “Reactive” control strategy. This difference is caused by both the decrease in maximum stage during each event as well as the valve being set to an opening percentage that was a function of time until forecasted rainfall, unlike the “Reactive” control strategy where the valve was fully opened once the detention time had been exceeded. The decrease in maximum stage of the temporary storage/dry extended detention basin of the “Dry Proactive” and “Wet Proactive” control strategies as they compare to the “Reactive” control strategy were caused by intra-storm discharges from the system triggered by rules (DP6) and (WP6) where forecasted runoff volume exceeded available storage (as seen in Figure 5.6c) as well as the pre-event drawdown (“Wet Proactive” only). No intra-storm discharges were observed for the “Reactive” control strategy due to rule (R1) and the conditions of rule (R5) not being met (as previously discussed). The impact of the control rules of the “Wet Ideal” control strategy (WI1 and WI2) can be observed by the increased and sporadic intra-storm discharges when compared to all others in this study. However, it did accomplish its primary objective of reducing the stage and usage of the temporary storage zone. Though not expressly exhibited in Figure 5.6, control rules (R2) through (R4) were utilized throughout this long-term simulation to ensure minimum rainfall requirements were met. As was expected, no difference in simulation results were observed for both the "Reactive" and "Uncontrolled" control strategies when implemented on the wet pond and dry extended detention basin scenarios. Therefore, any results reported from these two control strategies apply to both the wet pond and dry extended detention basin scenarios.

5.4.2. Dry Extended Detention Basin Results

To examine and compare the effectiveness of each analyzed control strategy over the entirety of the long-term simulation (one year), exceedance plots for parameters of interest were created. These exceedance plots can be found below in Figure 5.7 and include the stage (m) of the dry extended detention basin, discharge leaving the system (m^3/s), and utilized storage (%) of the basin (volume detained up to the overflow weir) for both the large and small basin models. Additionally, comparison of key performance metrics (peak discharge, distribution of water released, and number of overflows) comparing each control strategy can be seen below in Table 5.3. As previously explained, the "Uncontrolled" control strategy represented a baseline comparison in which no real-time control of the system occurred.

5.4.2.1 Reactive Control Strategy Results

For the large basin, the "Reactive" control strategy generated the highest maximum stage and volume usage, with a 47% and 88% increase in stage and storage, respectively, compared to the baseline "Uncontrolled". However, these higher stages did not lead to an increase in peak

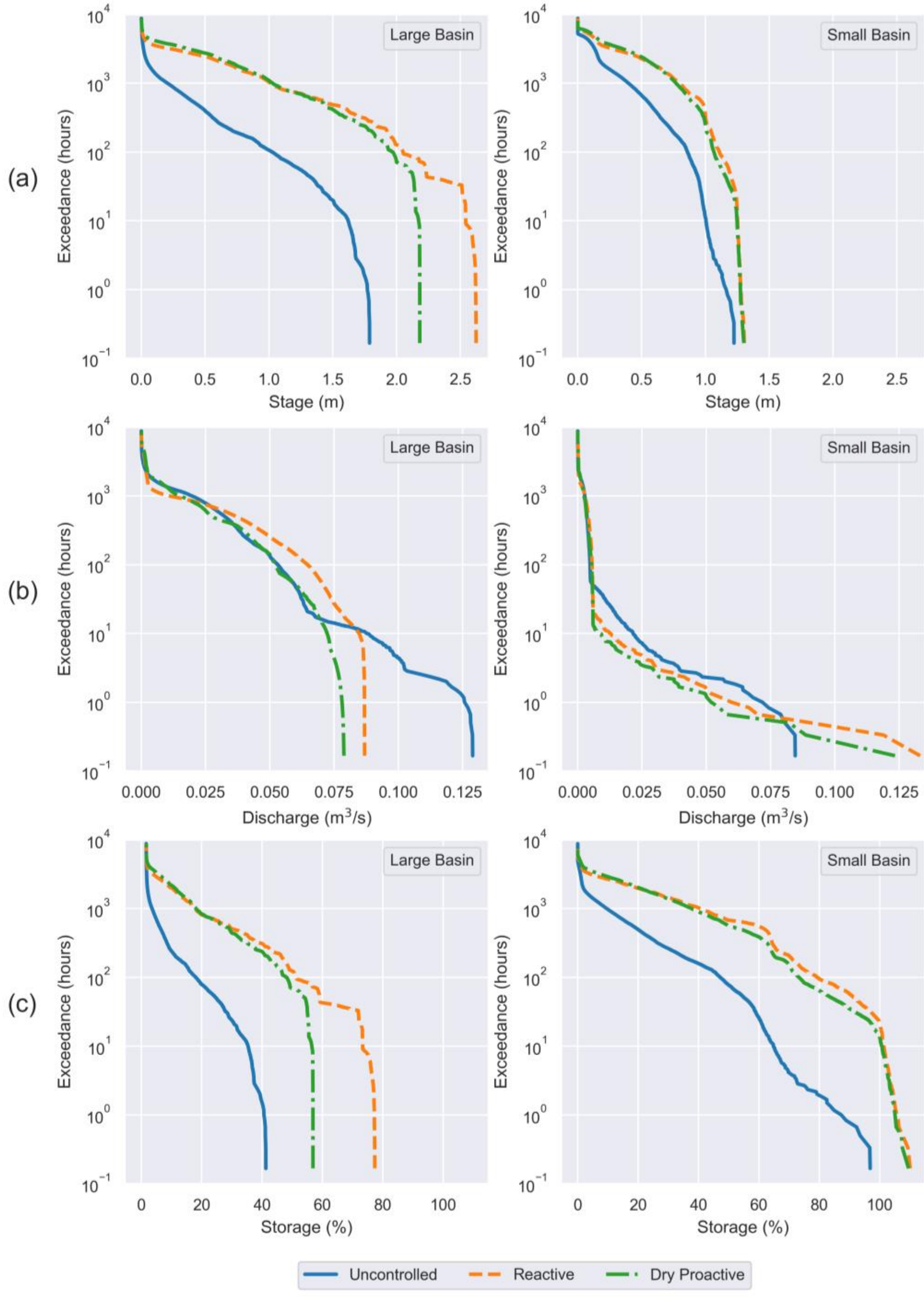

Figure 5.7. Dry extended detention basin long-term simulation exceedance plots displaying (a) stage (m) of the basin, (b) discharge leaving the system (m^3/s), and (c) storage (%) of the basin for all control strategies analyzed in this study.

Table 5.3. Comparison of performance metrics for the dry extended detention basin control strategies.

		Control Strategy		
Model	**Event**	**Uncontrolled**	**Reactive (% change)[1]**	**Dry Proactive (% change)[1]**
Large Basin	Peak Discharge (m^3/s)	0.129	0.087 (-33 %)	0.079 (-39 %)
	Peak Intra-storm Discharge (m^3/s)	0.129	0.087 (-33 %)	0.073 (-43 %)
	Peak Inter-storm Discharge (m^3/s)	0.064	0.085 (+34 %)	0.079 (+24 %)
	Intra-storm Volume Released (m^3)	120629	10639 (-91 %)	18117 (-85 %)
	Inter-storm Volume Released (m^3)	46874	156150 (+233 %)	148826 (+218 %)
	Overflows (h)	0.00	0.00 (+0 %)	0.00 (+0 %)
Small Basin	Peak Discharge (m^3/s)	0.085	0.133 (+57 %)	0.123 (+46 %)
	Peak Intra-storm Discharge (m^3/s)	0.085	0.133 (+57 %)	0.123 (+46 %)
	Peak Inter-storm Discharge (m^3/s)	0.005	0.006 (+19 %)	0.006 (+19 %)
	Intra-storm Volume Released (m^3)	14432	5197 (-64 %)	5699 (-61 %)
	Inter-storm Volume Released (m^3)	8705	17881 (+105 %)	17395 (+100 %)
	Overflows (h)	0.00	21.83 (+13,000 %)	13.33 (+7880 %)

[1]Percent (%) change relative to uncontrolled scenario.

discharge (overall or intra-storm) and was able to further attenuate peak flow by 33% (Figure 5.7; Table 5.3; Figure 5.8). This was primarily caused by the Bypass Orifice being completely closed to make full use of the available storage and to limit intra-storm discharges as visible by the significant shift of when stormwater was released from the basin (91% reduction in intra-storm volume released; Table 5.3) and by comparing the magnitudes and durations of intra and inter-storm discharges (Figure 5.8). This difference was observed throughout the simulation when discharge of the “Uncontrolled” scenario spiked when stage reached or exceeded the invert of the Bypass Orifice. Therefore, for the large basin, the “Reactive” control strategy was successful in meeting its objective of limiting intra-storm discharges. However, the “Reactive” control strategy was not as successful when applied to the small basin. In this instance this control strategy actually exacerbated intra-storm discharge by increasing the rate at which detained stormwater overtopped the overflow weir of the outlet structure (a phenomena which never occurred for the large basin; Table 5.3) leading to a 57% increase in peak discharge when compared to the baseline “Uncontrolled” (as visible in Figure 5.7 and Figure 5.8). Even the baseline “Uncontrolled” approached this stage threshold on multiple occasions and would have surpassed it leading to an overflow if it were not for the Bypass Orifices. By closing the valve when rainfall began and keeping the Bypass Orifices completely closed at all times, the small basin reached the detention volume which triggers rule (R5) much quicker than the large basin and (due to its small orifice size) was quite limited in its ability to release water and prevent overtopping once the rule had been triggered. Therefore, for the small basin the “Uncontrolled” scenario outperformed the “Reactive” control strategy.

As visible in Figure 5.7 and Table 5.3, this control strategy produced discharges greater than the “Dry Proactive” control strategies for both basins and was caused by (1) only

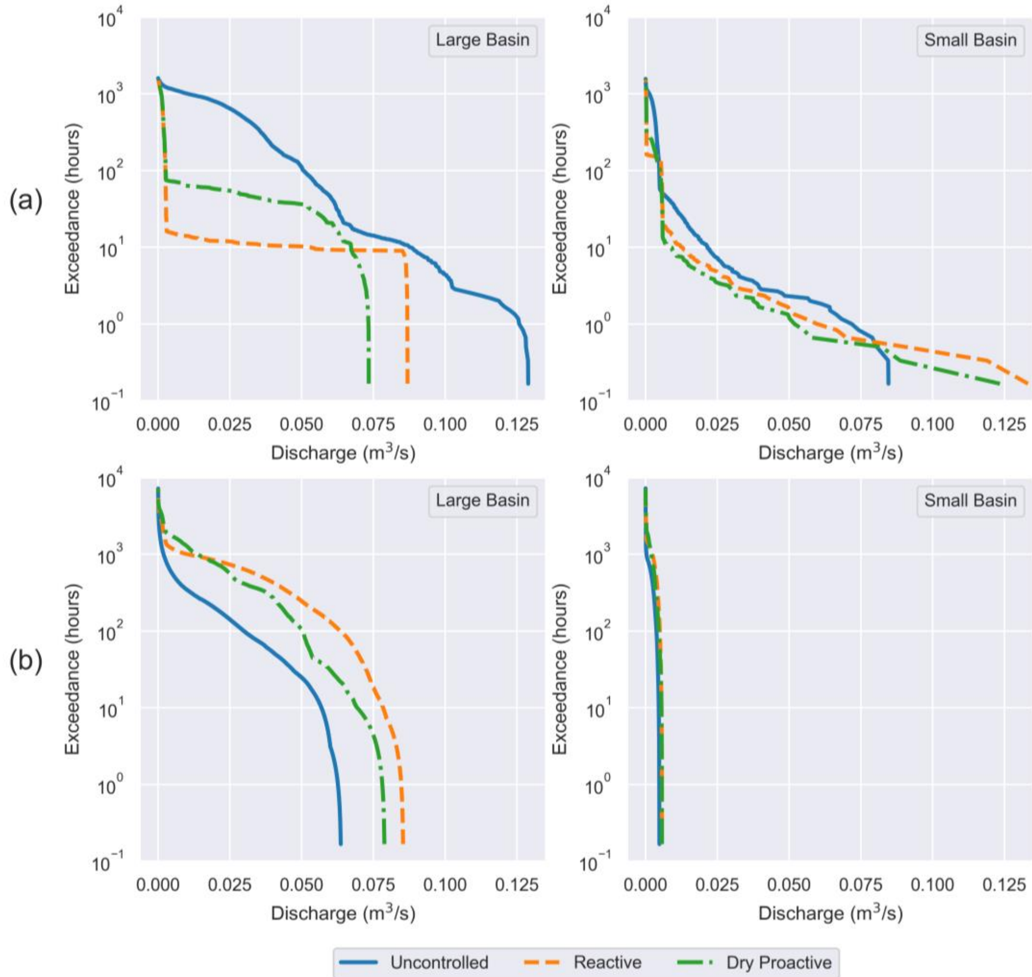

Figure 5.8. Dry extended detention basin exceedance plots for the large and small basins comparing when discharge (m^3/s) occurred including the distribution of (a) intra-storm and (b) inter-storm discharge.

discharging intra-storm when stage reached the maximum threshold and not proactively to limit exceedance and (2) fully opening the valve when draining basin after a storm. The latter consistently led to increases in inter-storm discharges, as seen in Figure 5.8, but was necessary for the system to prepare for incoming rainfall, i.e. since forecast data was not integrated into the decision framework the control strategy would not know when the next rainfall event would occur and therefore must act as soon as conditions allowed.

These results suggest that this control strategy would be best suitable for applications of retrofitting existing stormwater infrastructure if reduction of intra-storm or overall peak discharge is required, especially in instances when forecasted rainfall data is either unreliable, unavailable, or unable to be integrated into the decision framework. However, when implementing this control strategy special care should be taken to not implement it on stormwater infrastructure which already has a high frequency of overtopping or consistently approaches its maximum detention volume during rainfall events (such as the small basin in this study). In these instances, engineers and planners will exacerbate intra-storm discharge due to increased overtopping of the overflow weir and it may be best to leave that infrastructure as built.

5.4.2.2 Dry Proactive Control Strategy Results

When implemented on the large basin, the “Dry Proactive” control strategy was able to reduce peak discharge, stage, and storage (up to 9%, 17%, and 26%, respectively) when compared to the “Reactive” control strategy (Figure 5.7). But, similar to the “Reactive” control strategy, led to increases in stage and storage (up to 22% and 38%, respectively; Figure 5.7) with reductions in peak discharge (up to 39%; Table 5.3) when compared to the baseline “Uncontrolled”. The observed reduction in stage and storage when compared to the “Reactive” control strategy is caused by the proactive release of water when forecasted runoff exceeded available storage (rule DP6). The impacts of this proactive release of water are most visible in the increased duration of intra-storm discharges (Figure 5.6; Figure 5.8) and by the increased volume of water released intra-storm (Table 5.3). However, because of these proactive releases, intra-storm peak discharge was reduced (Table 5.3; Figure 5.8). Additionally, the most notable feature of the "Dry Proactive" control strategy (ability to attenuate inter-storm discharges; rules DP7 and DP8) substantially decreased the magnitude and duration of inter-storm discharges when compared to the "Reactive" control strategy (Table 5.3; Figure 5.8). However, when this control strategy was applied to the small basin, similar shortcomings to the "Reactive" control strategy were observed. Most notably, when compared to the baseline "Uncontrolled", it increased the frequency at which the basin's outlet structure was overtopped which led to substantial increases in intra-storm discharges (Table 5.3; Figure 5.8). Though it should be noted that, similarly to the large basin, this control strategy was able to further attenuate the observed discharge of the "Reactive" control strategy by releasing water earlier due to forecasted runoff exceeding available storage (rule DP6).

These results suggest that this control strategy is the ideal candidate for implementation on dry extended detention basins if reduction of discharge is the primary objective and if rainfall forecast data is able to be integrated into the decision framework. However, for similar reasons previously discussed in the "Reactive" control strategy results, special care should be taken when implementing this control strategy. Before implementation occurs, it is recommended that a thorough investigation be undertaken to ensure that the control strategy does not exacerbate any hydrologic issues such as increasing intra-storm discharges due to overtopping of the outlet structure.

5.4.2.3 Analysis of Historical 24-Hour Event Simulations

As previously stated, the purpose of the historical 24-hour event simulations was to investigate if larger, less frequent rainfall events substantially changed the conclusions or recommendations reached during analysis of the long-term performance of each control strategy. For the large basin, the control strategies actually performed worse than the “Uncontrolled” scenario during smaller isolated events as visible by the increase in peak discharge (1-year and 2-year; Figure 5.9). However, as the events became larger, the ability of each control strategy to mitigate peak flow increased and were able to reduce peak flow by as much as 56% (50-year; large basin – dry proactive; Figure 5.9). Additionally, and similarly to the long-term simulations, stage and storage was substantially increased (though not enough to cause basin overflows which would be detrimental to performance), and the “Dry Proactive” control strategy was able to mitigate discharge better than the “Reactive” control strategy (Figure 5.9).

Conversely, the RTC equipped small basin improved flow conditions during small, isolated events (1-year, 2-year, and 5-year; Figure 5.9) while exacerbating peak discharge during larger rainfall events. This significant increase in peak discharge (>100% increase for large events; Figure 5.9) was the direct result of water overtopping the outlet riser (a conclusion reached during analysis of the long-term simulations). Additionally, due to the frequency and rate at which this basin reaches its maximum detainable volume, the increase in stage and storage was not as substantial for the small basin as it was for the large basin (Figure 5.9).

These results corroborate the conclusions reached during the long-term simulations of these dry extended detention basins. Specifically, that implementing RTC has the potential to improve basin hydrology by decreasing the magnitude of peak discharge even during larger, less

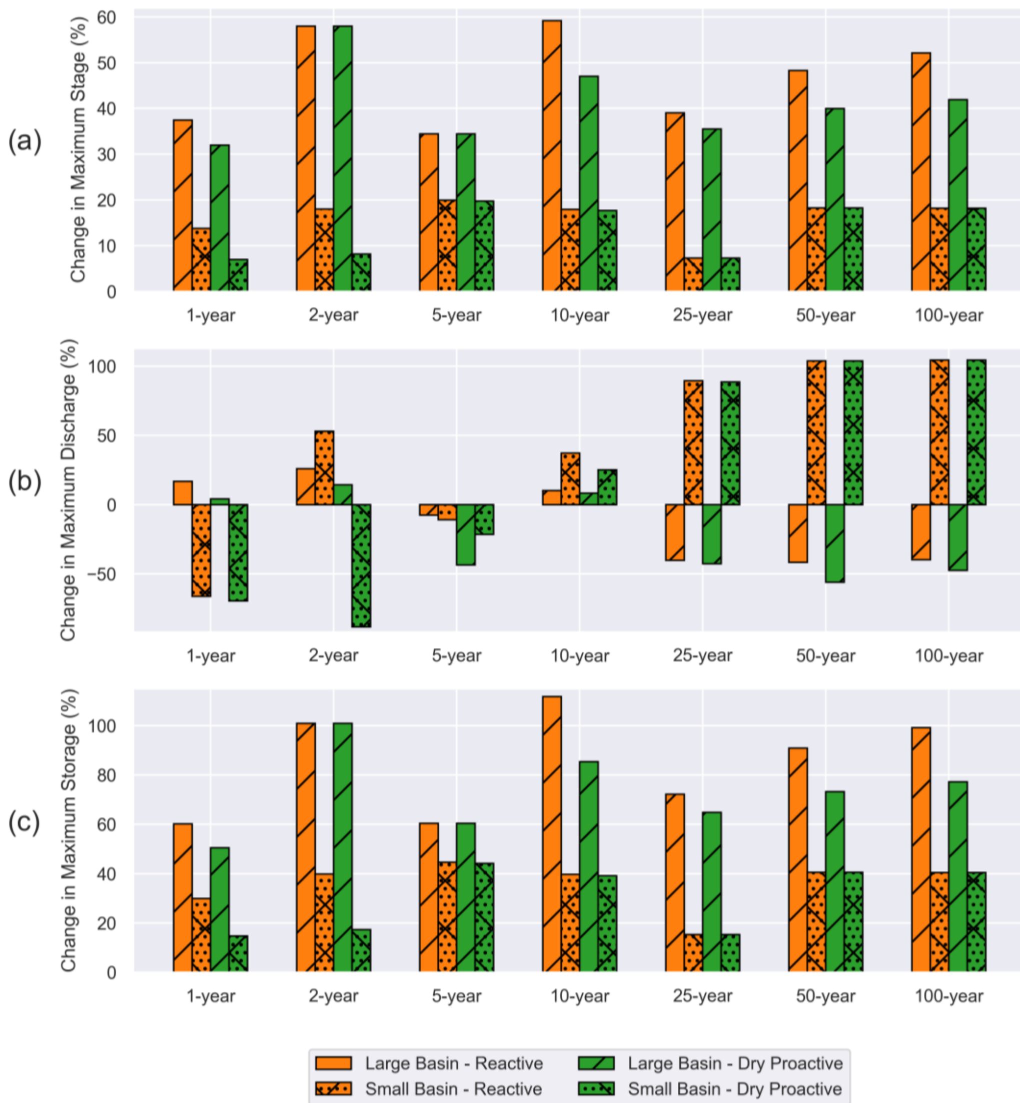

Figure 5.9. Results of the dry extended detention basin historical 24-hour event simulations displaying the maximum change in (a) stage, (b) discharge, and (c) storage relative to the uncontrolled scenario.

frequent events. Furthermore, control strategies which integrate rainfall forecasts for proactive release during storms or to attenuate inter-storm discharges are able to further improve hydrologic performance (by decreasing peak discharge) when compared to their “Reactive” counterparts. However, as was concluded during the long-term simulations, special care should be taken to ensure that implementation of RTC does not exacerbate existing conditions such as increasing the frequency of basin overflows.

5.4.3. Wet Pond Results

As was previously stated, no change in system performance or function occurred between the dry extended detention basin or wet pond scenarios when the “Uncontrolled” or “Reactive” control strategies were implemented. Therefore, results comparing the “Reactive” control strategy to the “Uncontrolled” baseline are the same for either SCM and the results explored in previous sections (see 5.4.2.1 Reactive Control Strategy Results) are applicable to the wet pond scenarios as well.

Similarly to the dry extended detention basin results, exceedance plots were created to assist in the examination and comparison of the effectiveness of each analyzed control strategy. These exceedance plots can be found below in Figure 5.10 and include the stage (m) of the wet pond’s temporary storage zone, discharge leaving the system (m^3/s), and utilized storage (%) of the temporary storage zone (volume detained up to the overflow weir above the permanent pool) for both the large and small basin models. Additionally, comparison of key performance metrics (peak discharge, distribution of water released, and number of overflows) comparing each control strategy for the wet pond scenarios can be seen below in Table 5.4.

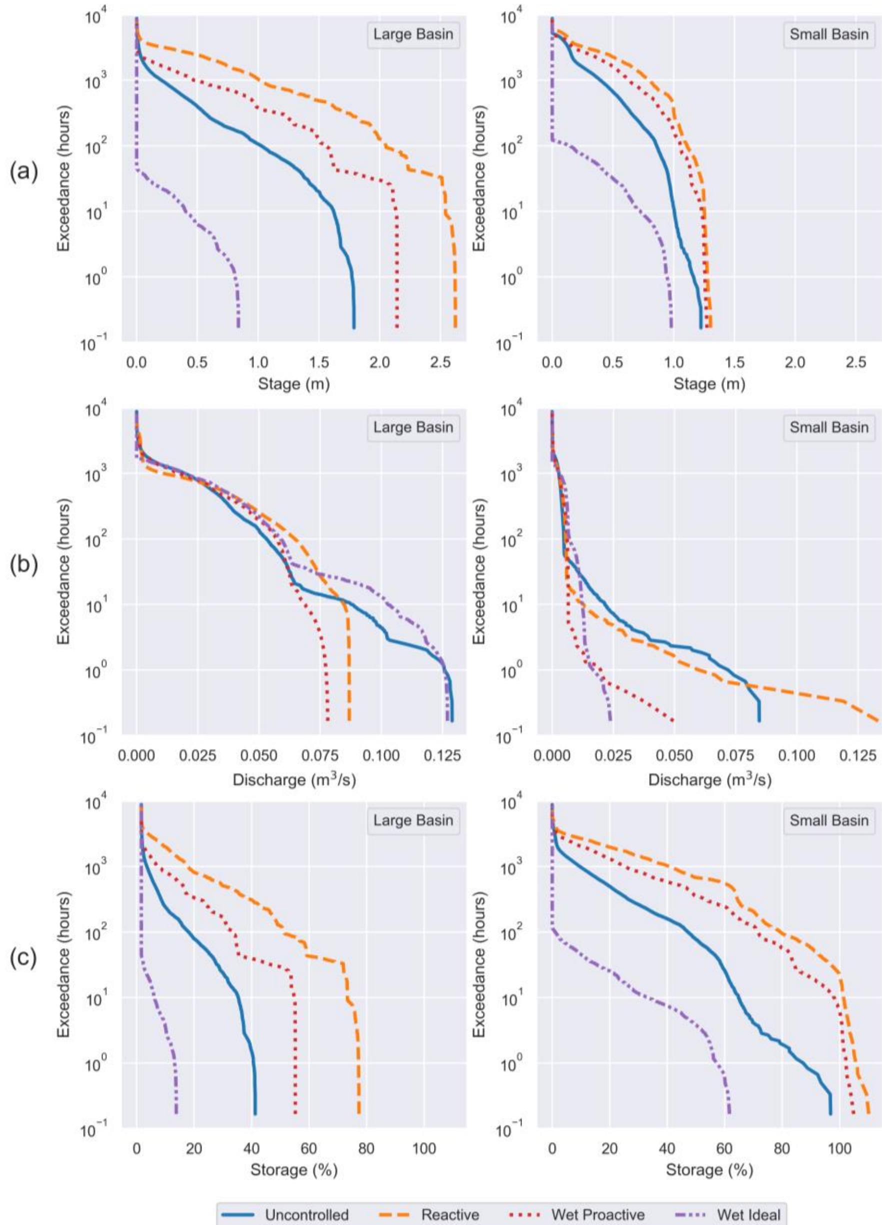

Figure 5.10. Wet pond long-term simulation exceedance plots displaying (a) stage (m) of the wet pond's temporary storage zone, (b) discharge leaving the system (m^3/s), and (c) storage (%) of the temporary storage zone for all control strategies analyzed in this study.

Table 5.4. Comparison of performance metrics for the wet pond control strategies.

Model	Event	Uncontrolled	Reactive (% change)[1]	Wet Proactive (% change)[1]	Wet Ideal (% change)[1]
			Control Strategy		
Large Basin	Peak Discharge (m^3/s)	0.129	0.087 (-33 %)	0.078 (-39 %)	0.127 (-2 %)
	Peak Intra-storm Discharge (m^3/s)	0.129	0.087 (-33 %)	0.069 (-46 %)	0.127 (-2 %)
	Peak Inter-storm Discharge (m^3/s)	0.064	0.085 (+34 %)	0.078 (+23 %)	0.063 (-0 %)
	Intra-storm Volume Released (m^3)	120629	10639 (-91 %)	7542 (-94 %)	76793 (-36 %)
	Inter-storm Volume Released (m^3)	46874	156150 (+233 %)	161758 (+245 %)	92495 (+97 %)
	Overflows (h)	0.00	0.00 (+0 %)	0.00 (+0 %)	0.00 (+ 0%)
Small Basin	Peak Discharge (m^3/s)	0.085	0.133 (+57 %)	0.050 (-41 %)	0.024 (-72 %)
	Peak Intra-storm Discharge (m^3/s)	0.085	0.133 (+57 %)	0.050 (-41 %)	0.024 (-72 %)
	Peak Inter-storm Discharge (m^3/s)	0.005	0.006 (+19 %)	0.007 (+37 %)	0.012 (+143 %)
	Intra-storm Volume Released (m^3)	14432	5197 (-64 %)	2879 (-80 %)	11176 (-23 %)
	Inter-storm Volume Released (m^3)	8705	17881 (+105 %)	20408 (+134 %)	12052 (+38 %)
	Overflows (h)	0.00	21.83 (+13,000 %)	6.17 (+3600 %)	0.00 (+0 %)

[1]Percent (%) change relative to uncontrolled scenario.

5.4.3.1 Wet Proactive Control Strategy Results

The “Wet Proactive” control strategy was able to attenuate peak intra-storm and overall discharge by as much as 46% and 39%, respectively, for the large basin and 41% (both overall and intra-storm) for the small basin when compared to the baseline “Uncontrolled” (Figure 5.10; Table 5.4; Figure 5.11). Most notably, this control strategy represents the first control strategy implemented on the small basin to improve conditions when compared to the baseline “Uncontrolled” even with overflows of the outlet riser still occurring (Figure 5.10; Table 5.4). This increased performance observed for both basins is the direct result of pre-storm drawdown of the permanent pool and proactive intra-storm discharges (as visible by the increased duration in intra-storm discharge; Figure 5.11). These results suggest that this control strategy is suitable for both new designs and wet pond retrofits, especially to reduce intra-storm and overall peak discharges (Table 5.4; Figure 5.11), and likely does not require any special consideration as was the case with the dry extended detention basins.

5.4.3.2 Wet Ideal Control Strategy Results

The “Wet Ideal” control strategy did accomplish its objective of limiting the usage of the temporary storage zone (in order to reduce its required design volume) with substantial decreases in stage and storage when compared to all other control strategies (Figure 5.10). The maximum stage and storage observed during the long-term simulations was 53% and 67%, respectively, less than what was observed during the baseline “Uncontrolled” for the large basin and 20% and 36%, respectively, less for the small basin (Figure 5.10). In fact, the “Wet Ideal” control strategy only utilized 14% of the temporary storage zone when applied to the large basin and 62% when it was applied to the small basin (as seen in Figure 5.10). This equates to a usage of 35% of the entire volume of the wet pond (both permanent pool and temporary storage zone) for the large

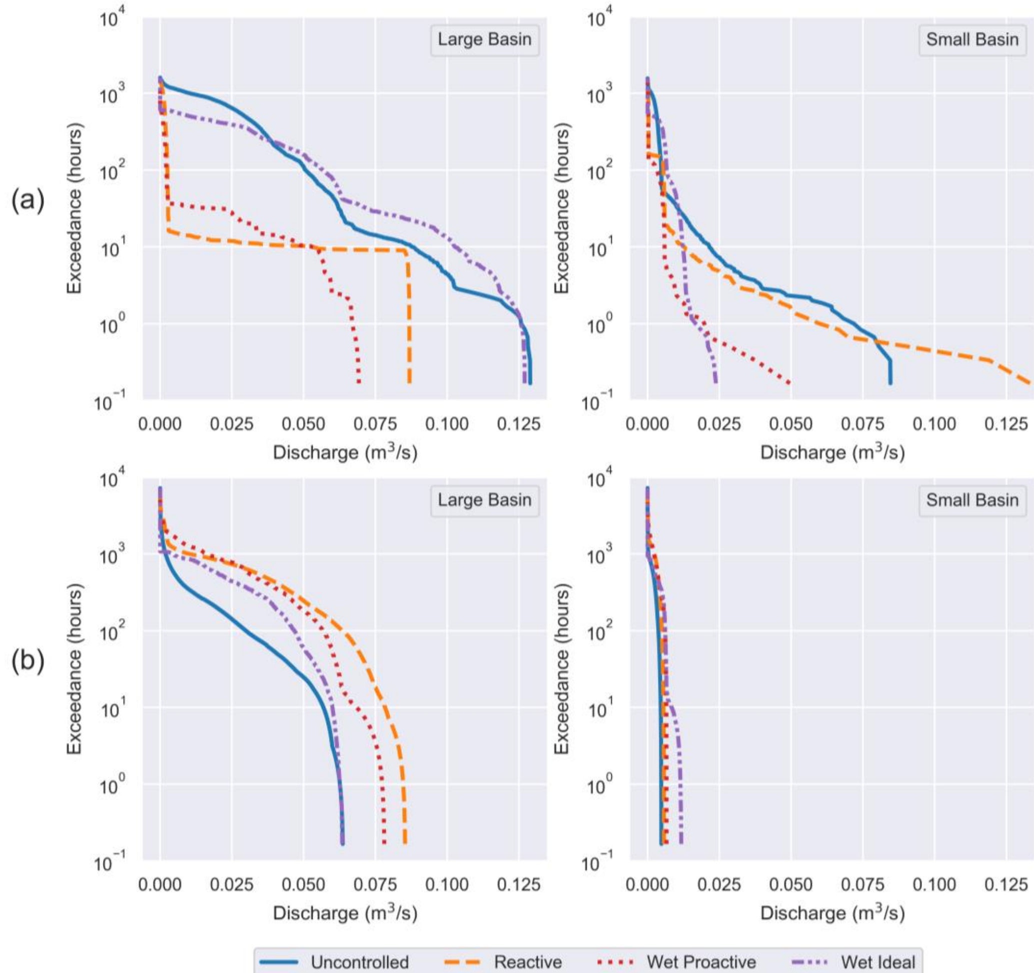

Figure 5.11. Wet pond exceedance plots for the large and small basins comparing when discharge (m^3/s) occurred including the distribution of (a) intra-storm and (b) inter-storm discharge.

basin and 82% for the small basin. This reduction in required volume follows results obtained from previous studies (Boyle et al. 2016; Wong and Kerkez 2018).

The observed reduction in stage and storage may come at the cost of substantial increases in peak and duration of discharges from the system. This was the case with the large basin when compared to the "Reactive" and "Wet Proactive" control strategies (Figure 5.10; Table 5.4). However, because this control strategy limited stage of the temporary storage zone, improvements to peak discharge were actually observed when this control strategy was applied to the small basin and it was the first control strategy to prevent any overflows (Figure 5.10; Table 5.4). Additionally, while this control strategy leads to a decrease in peak discharge when compared to the baseline "Uncontrolled", the duration of smaller flows is substantially higher (due to the increase in volume released intra-storm; Table 5.4), though this duration is not greater than other RTC strategies.

These results support the conclusion that the overall volume of the temporary storage zone could be substantially reduced (38-86% based on the results of the long-term simulations) if this control strategy is implemented on a wet pond, especially if implementation of this control strategy is planned during the design and construction phase. This reduction in required volume could provide an incentive to land developers to implement smart stormwater infrastructure over traditional passive systems while still keeping peak discharges at or below the levels created by passive infrastructure. The ability of this control strategy to decrease or change these parameters will be site specific and dependent on the modeled results of larger, less frequent events (explored in subsequent sections). Thus, reductions of the temporary storage zone could be greater or less than the 38-86% observed during the long-term simulations of this study. For example, there is evidence to suggest that wet ponds designed with permanent pools greater than the water quality volume (which was used in this study) may be able to further reduce the required volume of the temporary storage zone while also decreasing the drawdown of the permanent pool in anticipation of the next rainfall event.

5.4.3.3 Analysis of Historical 24-Hour Event Simulations

Similar to the dry extended detention basin results, historical 24-hour event simulations were conducted to investigate if larger, less frequent rainfall events substantially changed or corroborated the conclusions reached during the long-term analysis of each wet pond control strategy. As was explained in previous sections, the results for the “Reactive” control strategy are the same regardless of the SCM type. Overall, the “Wet Proactive” control strategy was able to better attenuate peak discharge during these events when compared to the “Reactive” control strategy and actually reduced peak discharge substantially when compared to the baseline “Uncontrolled” (Figure 5.12). However, it does appear that the ability of this control strategy to mitigate peak flow does decrease as the size of rainfall events increase (Figure 5.12). These results corroborate the conclusions of the long-term simulations in which the “Wet Proactive” control strategy is the most suitable choice for wet ponds if the objective is to reduce overall and intra-storm peak discharge.

The results of these isolated events do highlight the effectiveness of the “Wet Ideal” control strategy’s ability to reduce the necessary size of a wet pond’s temporary storage zone with significant reductions in stage and storage observed across all scenarios. Overall, this control strategy was able to reduce the required volume of the temporary storage zone by at a minimum 65% for the large basin and 19% for the small basin when compared to the baseline “Uncontrolled” while also consistently attenuating peak discharge (Figure 5.12). This equates to the control strategy only requiring 16% of the large basin’s and 62% of the small basin’s

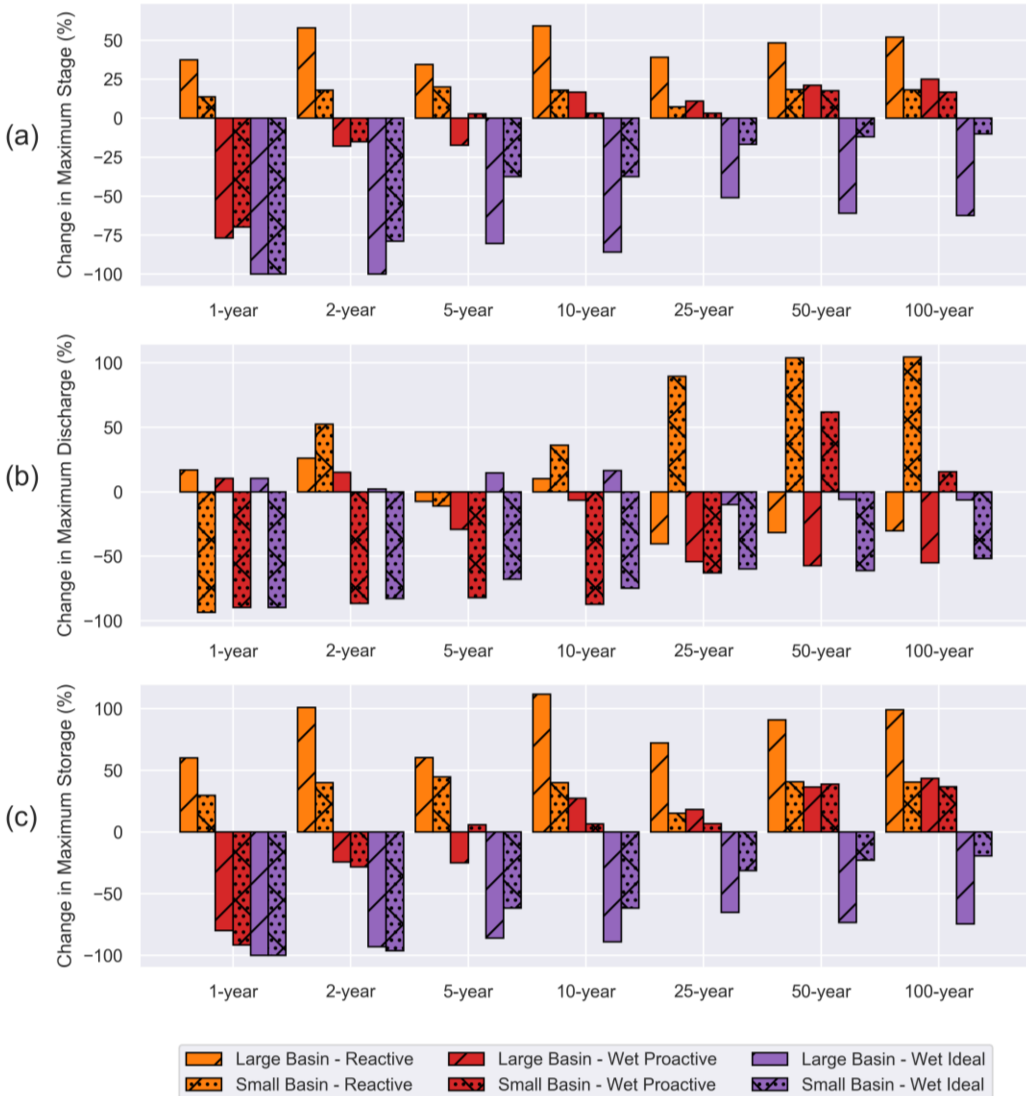

Figure 5.12. Results of the wet pond historical 24-hour event simulations displaying the maximum change in (a) stage of the temporary storage zone, (b) discharge, and (c) storage of the temporary storage zone relative to the uncontrolled scenario.

temporary storage zones (as compared to the 14% and 62%, respectively, of the long-term simulations) to achieve comparable or improved performance to that of an uncontrolled wet pond. Therefore, the results of this study support the conclusion that a wet pond's temporary storage zone could be reduced by 14-62% (dependent on site-specific factors) and achieve similar or improved hydrologic conditions compared to an uncontrolled SCM if this control strategy is implemented.

5.4.3.4 Analysis of Permanent Pool Stage

While both control strategies which allowed for pre-storm drawdown of the permanent pool ("Wet Proactive" and "Wet Ideal") did help to substantially decrease usage of the temporary storage zone and basin discharge, significantly low stages within the permanent pool occasionally occurred. As visible in the exceedance plots below (Figure 5.13), the "Wet Ideal" control strategy experienced much lower stages in the permanent pool compared to the "Wet Proactive" control strategy. For example, stage of the permanent pool fell below 75% of total stage (1.14 m) 28% and 8% (large and small basin, respectively) of the time when implementing the "Wet Ideal" control strategy as compared to 15% and 2% (large and small basin, respectively) when implementing the "Wet Proactive" control strategy. This disparity was caused by how each control strategy handled forecasted runoff volume with the "Wet Proactive" control strategy proactively draining the system if forecasted runoff exceeded the available storage of both the permanent pool and temporary storage zone combined, while the "Wet Ideal" control strategy only considered the available storage of the permanent pool. Therefore, in situations where pre-storm drawdown and exposure of side-slopes of the permanent pool is not accepted by the surrounding community for aesthetic reasons, limitations to the maximum drawdown may need to be implemented. While these limitations will reduce the effectiveness of both of these

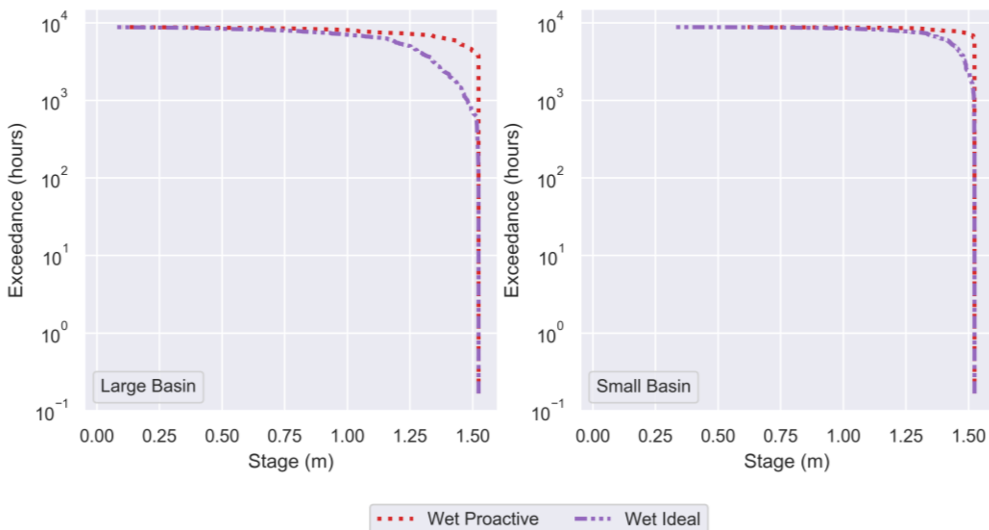

Figure 5.13. Exceedance plots comparing the stage (m) of the permanent pool for control strategies which allowed pre-storm drawdown for both the large and small basins.

strategies to accomplish their respective objectives, they still may prove more effective than passive or reactive control strategies.

5.4.4. Impact of Forecast Uncertainty

While it has been concluded that the control strategies which integrated rainfall forecasts into the decision framework (“Dry Proactive”, “Wet Proactive” and “Wet Ideal”) are the ideal candidates for meeting their respective objectives (within the constraints previously outlined), each are potentially impacted by data uncertainty within the forecast. Therefore, to examine the role of data uncertainty and to test if more accurate forecasts lead to increased performance, an additional series of long-term simulations were performed using each of these control strategies but replacing the existing forecast data with perfect forecast data based on the existing rainfall dataset. Each control strategy responded uniquely when forecast uncertainty was removed. To analyze and compare these responses, exceedance plots for stage (m) of the dry extended detention basin/temporary storage zone, discharge (m^3/s), and storage (%) were created (Figure 5.14) in addition to discharge exceedance plots showing the distribution of intra-storm and inter-storm discharges (Figure 5.15).

Forecast uncertainty primarily affected the large basin’s “Dry Proactive” control strategy by increasing the maximum observed stage and storage when perfect forecasts were used. This change was the cause of the control strategy’s proactive intra-storm discharges, as seen in Figure 5.15, which were substantially decreased and led to the increase in stage and storage. Therefore, it can be concluded in this instance that the forecast was over-estimating rainfall which caused the system to discharge at an increased rate intra-storm (Figure 5.15). Meanwhile, the “Wet

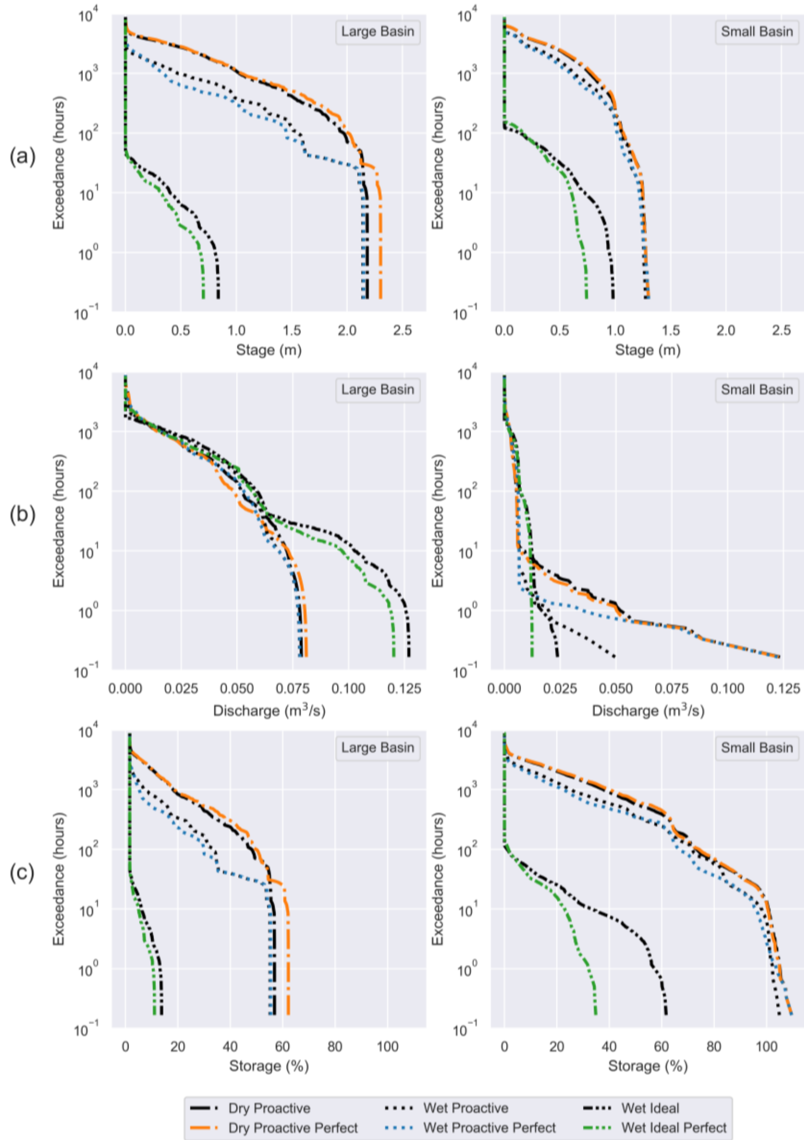

Figure 5.14. Long-term simulation exceedance plots for the large and small basins displaying (a) stage (m) of the temporary storage zone/ dry extended detention basin, (b) discharge leaving the system (m^3/s), and (c) storage (%) of the temporary storage zone/dry extended detention basin for every control strategy which utilized rainfall forecasts as well as their "Perfect" forecast counterpart.

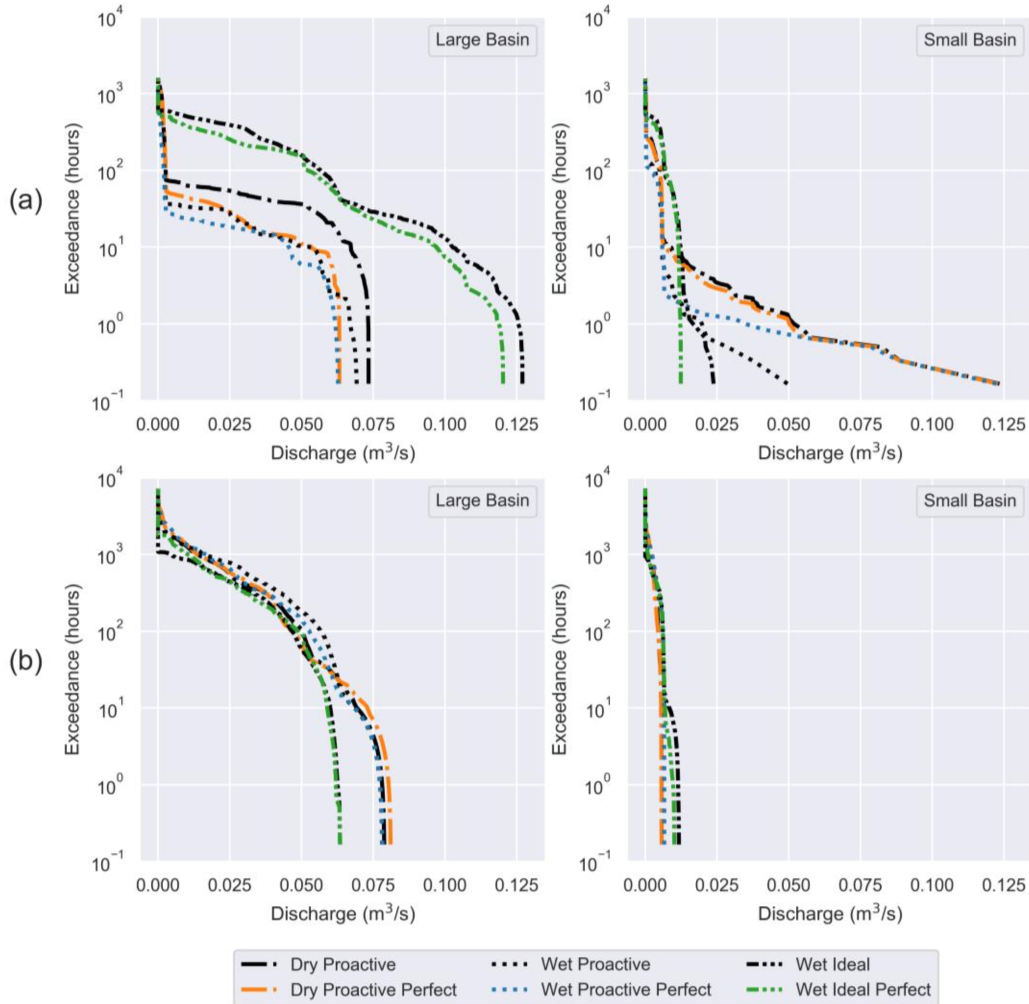

Figure 5.15. Exceedance plots for the large and small basins comparing when discharge (m^3/s) occurred including the distribution of (a) intra-storm and (b) inter-storm discharges for every control strategy which utilized rainfall forecasts as well as their "Perfect" forecast counterpart.

Proactive" control strategy was the most impacted by forecast uncertainty when applied to the small basin, as visible in Figure 5.14 and Figure 5.15, and use of perfect forecast data led to significant increases in overall and intra-storm discharge likely by underestimating the basin and watershed's response to future rainfall. The "Wet Ideal" control strategy experienced reductions in all parameters when perfect forecast data was used for both basins. Therefore, it can be concluded that this control strategy is the most impacted by data uncertainty and engineers and planners should observe improvements in basin performance as the accuracy of rainfall forecasts continue to improve.

5.5. Conclusions

Two dry extended detention basins and two wet ponds were modeled in PCSWMM to investigate and contextualize the impact of RTC on stormwater infrastructure. Four control strategies for the wet pond scenarios and three control strategies for the dry extended detention basin scenarios were analyzed in this study and represent a diverse selection of RTC methodology. These control strategies included: an uncontrolled baseline (both SCM scenarios), reactive control strategies which attempted to limit intra-storm discharge by reacting to current conditions such as rainfall (both SCM scenarios), proactive control strategies integrating rainfall forecasts into the decision framework to further attenuate intra and inter-storm discharge (both SCM scenarios), and a control strategy which attempted to limit usage of the wet pond's temporary storage zone (wet pond scenarios only). Simulations of each control strategy included (1) long-term (1-year) simulations to analyze long-term performance in addition to (2) simulations of historical 24-hour rainfall events to investigate how each control strategy would respond to larger, less frequent rainfall events.

The results of this study found that RTC has the potential to improve or attenuate SCM discharge to the receiving stream with control strategies which integrated rainfall forecasts into the decision framework able to meet this objective more consistently (up to a 43% reduction in intra-storm discharge as compared to the 33% possible with reactive strategies). Wet ponds equipped with RTC showed the most promise during this investigation, with control strategies which proactively drew down a portion of the wet pond's permanent pool before a rainfall event able to (in some cases) completely mitigate stormwater runoff. Due to this reason, RTC seems to impact the design parameters (such as required storage volume) of wet ponds more than dry extended detention basins. Specifically, control strategies which targeted reducing usage of the wet pond's temporary storage zone only required 14-62% (dependent on site-specific factors) of the temporary storage zone to achieve similar (or improved) performance to that of a static system. Therefore, it may be possible to reduce the overall volume of wet ponds integrated with RTC by 19-65%, which would be a benefit to economic resource allocation or would provide an incentive to land developers to install RTC stormwater infrastructure in lieu of traditional, static systems. While each control strategy explored in this study successfully met their respective objectives and improved system performance beyond existing conditions, special care should be taken to ensure that implementation of RTC does not exacerbate existing conditions such as increasing the frequency of outlet overtopping.

References

Boyle, R., A. Poresky, O. Cadwalader, and S. Landers. 2016. "Stormwater Real Time Controls at the Watershed Scale: Evaluating the Business Case and Developing an Implementation Roadmap for an Oregon MS4." In *Proc., Water Environment Federation*, 750-755. New Orleans, LA: WEF. https://doi.org/10.2175/193864716819705997.

City of Knoxville Stormwater Engineering Division. 2021. "Rainfall Data." Accessed March 18, 2021. https://knoxvilletn.gov/government/city_departments_offices/engineering/stormwater_engineering_division/rainfall_data.

CHI Support. 2021. "SRTC." Accessed March 18, 2021. https://support.chiwater.com/.

Gaborit, E., D. Muschalla, B. Vallet, P. A. Vanrolleghem, and F. Antcil. 2013. "Improving the performance of stormwater detention basins by real-time control using rainfall forecasts." *Urban Water Journal*, 10 (4), 230-246. https://doi.org/10.1080/1573062X.2012.726229.

Gaborit, E., F. Antcil, G. Pelletier, and P. A. Vanrolleghem. 2016. "Exploring forecast-based management strategies for stormwater detention ponds." *Urban Water Journal*, 13 (8), 541-851. https://doi.org/10.1080/1573062X.2015.1057172.

Georgia Stormwater Management Manual. 2016. Atlanta Regional Commission.

Gilpin, A. and M. Barrett. 2014. "Interim Report on the Retrofit of an Existing Flood Control Facility to Improve Pollutant Removal in an Urban Watershed." In *World Environmental and Water Resources Congress 2014*, 65-74. Portland, Oregon: ASCE. https://doi.org/10.1061/9780784413548.009.

Huffman, R. L., D. D. Fangmeier, W. J. Elliot, and S. R. Workman. 2013. *Soil and Water Conservation Engineering*. Seventh edition. St. Joseph, MI: ASABE.

Jacopin, C., E. Lucas, M. Desbordes, and P. Bourgogne. 2001. “Optimisation of Operational Management Practices for the Detention Basins.” *Water Sci. Technol.,* 44 (2-3), 277−285. https://doi.org/10.2166/wst.2001.0780.

Kerkez, B., C. Gruden, M. Lewis, L. Montestruque, M. Quigley, B. Wong, A. Bedig, R. Kertesz, T. Braun, O. Cadwalader, A. Poresky, and C. Pak. 2016. “Smarter Stormwater Systems.” *Environ. Sci. Technol.*, 50 (14), 7267-7273. https://doi.org/10.1021/acs.est.5b05870.

Knox County, Tennessee Stormwater Management Manual. 2008. Knox County Tennessee Department of Engineering and Public Works.

Mullapudi, A., M. Bartos, B. Wong, and B. Kerkez. 2018. “Shaping Streamflow Using a Real-Time Stormwater Control Network.” *Sensors*, 18 (2259), 1-11. https://doi.org/10.3390/s18072259.

Muschalla, D., B. Vallet, F. Antcil, P. Lessard, G. Pelletier, and P. A. Vanrolleghem. 2014. “Ecohydraulic-driven real-time control of stormwater basins.” *J. Hydrology*, 511 (2014), 82-91. https://doi.org/10.1016/j.jhydrol.2014.01.002.

National Oceanic and Atmospheric Administration (a). 2021. “Knoxville Climate Normals and Records.” *National Weather Service*. Accessed March 18, 2021. https://www.weather.gov/mrx/tysclimate.

National Oceanic and Atmospheric Administration (b). 2021. “National Digital Forecast Database.” *The Meteorological Development Laboratory*. Accessed March 18, 2021. https://vlab.ncep.noaa.gov/web/mdl/ndfd.

National Oceanic and Atmospheric Administration (c). 2021. “NOAA Atlas 14 Point Precipitation Frequency Estimates: TN.” *Hydrometeorological Design Studies Center*.

Accessed March 18, 2021.
https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_map_cont.html?bkmrk=tn.

Natural Resources Conservation Service. 2021. “Web Soil Survey.” Accessed March 14, 2021. https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm.

Rimer, S. P., A. Mullapudi, S. C. Troutman, and B. Kerkez. 2019. “A benchmarking framework for control and optimization of smart stormwater networks: demo abstract.” In *Proc., 10th ACM/IEEE International Conference on Cyber-Physical Systems*, 350-351. New York, NY: Association for Computing Machinery. https://doi.org/10.1145/3302509.3313336.

Soil Conservation Service. 1986. “Urban Hydrology for Small Watersheds.” In *Technical Release 55*. Springfield, Virginia: National Technical Information Service.

U.S. Geological Survey. 2021. “USGS 03535400 BEAVER CREEK AT SOLWAY, TN.” *National Water Information System: Web Interface*. Accessed March 18, 2021. https://waterdata.usgs.gov/nwis/uv/?site_no=03535400&PARAmeter_cd=00045.

Wong, B. P., and B. Kerkez. 2018. “Real-Time Control of Urban Headwater Catchments Through Linear Feedback: Performance, Analysis, and Site Selection.” *Water Resources Research*, 54 (10), 7309-7330. https://doi.org/10.1029/2018WR022657.

Xu, W. D., M. J. Burns, F. Cherqui, and T. D. Fletcher. 2021. “Enhancing stormwater control measures using real-time control technology: a review.” *Urban Water J.*, 18 (2), 101-114. https://doi.org/10.1080/1573062X.2020.1857797.

CHAPTER 6: SUMMARY AND CONCLUSIONS

This dissertation explored novel applications of smart stormwater infrastructure through a diverse collection of case studies and modeling investigations. The process of retrofitting existing stormwater infrastructure with real-time controllable outlets and sensors demonstrates strong potential for building resiliency into stormwater infrastructure. Specifically, this technology can and should be leveraged by designers and engineers to improve the performance of stormwater control measures (SCMs) and ensure that the infrastructure is adaptable to changing watershed restoration objectives or a changing climate.

Chapter 2 investigated the design and application of a low-cost, accurate stream gauging station. The purpose of this design was to assist in the real-time data collection required to make data driven decisions regarding placement of SCMs outfitted with real-time control (RTC), to inform the control decisions of RTC stormwater infrastructure, or to measure the in-stream hydrologic impacts of SCMs equipped with RTC. Existing systems which remotely monitor stream stage and flow are cost and maintenance prohibitive to most municipalities which has left many waterways unmonitored. Therefore, a novel stream gauging station was designed that was low-cost (<$200), accurate (MAE < 1.78 cm), and easy to install to provide municipalities with a better alternative to cover gaps in their existing networks. Additionally, the design and application of environmental instrumentation and controls may appear daunting to members of local municipalities. This system provides an easier transition into the design and application of RTC systems by providing individuals with a simpler design problem that is helpful in developing these skills before larger, more advanced problems are undertaken. The design of this system was especially helpful for collecting the hydrologic data necessary for quantifying the in-stream impact of RTC stormwater infrastructure in Chapter 4.

Chapter 3 investigated integration of real-time water quality data into the decision framework of stormwater infrastructure retrofitted with RTC. A dry extended detention basin was retrofitted with a controllable outlet and a turbidity sensor with the objective of reducing turbidity in the basin's discharge. When rainfall was detected the basin's valve would close and detain stormwater runoff until either a maximum detention time was reached (to ensure that basin capacity was available for subsequent rainfall events), or turbidity at the outlet fell below a threshold deemed appropriate for surface waters. This methodology was found to be more successful in meeting water quality objectives than a conventional, static system. While comparable performance would be obtained by a system equipped with RTC and implementing a predetermined detention time (equal to the maximum detention time of this study), this control strategy would not provide the numerous hydrologic advantages of the water-quality informed system such as not detaining water longer than necessary and therefore ensuring capacity in the system for any subsequent rainfall.

While the water-quality informed RTC strategy was successful, it may not be feasible for municipalities to install such a system on every SCM within their jurisdiction as large-scale implementation may prove to be cost and maintenance prohibitive. To provide an alternative solution, a modeling investigation was undertaken to examine if control via a real-time water quality sensor could be replaced by a site-specific model once a period of data collection had occurred. A diverse selection of traditional statistical models and machine learning techniques were created and validated to ensure that system performance would remain comparable to decisions made using real-time turbidity measurements. Creation of these models focused on using predictors that could be derived without a turbidity sensor such as basin stage or cumulative rainfall. It was determined that a logistic regression model or a more advanced Long

Short-Term Memory (LSTM) network were good candidates to be the basin's site-specific model. While the LSTM model outperformed all others in this study, the complexity and computational expense of generating a decision using the LSTM model may force future users to abandon this model in favor of the more simplistic logistic regression model. However, either model provides a feasible solution for municipalities looking for a more cost-effective solution to implementing water-quality informed RTC of stormwater infrastructure.

While Chapter 3 focused on impacts at the basin or site scale, Chapter 4 moved beyond site-specific observations and attempted to quantify the in-stream impact of discharge from SCMs equipped with RTC. These impacts were deemed important as benefits to hydrologic conditions should not be at the cost of water quality. To accomplish this, the dry extended detention basin outfitted with RTC from Chapter 3 had its control strategy altered; when rainfall was detected, the basin's valve would close and detain stormwater runoff for 72 hours following the end of rainfall. Once this detention period had elapsed the valve was opened, and the in-stream hydrologic and water quality impact was quantified using sensors installed within the receiving stream (hydrologic parameters where quantified using the station developed in Chapter 2). Specifically, these sensors included a custom stream gauging station for measuring stage and a multiparameter sonde measuring dissolved oxygen, temperature, and turbidity.

The results of this study revealed noticeable impacts to in-stream stage, discharge, temperature, and turbidity with limited impact to dissolved oxygen. Specifically, stage and discharge were only elevated while the basin was discharging and did not exceed any concerning threshold due to the size of the basin's orifice and maximum stage. In-stream temperature (caused by the detained stormwater of the basin being heated via solar radiation) was elevated during and following the basin discharging and may be a concern during warm weather events as some events were observed to exceed the state of Tennessee's maximum rate of change. Turbidity was substantially elevated while the basin was discharging and was likely caused by sediment being discharged from the basin or resuspension of settled sediment in the stream. While the observed impact isn't ideal, it may not be a concern or negatively impact aquatic life due to the magnitude and duration of occurrence. Even though dissolved oxygen impacts were limited for the majority of events in this study, time of day and ambient temperature when the basin discharges appeared to play an important role in this impact. Specifically, when the basin discharged during the evening of warm days, the basin discharging was able to improve in-stream dissolved oxygen conditions and actually decreased the time the stream spent below the threshold harmful to fish and aquatic life. Therefore, it may be possible to leverage this technology to time basin discharges such that in-stream dissolved oxygen is prevented from falling below these harmful thresholds; though the required volume of detained water or number of systems to consistently improve conditions is unknown.

The comprehensive modeling investigation presented in Chapter 5 contextualized the impacts that a diverse selection of control strategies has on the hydrology and design parameters of both dry extended detention basins and wet ponds. Two dry extended detention basins and wet ponds were modeled in PCSWMM. The results of this study found that RTC has the potential to further improve or attenuate SCM discharge to the receiving stream, with control strategies which integrated rainfall forecasts into the decision framework able to meet this objective more consistently. Wet ponds showed the most promise during this investigation, with control strategies which proactively drew down a portion of the wet pond's permanent pool able to (in some cases) completely mitigate stormwater runoff. Control strategies which target reducing usage of the wet pond's temporary storage zone were able to decrease the necessary volume of the wet pond by 16-65% dependent on site-specific parameters. While each control strategy explored in this study successfully met their respective objectives and improved system performance beyond existing conditions, special care should be taken to ensure that implementation of RTC does not exacerbate existing conditions such as increasing the frequency of outlet overtopping (as seen in the results of the small dry extended detention basin).

REFERENCES

Anderson, C. W. 2005. “Chapter A6. Section 6.7. Turbidity.” In *Techniques of Water-Resources Investigations*. Reston, VA: U.S. Geological Survey.

Bilodeau, K., G. Pelletier, and S. Duchesne. 2019. “Real-time control of stormwater detention basins as an adaptation measure in mid-size cities.” *Urban Water Journal*, 15 (9), 858-867. https://doi.org/10.1080/1573062X.2019.1574844.

Boyle, R., A. Poresky, O. Cadwalader, and S. Landers. 2016. “Stormwater Real Time Controls at the Watershed Scale: Evaluating the Business Case and Developing an Implementation Roadmap for an Oregon MS4.” In *Proc., Water Environment Federation*, 750-755. New Orleans, LA: WEF. https://doi.org/10.2175/193864716819705997.

Campbell Scientific. 2017. “OBS501 Smart Turbidity Meter with ClearSensor Technology”. Accessed December 16th, 2020. https://s.campbellsci.com/documents/us/manuals/obs501.pdf.

CHI Support. 2021. “SRTC.” Accessed March 18, 2021. https://support.chiwater.com/.

City of Knoxville Stormwater Engineering Division. 2021. “Rainfall Data.” Accessed March 18, 2021. https://knoxvilletn.gov/government/city_departments_offices/engineering/stormwater_engineering_division/rainfall_data.

Clary, J., J. Jones, M. Leisenring, P. Hobson, and E. Strecker. 2020. “International Stormwater BMP Database: 2020 Summary Statistics.” The Water Research Foundation. Accessed February 1st, 2020. https://www.waterrf.org/system/files/resource/2020-11/DRPT-4968_0.pdf.

Cryer, J., and K. Chan. 2008. *Time Series Analysis With Applications in R*. Second Edition. New York, NY: Springer Science+Business Media, LLC.

Dunne, T. and L. B. Leopold. 1978. *Water in Environmental Planning*. San Francisco, CA: W.H. Freeman and Company.

Eder, A., M. Exner-Kittridge, P. Strauss, and G. Blöschl. 2014. "Re-suspension of bed sediment in a small stream – results from two flushing experiments." *Hydrology and Earth Science Systems*, 18, 1043-1052. https://doi.org/10.5194/hess-18-1043-2014.

Gaborit, E., D. Muschalla, B. Vallet, P. A. Vanrolleghem, and F. Antcil. 2013. "Improving the performance of stormwater detention basins by real-time control using rainfall forecasts." *Urban Water Journal*, 10 (4), 230-246. https://doi.org/10.1080/1573062X.2012.726229.

Gaborit, E., F. Antcil, G. Pelletier, and P. A. Vanrolleghem. 2016. "Exploring forecast-based management strategies for stormwater detention ponds." *Urban Water Journal*, 13 (8), 541-851. https://doi.org/10.1080/1573062X.2015.1057172.

Ganegedara, T. 2018. "Long Short-Term Memory Networks." In *Natural Language Processing with TensorFlow : Teach Language to Machines Using Python's Deep Learning Library*. Birmingham, UK: Packt Publishing Ltd., 201-228.

Georgia Stormwater Management Manual. 2016. Atlanta Regional Commission.

Genuer, R. and J. Poggi. 2020. *Random Forests with R*. Cham, Switzerland: Springer International Publishing.

Gilpin, A. and M. Barrett. 2014. "Interim Report on the Retrofit of an Existing Flood Control Facility to Improve Pollutant Removal in an Urban Watershed." In *World Environmental and Water Resources Congress 2014*, 65-74. Portland, Oregon: ASCE. https://doi.org/10.1061/9780784413548.009.

Hoppe, H., S. Messmann, A. Giga, and H. Gruening. 2011. "A real-time control strategy for separation of highly polluted storm water based on UV–Vis online measurements – from theory to operation." *Water Sci. Technol.*, 63 (10), 2287-2293. https://doi.org/10.2166/wst.2011.164.

Huffman, R. L., D. D. Fangmeier, W. J. Elliot, and S. R. Workman. 2013. *Soil and Water Conservation Engineering*. Seventh edition. St. Joseph, MI: ASABE.

Jacopin, C., E. Lucas, M. Desbordes, and P. Bourgogne. 2001. "Optimisation of Operational Management Practices for the Detention Basins." *Water Sci. Technol.,* 44 (2-3), 277−285. https://doi.org/10.2166/wst.2001.0780.

Kerkez, B., C. Gruden, M. Lewis, L. Montestruque, M. Quigley, B. Wong, A. Bedig, R. Kertesz, T. Braun, O. Cadwalader, A. Poresky, and C. Pak. 2016. "Smarter Stormwater Systems." *Environ. Sci. Technol.,* 50 (14), 7267-7273. https://doi.org/10.1021/acs.est.5b05870.

Knox County, Tennessee Stormwater Management Manual. 2008. Knox County Tennessee Department of Engineering and Public Works.

Middleton, J. R. and M. E. Barrett. 2008. "Water Quality Performance of a Batch-Type Stormwater Detention Basin." *Water Environ. Res.*, 80 (2), 172-178. https://doi.org/10.2175/106143007X220842.

Mullapudi, A., M. Bartos, B. Wong, and B. Kerkez. 2018. "Shaping Streamflow Using a Real-Time Stormwater Control Network." *Sensors*, 18 (2259), 1-11. https://doi.org/10.3390/s18072259.

Muschalla, D., B. Vallet, F. Antcil, P. Lessard, G. Pelletier, and P. A. Vanrolleghem. 2014. "Ecohydraulic-driven real-time control of stormwater basins." *J. Hydrology*, 511 (2014), 82-91. https://doi.org/10.1016/j.jhydrol.2014.01.002.

National Oceanic and Atmospheric Administration (a). 2021. “Knoxville Climate Normals and Records.” *National Weather Service*. Accessed March 18, 2021. https://www.weather.gov/mrx/tysclimate.

National Oceanic and Atmospheric Administration (b). 2021. “National Digital Forecast Database.” *The Meteorological Development Laboratory*. Accessed March 18, 2021. https://vlab.ncep.noaa.gov/web/mdl/ndfd.

National Oceanic and Atmospheric Administration (c). 2021. “NOAA Atlas 14 Point Precipitation Frequency Estimates: TN.” *Hydrometeorological Design Studies Center*. Accessed March 18, 2021. https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_map_cont.html?bkmrk=tn.

Natural Resources Conservation Service. 2021. “Web Soil Survey.” Accessed March 14, 2021. https://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm.

NCDEQ Stormwater BMP Manual. 2017. North Carolina Department of Environmental Quality.

Normand, A. E. 2019. “U.S. Geological Survey (USGS) Streamgaging Network: Overview and Issues for Congress.” *R45695*, Congressional Research Service, Washington, D.C.

Particle. 2021. “Boron Datasheet.” *Particle Docs*. Accessed January 13, 2021. https://docs.particle.io/datasheets/boron/boron-datasheet/.

Pyzoha, D. S. 1994. *Implementing a Stormwater Management Program*. Boca Raton, FL: Lewis Publishers.

Rimer, S. P., A. Mullapudi, S. C. Troutman, and B. Kerkez. 2019. “A benchmarking framework for control and optimization of smart stormwater networks: demo abstract.” In *Proc., 10th ACM/IEEE International Conference on Cyber-Physical Systems*, 350-351. New

York, NY: Association for Computing Machinery. https://doi.org/10.1145/3302509.3313336.

Sazzad, S., W. McDonald, and A. J. Parolari. 2019. “Improved reliability of stormwater detention basin performance through water quality data-informed real-time control.” *J. Hydrol.*, 573 (2019), 422-431. https://doi.org/10.1016/j.jhydrol.2019.03.012.

Scherz, P. and S. Monk. 2016. *Practical Electronics for Inventors*. New York, NY: McGraw-Hill Education.

Soil Conservation Service. 1986. “Urban Hydrology for Small Watersheds.” In *Technical Release 55*. Springfield, Virginia: National Technical Information Service.

Strassler, E., J. Pritts, and K. Strellec. 1999. “Description and Performance of Storm Water Best Management Practices.” In *Preliminary Data Summary of Urban Stormwater Best Management Practices*. Washington, DC: U.S. Environmental Protection Agency.

Streeter, V. L. and E. B. Wylie. 1985. *Fluid Mechanics*. New York, NY: McGraw-Hill.

Swenson, H. A., and H. L. Baldwin. 1965. “A primer on water quality”. In *General Interest Publication*. Washington, DC: U.S. Government Printing Office. https://doi.org/10.3133/7000057.

The Federal Interagency Stream Restoration Working Group. 2001. *Stream Corridor Restoration: Principles, Processes, and Practices*. Washington, DC: U.S. Government Publishing Office.

U.S. Environmental Protection Agency. 2019. “Chapter 0400-40-03 General Water Quality Criteria.” In *Rules of the Tennessee Department of Environment and Conservation*. https://www.epa.gov/sites/production/files/2014-12/documents/tn-chapter1200-4-3.pdf.

U.S. Environmental Protection Agency. 2009. “Environmental Impact and Benefits Assessment for Final Effluent Guidelines and Standards for the Construction and Development Category.” Accessed December 16th, 2020. https://www.epa.gov/sites/production/files/2015-06/documents/cd_envir-benefits-assessment_2009.pdf.

U.S. Geological Survey. 2021. “USGS 03535617 CONNER CREEK AT STEEL RD. NEAR SOLWAY, TN.” *National Water Information System: Web Interface*. Accessed January 12, 2021. https://nwis.waterdata.usgs.gov/nwis/inventory/?site_no=03535617.

Wong, B. P., and B. Kerkez. 2018. “Real-Time Control of Urban Headwater Catchments Through Linear Feedback: Performance, Analysis, and Site Selection.” *Water Resources Research*, 54 (10), 7309-7330. https://doi.org/10.1029/2018WR022657.

Xu, W. D., M. J. Burns, F. Cherqui, and T. D. Fletcher. 2021. “Enhancing stormwater control measures using real-time control technology: a review.” *Urban Water J.*, 18 (2), 101-114. https://doi.org/10.1080/1573062X.2020.1857797.

YSI. 2020. “EXO User Manual.” Accessed February 1st, 2020. https://www.ysi.com/File%20Library/Documents/Manuals/EXO-User-Manual-Web.pdf.

VITA

Aaron Akin served as a Graduate Research and Teaching Assistant within the Department of Civil and Environmental Engineering at the University of Tennessee-Knoxville while obtaining his Ph.D. in Water Resources Engineering. He received his M.S. in Biological and Agricultural Engineering and his B.S. in Biological Systems Engineering from Kansas State University in 2018. His passion for DIY electronics and urban sustainability evolved into a career working at the convergence of big data, technology, and the environment. His research focused on the development of novel instrumentation and controls for cyber-physical systems, smart stormwater systems, and intelligent water resources engineering. His work has led to five scientific publications (2 journal articles, 2 conference papers, and 1 thesis) and one patent filed (1 patent filed, 1 invention disclosure). He has been most notably honored with the Tennessee Fellowship for Graduate Excellence (2020) from the University of Tennessee and the Irrigation Foundation Scholarship (2017) from the Irrigation Association.