

# Tradeoffs and future directions in real-time stormwater infrastructure management: quantity, quality, and ecology

## Abstract

Recent research has applied real-time sensing and control theory to stormwater systems for improving water quantity metrics such as flooding and erosion, as well as water quality metrics like nutrient (e.g., nitrate, phosphorus) removal. Meanwhile, ecological management often relies on a combination of experiential heuristics and manual interventions that are limited in data assimilation and the timeliness and precision of control. This work begins to bring ecosystem management into the smart city space by applying real-time control tools to a simulated wetland system. First, a state space model is constructed to represent the influence of water level fluctuations on a wetland ecosystem. Then several control strategies are applied to a simulated network under historical precipitation to examine the tradeoffs and synergies of managing a simulated stormwater network for quantity, quality, or ecological goals. Despite the limitations of a linear representation of wetland dynamics, results suggest that water quality and ecological goals may have synergies. Further, there is also evidence that control strategies already adopted for quantity and quality goals may be positively impacting ecosystems. There is fruitful work ahead in constructing better control-amenable models for wetland dynamics. Likewise, real-time ecological state estimation would improve these methods. All models, code, and figures are freely available at <https://github.com/dantzert/501-wetlands>.

## Introduction

### Real Time Control of Stormwater Assets

#### *Reducing flooding*

Traditional methods of alleviating flooding typically involve large investments in gray infrastructure such as detention and retention basins, storm sewer pipes, and other drainage systems. These systems are typically designed to reduce flooding to acceptable levels under design storms. Design storms provide an upper bound for what the system is designed to handle. Storms are defined by recurrence intervals (10, 25, 100 year) which may be interpreted probabilistically. That is, there is a one percent chance of a 100 year storm occurring in any given year. The design storm approach limits consideration to extreme events and recurrence intervals have unclear meaning under nonstationary climates. This approach is more rooted in legislation than science.

The response and performance of these static “gray” assets is fixed, unable to leverage additional capacity during small events or adapt under changing loads. They are generally built to solve one problem, reduce flooding during large storms.

“Smart” stormwater systems use sensors (e.g., depth, discharge, soil moisture), weather forecasts, and actuators (such as valves and inflatable dams) to dynamically redesign the infrastructure system in response to precipitation events.<sup>1</sup> Initial efforts have focused on rule-based controllers defined by operators, researchers, and engineers familiar with the constraints and objectives of their particular systems. These approaches generally make use of EPA SWMM, python libraries for interacting with SWMM models during runs (`swmmpython` and `pyswmm`), and other python libraries to enable machine learning, calculations, or other utilities. The standard approach is to use python scripts that get and set variables within SWMM. However, other models have been proposed that are more amenable to real-time control and data assimilation than SWMM.<sup>2</sup>

### *Removing nutrients and pollutants*

By definition, most storms don’t have ten year or greater recurrence intervals and hence do not stress the flood reduction capacity of stormwater systems. Further, as effluent water quality is often strongly controlled by retention time and nutrient runoff can cause severe environmental disasters (fish kills, Toledo drinking water) there has been strong motivation to transform stormwater systems into distributed wastewater treatment facilities.<sup>3</sup> One enabling tool in this pursuit is a water quality toolbox for PySWMM called *StormReactor*,<sup>4</sup> which provides the water quality analysis in this study.

## Ecological Restoration and Protection

### *Experiential Heuristics*<sup>5</sup>

Natural Resource Management is more typically the domain of biologists and ecologists than engineers. As such, the application of systems engineering concepts and wireless sensor networks has been more limited as these professionals practice in a more observational and qualitative manner. Therefore, although there is a great deal of existing knowledge about the interactions, input responses, and constraints of natural systems, these relationships are typically not codified in a manner amenable to algorithmic control. Personal experience with an ecosystem and frequent work in that environment seem to be requisites for successfully managing ecosystems. Managers often attain great results this way. However, the time-intensive process of manual observation and management limits the scope (areal extent) and granularity (timescale and number of tuning parameters) of management programs. That is, we currently have a bottleneck in our information processing of natural systems by relying on human observation.

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<sup>1</sup> [Emerging investigators series: building a theory for smart stormwater systems† Abhiram Mullapudi, Brandon P. Wong and Branko Kerkez \\*](#)

<sup>2</sup> [Pipedream: An interactive digital twin model for natural and urban drainage systems – ScienceDirect](#)

<sup>3</sup> [Balancing water quality and flows in combined sewer systems using real-time control† Sara C. Troutman , Nancy G. Love and Branko Kerkez](#)

<sup>4</sup> [StormReactor: An open-source Python package for the integrated modeling of urban water quality and water balance Brooke E.Mason, AbhiramMullapudi, BrankoKerkez](#)

<sup>5</sup> [Wetland Management For Waterfowl Handbook](#)

### *Manual control methods*

The number of controlled assets, decision frequency, and action frequency are also limited by reliance on manual interventions. The US Fish and Wildlife Wetland Management Manual specifies that water levels in retention cells ought to be changed by removing wooden boards placed inside of control structures. This approach is not unique to ecological management and is often used to manage the levels of small private lakes in the American midwest. However, far more precise, distributed, and frequent control is possible through the implementation of wireless actuator (valves or adjustable weirs) networks for real-time control of semi-aquatic systems.

## Bringing ecological management into the smart city framework

As human populations increase and environmental conditions deteriorate, it is becoming increasingly clear that natural systems are indispensable parts of our economic and technical systems. That is, *natural resources are infrastructure*. By implementing real-time sensing and control within natural systems we will enhance our understanding of these systems, promote their flourishing, and derive increased value from enhanced environmental services such as water treatment, flood mitigation, and the creation of habitat for endangered and sport species.

This study examines the tradeoffs between water quantity, water quality, and ecological goals in a simulated case study of a subcatchment of the stormwater system in Ann Arbor, Michigan. The results will suggest how control for quality and quantity may already be affecting our ecosystems. A linearized, state space model for a wetland ecosystem is also developed. This model provides qualitative feedback on the effect of water level management on ecosystem state in alignment with experience and expectations expressed in the wetland management manual. Representing the wetland ecosystem as a state space model also provides a framework to examine questions of controllability and observability from a systems engineering perspective.

## Methods

### Modeling a linked stormwater and ecological system (NO.inp)



**Figure 1.** Stormwater system and SWMM abstraction in southeast Ann Arbor, MI. The upstream basin is Ellsworth in the bottom left. Mary Beth Doyle Wetland (top right) has an inlet basin (topmost storage node) and a storage node to represent the wetland. The wetland discharges to a channel that leads to the Huron River.

#### *Upstream detention basin*

The upstream basin has two influent streams and receives overland flow as well. This is simplified to a single contributing subcatchment in the SWMM model. The actual control structure at Ellsworth has two controllable valves but this is simplified to one valve with a large area.

## *Wetland*

The wetland is modeled as two storage nodes connected by stream reaches. The upstream storage node is an uncontrolled retention (typically wet) basin. This drains into the wetland over a concrete paver cascade. This cascade is assumed to provide influent water of constant dissolved oxygen content into the wetland.

In the volume and flow calculations the wetland is represented as one storage node with a valve at the outlet. However, for water quality calculations the wetland is modeled as three CSTRs (completely stirred tank reactors) in series. The details of this representation can be found in Mason et al 2021.<sup>6</sup>

## *Representation of nitrate generation and removal*

Nitrate generation is modeled using default EPA SWMM subcatchment pollutant generation. In this representation, nitrate is washed off of the subcatchments and into storage nodes.

Removal of nitrate and depletion of dissolved oxygen are both modeled by a linearized model of a CSTR reactor as:

$$\frac{dC}{dt}V = Q_{in}C_{in} - Q_{out}C - kCV$$

Where  $C$  is the tank concentration,  $C_{in}$  is the influent concentration,  $V$  is the tank volume,  $Q_j$  are the volumetric flow rates, and  $k$  is a linear removal coefficient.  $k_{DO}$  is assumed to be 0.2/hr<sup>7</sup> and nitrate treatment is assumed to begin when dissolved oxygen levels drop below 1 mg/L. The nitrate reaction rate is assumed to be 1.5/day (ibid.) once anoxic conditions are reached, and zero otherwise when dissolved oxygen levels are above this threshold.

Treatment is quantified as the difference between wetland influent and effluent cumulative nitrate load. That is, how much less nitrate exits the wetland than enters it. This is not truly an entire system metric as there is the possibility of flow through an overflow channel near the wetland, but rather a measure of the effectiveness of the wetland as a treatment asset. But because the wetland is the only treatment asset in the simulation it does capture all the nitrate removal in the simulation.

## *Control assumptions - fully instrumented with remote controlled valves at outlets*

This watershed is assumed to be outfitted with water level sensors at all three storage nodes as well as dissolved oxygen and nitrate sensors at the wetland and upstream basin storage nodes. These data streams provide the output for the feedback control implemented in the control scenarios. The system is also assumed to have two remotely controllable valves at the outlet of the wetland and the upstream basin that are able to query an online database of sensor readings and change their open percentage every fifteen minutes. The simulation step of the model is a second.

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<sup>6</sup>

[https://www.sciencedirect.com/science/article/abs/pii/S1364815221002176?casa\\_token=1Tiznll1dfgAAAAA:grYNQHfXbAqNBRSBpfCuPIVqcfD-hy63hkNRyYaC2K4zY\\_A5-gCoVQJKvXNvj7L0RFg1acy](https://www.sciencedirect.com/science/article/abs/pii/S1364815221002176?casa_token=1Tiznll1dfgAAAAA:grYNQHfXbAqNBRSBpfCuPIVqcfD-hy63hkNRyYaC2K4zY_A5-gCoVQJKvXNvj7L0RFg1acy)

<sup>7</sup> K.R. Reddy, W.H. Patrick, Nitrogen Transformations and Loss in Flooded Soils and Sediments Crit. Rev. Environ. Contr., 13 (1984), pp. 273-309,

*Precipitation from a historical rainfall record for the nearest rain gage*

A one year historical rainfall record from a rain gauge near the case study system was used as forcing. The inclusion of more historic rainfall data might make the conclusions of this investigation more robust, but the coarseness of the representation of wetland dynamics is a more strongly limiting factor. Further, pyswmm (especially with real-time control) is computationally intensive. Each control scenario took about two hours to run using an Intel(R) Core(TM) i7-1065G7 CPU @ 1.30GHz 1.50 GHz processor with 32 GB of RAM available.

The use of design storms is standard practice in the design of stormwater infrastructure as well as other stormwater impacted infrastructure such as bridges. Design storms are not suitable for this type of analysis because ecosystems respond with large latencies and other goals (flood reduction) will take precedence over habitat creation during extreme events anyhow. The selected year does not include much extreme precipitation and so the uncontrolled and quantity control scenarios look very similar.

*No data assimilation - pure simulation*

Though data assimilation and field validation of these ideas is a future direction of research this study is purely en silico. However, the SWMM model is calibrated and provided by a community partner and so represents more than a “toy system.” This system representation and the methods for modeling water quality have previously been accepted for publication in Environmental Modelling & Software (Mason 2021).

*Linearized State Space Model of Wetland Dynamics (wetland\_ss.m)*

The interaction between six types of life and their response to water level changes in the Mary Beth Doyle wetland are represented using a linearized state space representation. This method approximates the rate of change of a state variable as a linear function of the state variables and inputs:

$$\begin{aligned}\frac{dx}{dt} = \dot{x} &= Ax + Bu \\ y &= Cx\end{aligned}$$

where  $x \in \mathbb{R}^n$  are the state variables of the system (number of ducks, kilograms of smartweed, etc.),  $u \in \mathbb{R}^p$  are the inputs to the system (water level and the water level time series frequency characteristics), and  $y$  is the output.  $A, B, C$  are all matrices of constant real values. The values for these matrices are based on information presented in the US Fish and Wildlife Wetland Management Manual. This representation does not include time varying effects and so seasonal and migratory dynamics are not captured.

States ( $x$ )

Generalizing across qualitative tabular data in the wetland management manual, six wildlife types are modeled: desirable vegetation, undesirable vegetation, aquatic invertebrates, dabbling waterfowl, diving waterfowl, and mammals. The goal of managers in the wetland management manual is generally to provide good habitat for waterfowl of both kinds.

### Interaction (A)

Much of the knowledge encoded in the wetland management manual is heuristic or qualitative. Therefore this matrix is presented with only two parameters and intended to be qualitatively suggestive. I define two parameters  $\alpha$  (strong) and  $\beta$  (weak) for these interactions.

**Table 1.** States are enumerated along the leftmost column. The way that other states impact them is indicated in the entries of the table.

(A) Interactions	Desirable Vegetation	Undesirable Vegetation	Invertebrates	Dabblers	Divers	Mammals
Desirable Vegetation	$-\alpha$	$-\beta$	0	$-\beta$	$-\beta$	$-\beta$
Undesirable Vegetation	$-\beta$	$-\alpha$	0	0	0	0
Invertebrates	$\alpha$	0	$-\alpha$	$-\beta$	$-\beta$	$-\beta$
Dabblers	$\alpha$	0	$\alpha$	$-\alpha$	0	$-\beta$
Divers	$\beta$	0	$\alpha$	$-\beta$	$-\alpha$	$-\beta$
Mammals	$\frac{\beta}{4}$	0	$\frac{\beta}{4}$	$\frac{\beta}{4}$	$\frac{\beta}{4}$	$-\alpha$

As an example, the rate of change of the prevalence of dabbling waterfowl is strongly boosted by the presence of desirable vegetation and invertebrates, while it is strongly reduced by the presence of other dabblers (self-inhibition) and weakly reduced by the presence of mammals.

### Input Response (B)

Wildlife are dependent not only on the immediate water level, but also the flooding regime (frequency and intensity) within a wetland. To represent this dependency the input to the system consists of immediate water levels and frequency characteristics of the water level time series. The B matrix represents the impact of both of these inputs on the state variables. Note that mammals are only affected indirectly by water levels as they are assumed to be grazing and predating on the other wildlife but living outside of the water.

**Table 2.** States are enumerated along the left-hand column. Inputs are along the top row. Impacts are indicated as in Table 1.

(B) Input Response	Immediate Water Level	Strength of Slow Oscillations	Strength of Medium Oscillations	Strength of Fast Oscillations	Strength of Rapid Oscillations
Desirable Vegetation	0	$\beta$	$\beta$	$-\beta$	$-\beta$
Undesirable Vegetation	0	0	0	$\beta$	$\beta$
Invertebrates	$\alpha$	$\beta$	0	$-\beta$	$-\beta$
Dabblers	$\beta$	0	0	0	0
Divers	$\alpha$	0	0	0	0
Mammals	0	0	0	0	0

One goal of control can be seen in the desirable and undesirable vegetation rows. In this simplified representation of the wetland system managers will generally want to provide slower oscillations as rapid drawdowns are more likely to lead to monocultures and decreased seed production.

u - Generating frequency characteristics of water level time series (input\_processing.m)

The wetland water level time series is taken as an output from the stormwater simulation for each control scenario. A rolling discrete fourier transform (DFT) is computed for every day in the time series. The DFT yields the relative strength of different frequencies of oscillation (e.g., weekly vs hourly) within the record. The DFT is binned to slow (slower than biweekly), medium (between biweekly and daily), fast (between daily and hourly), and rapid (faster than hourly) oscillation frequencies.

Observation (C) - assumption of automated audio analysis (not used in this study)

Though not used in this paper (as the states are viewed directly) an output filter ( $y = Cx$ ) could be implemented that identifies animals that use characteristic vocalizations to communicate. If an audio monitoring sensor were incorporated into a wireless sensor network<sup>8</sup>, the records could be analyzed as in Sprengel et al<sup>9</sup> to estimate the prevalence of indicator species. These indicator species could be used to infer the presence of other life such as vegetation or invertebrates those species are known to be dependent on. More details are presented in the future directions section.

<sup>8</sup> [Real-time water systems Lab at the University of Michigan](#)

<sup>9</sup> [Audio Based Bird Species Identification using Deep Learning Techniques](#)

## Control Scenarios (main.py)

Control algorithms are developed for several scenarios to test the tradeoffs of prioritizing ecology, quantity, and quality goals. For the details of how these algorithms are implemented, consult [github](#).<sup>10</sup>

### *Uncontrolled*

The uncontrolled scenario represents both valves as being completely open the entire simulation.

### *Quantity (flooding and streamflow / erosion)*

The quantity control algorithm implements a proportional feedback controller that attempts to keep flow rates in the stream below a threshold. That is, to flatten the hydrograph. There is also an emergency flood prevention control that completely opens the valve when an asset is about to surcharge.

### *Quality (nitrate removal)*

The nitrate removal algorithm is implemented as in Mason et al 2021.

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1 Compute wetland's DO and nitrate concentrations:

$$\frac{dC}{dt} = \frac{Q_{in_t} \cdot C_{in_t} - Q_{out_t} \cdot C_{out_t}}{V_t} - k_t \cdot C_t$$

2 for i in controllable valves do
3   if  $DO^t > 1\text{mg/L}$  then
4     if  $d_W \leq 3m$  then
5       valveW = 0
6       valveDB =  $f \cdot Q_{max}/A_{DB}\sqrt{2 \cdot g \cdot d_{DB}}$ 
7     else
8       valveW =  $f \cdot Q_{max}/A_W\sqrt{2 \cdot g \cdot d_W}$ 
9       valveDB = 0
10    else if  $DO \leq 1\text{mg/L}$  then
11      if  $C_t \leq 5\text{mg/L}$  then
12        valvei =  $f \cdot Q_{max}/A_i\sqrt{2 \cdot g \cdot d_i}$ 
13      else
14        if  $d_W \leq 3m$  then
15          valvei = 0
16        else
17          valveW =  $f \cdot Q_{max}/A_W\sqrt{2 \cdot g \cdot d_W}$ 
18        valveDB = 0
19 end

```

**Figure 2.** Nitrate removal algorithm reproduced from Mason et al 2021. The upstream basin's valve is indicated as "DB" (detention basin) while the wetland is indicated as "W."

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<sup>10</sup> <https://github.com/dantzert/501-wetlands/blob/4be388b70b863917999259611be8643f9efaabad/main.py#L154>

### *Fish and Wildlife management scenarios*

Control algorithms for waterfowl habitat are developed as proportional feedback controllers to achieve the water levels specified in Table 5 of the Wetland Management Manual. Table 5 is reproduced here to clarify the presentation.

**Table 5. Water level scenario for target species on three moist-soil impoundments and associated waterbird response.**

Period	Unit A		Unit B		Unit C	
	Scenario	Water level Response	Scenario	Water level Response	Scenario	Water level Response
<b>Early fall</b>	Dry	None	Dry	None	Gradual flooding starting 15 days before the peak of early fall migrants; water depth never over 4 inches	Good use immediately; high use by teal, pintails, and rails within 2 weeks
<b>Mid fall</b>	Dry	None	Flood in weekly 1–2-inch increments over a 4-week period	Excellent use by pintails, gadwalls, and wigeons	Continued flooding through September	Excellent use by rails and waterfowl
<b>Late fall</b>	Flood in weekly 2–4-inch increments over a 4–6-week period	Excellent use immediately by mallards and Canada geese	Continued flooding, but not to full functional capacity	Excellent use by mallards and Canada geese	Continued flooding to full functional capacity	Good use by mallards and Canada geese
<b>Winter</b>	Maintain flooding below full functional capacity	Good use by mallards and Canada geese when water is ice free	Maintain flooding below full functional capacity	Good use by mallards and Canada geese when water is ice free	Continued flooding to full pool	Good use by mallards and Canada geese when water is ice free
<b>Late winter</b>	Schedule slow drawdown to match northward movement of migrant waterfowl	Excellent use by mallards, pintails, wigeons, and Canada geese	Schedule slow drawdown to match northward movement of early migrating waterfowl	Excellent use by mallards, pintails, wigeons, and Canada geese	Schedule slow drawdown to match northward movement of waterfowl	Good use by mallards and Canada geese when water is ice free
<b>Early spring</b>	Continued slow drawdown to be completed by 1 May	Excellent use by teals, shoveler, shorebirds, and herons	Drawdown completed by 15 April	Excellent shorebird use	Drawdown completed by 15 April	Excellent shorebird use

## Evaluation

### *Quantity metrics - flooding and streamflow (flooding is bad, spiky is bad)*

Quantity metrics are evaluated only qualitatively by examining the water level record for the upstream basin and the wetland, as well as the inflow and outflow from the wetland. Generally, surcharging (for this study, levels above 10 ft or 3 meters at either asset) is undesirable as this indicates localized flooding near the storage asset. Additionally, a flatter, dampened hydrograph (streamflow time series) is generally preferable to sudden flashes of water through a river. Milder

streamflow magnitude variations are generally better for navigability, human safety, ecology, and reducing scour.

*Quality - cumulative nitrate load entering wetland versus that exiting*

Water treatment is measured as the nitrate removal effectiveness of the wetland. That is, the percentage difference between cumulative nitrate load entering and exiting the wetland.

$$\text{Effectiveness} = 1 - (\text{influent} / \text{effluent})$$

Such that complete removal of nitrate results in a score of 1 and no removal a score of 0. In reality, some settling and reactions would occur during streamflow and residence in any storage asset, but the wetland is assumed to be the primary treatment asset and so its treatment effectiveness is taken as a proxy for the treatment effectiveness of the entire system.

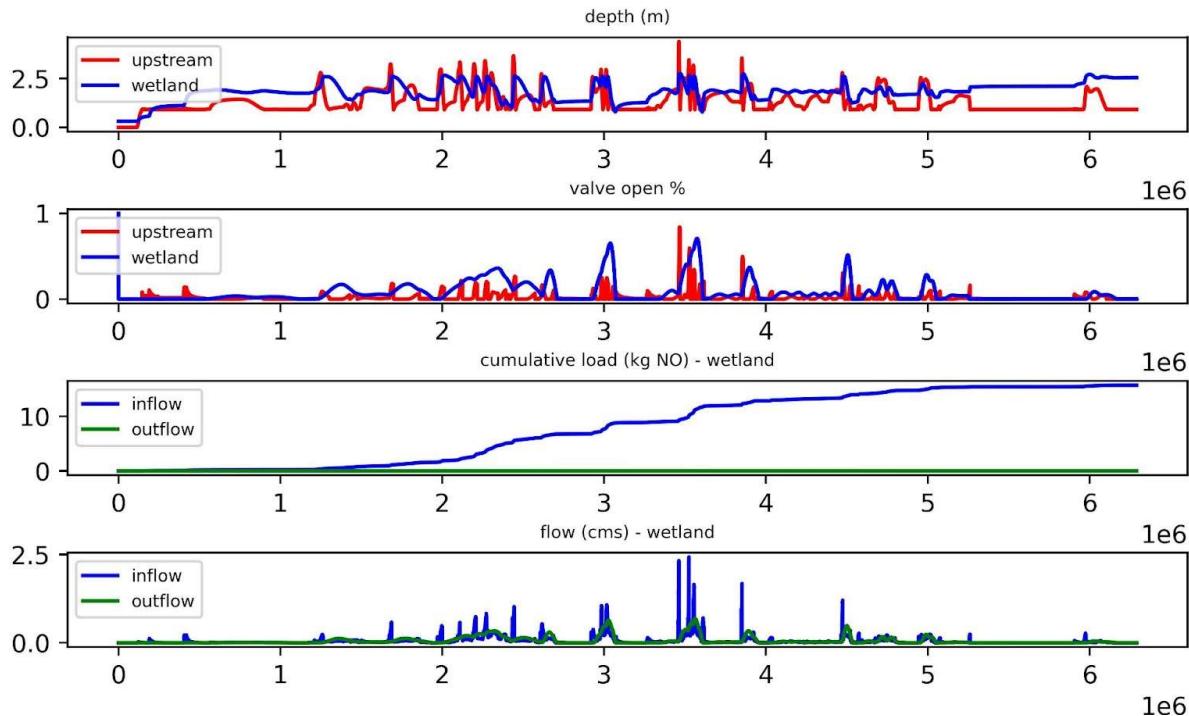
*Ecological - qualitative abundance of desirable vegetation and waterfowl*

The effect of the control scenarios on the wildlife in the wetland is evaluated by simulating the state space system's response to an input  $u$  that is derived from the water level time series within the wetland. This simulation generates a qualitatively suggestive estimation of the response of the wetland to water level manipulations.

The flow rate through the wetland is not considered here. Nor are other factors such as soil type and water quality that would certainly influence wildlife in the area.

# Results

## Stormwater system simulation

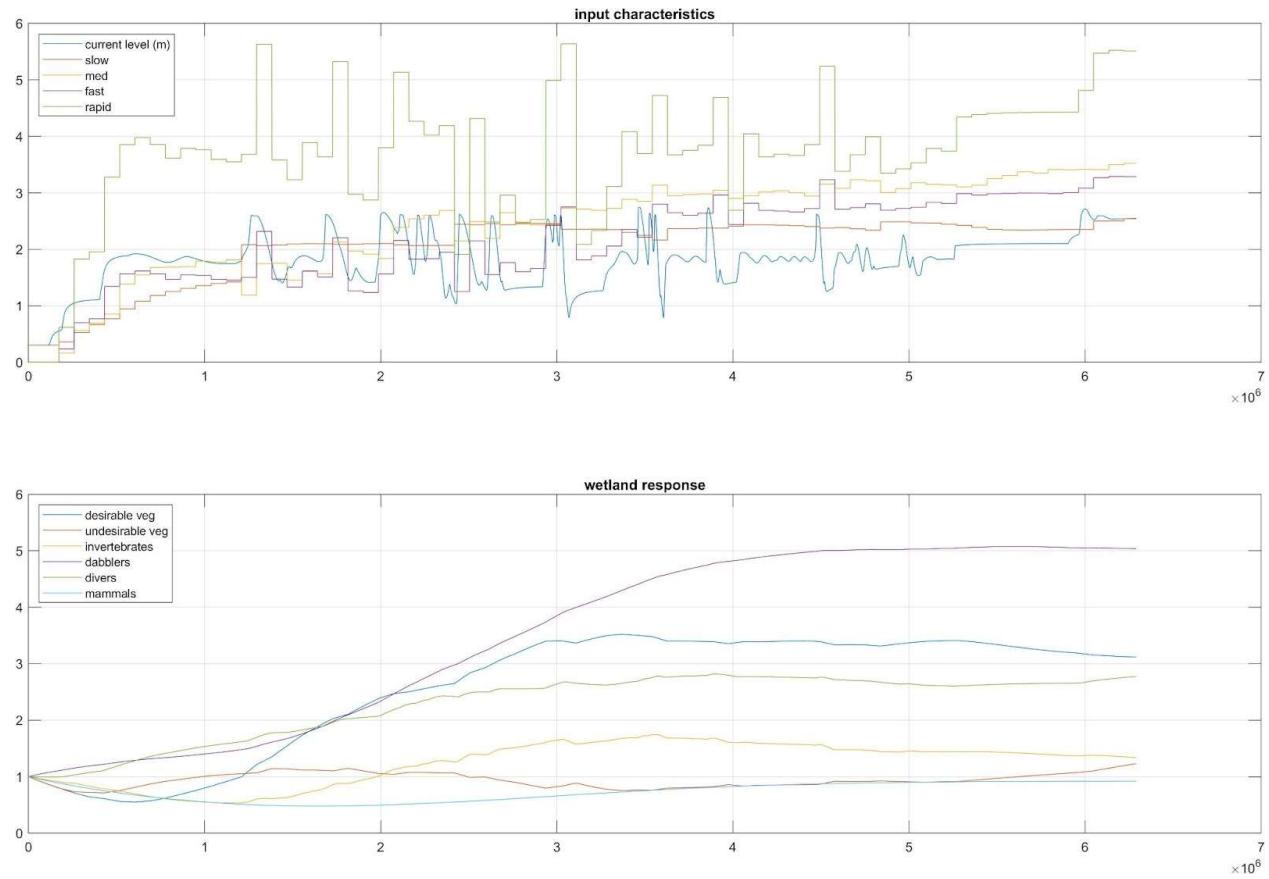


**Figure 2.** Results from the USFWS Control Scenario A simulation. The x axis is time in seconds and the simulation runs from January of 2010 to December of 2010.

The top panel shows water levels in the upstream basin and wetland. Surcharging is visible in the upstream basin in the late summer (between 3 and 4) due to a large storm. The second panel shows the valve open percentage at the outlet of each asset. All of the fish and wildlife control scenarios display gradual control adjustments as they were designed to make drawdowns and flooding slow for the sake of wildlife.

The third panel shows influent and effluent cumulative load of nitrate for the wetland. Removal is very effective in this case, though not for all scenarios. The last panel shows the inflow and outflow for the wetland in cubic meters per second. The buffering capacity of the wetland is clear in the relative magnitudes of the inflow and outflow hydrographs. Results for the other five scenarios are formatted identically and included in Appendix A1 for reference.

## Simulated wetland response



**Figure 3.** Simulated wetland response for USFWS Scenario A. The x axis is time in seconds and the simulation runs from January of 2010 to December of 2010.

The top panel shows the input characteristics. The blue line is the immediate water level and is identical to the blue line in the top panel of the stormwater system simulation results (figure 2). The water level provides the linking between the two models. The other time series in the top panel are measurements of the strength of various frequencies of oscillation of the water level time series. These are discrete as they are only updated every day to reduce computational burden.

The bottom panel shows the simulated wetland response based on the state space realization explained earlier. All simulations start with the initial state at one for every state for lack of a better assumption. Results for the other five scenarios are formatted identically and included in Appendix A2 for reference.

## Performance

**Table 3.** Summary of performance along three metrics. Control scenarios are ranked 1-5 (best to worst) for ecology and quantity, with quantitative scores for nitrate removal.

	Ecology (waterfowl abundance)	Water quality* (nitrate removal efficiency)	Quantity (hydrograph flattening and flood avoidance)
FWS_A	1	99.88%	2
FWS_B	2	99.87%	2
FWS_C	2	99.87%	2
Uncontrolled	5	81.99%	3
Quantity	4	84.97%	1
Nitrate removal	3	97.33%	4

\*The FWS scenarios had only about 75% of the influent nitrate load as the other three scenarios. This is likely due to surcharging at the upstream basin in these scenarios.

### *Ecology (waterfowl abundance)*

Unsurprisingly, the Fish and Wildlife Service Scenarios have the best ecological outcomes. The next is nitrate removal. This makes sense because the treatment process is primarily dependent on lengthening the residence time. The nitrate removal strategy may have had better results for ecology if the control did not pulse out water as it was treated, but released more smoothly. This pulsing resulted in rapid oscillations which reduced desirable vegetation in the wetland model. The quantity control and uncontrolled scenarios had rapid variations in water level which were not good for the wetland ecosystem. The quantity control strategy was not very active in this simulation year as precipitation was mild relative to its requirements. As a result, its water level and discharge time series look very similar to the uncontrolled case.

### *Water quality (nitrate removal)*

The FWS control scenarios perform slightly better than the nitrate removal scenario. This is likely because the nitrate removal control strategy has a nitrate concentration threshold below which releases are considered acceptable, while the wildlife prioritizing strategies create long detention times and depress nitrate levels even further before releasing. Quantity control is slightly better than uncontrolled.

### *Quantity (flooding and hydrograph shaping)*

The nitrate removal scenario has a large degree of localized flooding at the upstream asset. However, it does display a strongly dampened hydrograph only once exceeding two cubic meters per second inflow and never exceeding a half cubic meter per second outflow. The wildlife scenarios all have some upstream surcharging but display good hydrograph damping. The quantity control strategy never surcharges either asset and dampens the wetland outflow greatly.

## Discussion

### *Linear state space representation of wetland dynamics*

The matrices defining the wetland system are qualitative as input-output relationships have not yet been quantitatively specified (step-response data) for wetland ecosystems. A principal aim of future research would be to justify a quantitatively accurate representation of these systems.

A time-invariant system may appear problematic. However, the lack of time variance within the system does not prevent the consideration of seasonal factors like temperature and migratory patterns. These factors could be provided as time-varying inputs to the system.

Representing the interaction of wetland species as linear differential equations is also a large simplification. However, given the dearth of data available for *quantifying* these relationships, can a nonlinear model be more strongly justified? Representing the system in linear, time-invariant (LTI) form allows the application of an array of control theoretic tools not available for less constrained models. For initial explorations of the controllability and observability of natural systems this gain in tractability may be worth the loss in accuracy. The goal of system identification for control is to understand the system well enough to manipulate it, and it need be no more accurate than this.

As an example of the process of estimating parameters for a linear model, consider the relationship between mice and owls. Given estimates of an owl's caloric needs and those provided by an average mouse, the average number of mice consumed per day by each owl could be estimated. Further, assume that requisite foraging effort decreases as the mouse population density increases. Thus, the rate of change of owl population depends positively on the mouse population, while mice are consumed at the rate of (mice per owl-day) X (number of owls present). Using these mass-balance calculations estimates for linear interaction terms that create the predicted dynamics could be calculated. The uncertainties related to this estimation process are considerable and estimates should be revised to more closely model observed dynamics as real-time ecosystem state information becomes available for specific sites.

### *Representation of Nitrate Removal*

The only treatment modeled in this work is a series of three CSTRs representing the wetland. Nitrate removal is taken as a linear piecewise function of dissolved oxygen content. Clearly, much could be done to more accurately represent the removal of nitrate. Additionally, nitrate removal is taken as a proxy for water quality generally. This is problematic because communities struggle with different nutrients and pollutants (nitrogen, phosphorus, total dissolved solids, etc) and thereby may desire different strategies for their water quality goals.

### *Control scenarios*

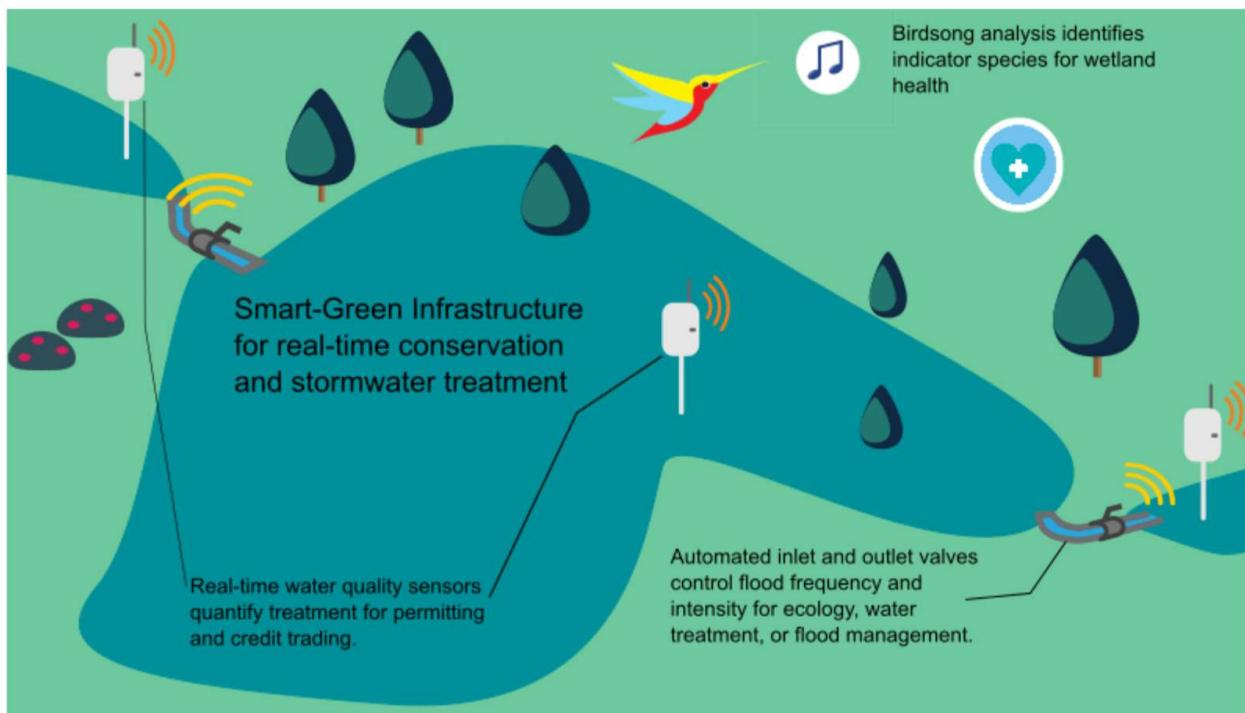
The control scenarios presented here are only meant to be typical and provide an example for discussion. The development of a control strategy for water quality or quantity goals is an onerous task in itself, specific to the system in question and owner preferences in performance.

# Conclusions and Future Directions

## Trade offs in management goals

This work suggests that water quality and ecological strategies may have synergies. That is, water quality strategies may have desirable ecological effects and vice versa. Also, note that the uncontrolled scenario is worst in two metrics (ecology and treatment), and second worst in the third. This suggests that currently implemented real-time control for flood avoidance or water treatment is likely having positive impacts on wildlife.

## Future Directions



**Figure 4.** Visual abstract of a smart wetland.

### *Controllability assumptions are feasible (reference K in figure 5)*

Valves accessing real-time data to make automated control decisions is feasible given current technology and will be implemented by the end of summer 2022 in a case study in southeast Michigan.

### *Observability of the wetland system and data assimilation (reference C in figure 5)*

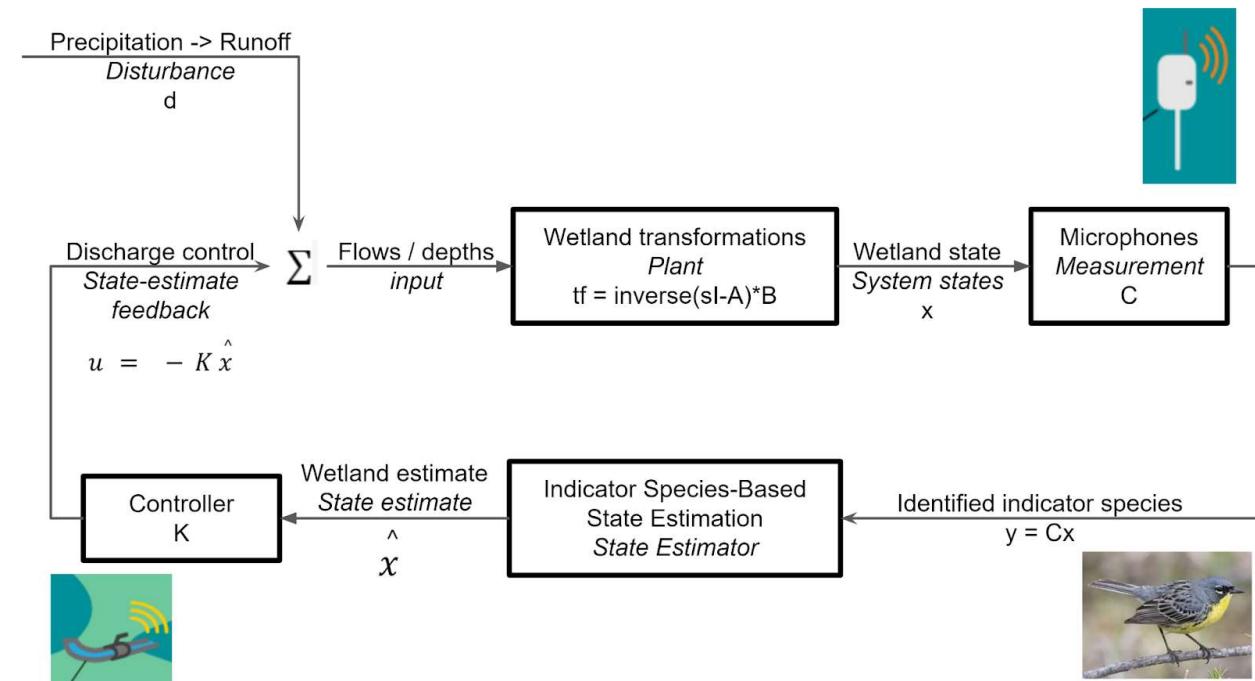
Water parameters such as depth, discharge, and quality metrics are generally available in the context of wireless sensor networks, though these measurements can be expensive. Depth and water quality indicators will provide some indication of which species may be present in an

ecosystem. For example, if dissolved oxygen levels are consistently below 4 milligrams per liter, brook trout are unlikely to be present.<sup>11</sup>

Further, methods exist for real-time ecosystem state identification through automated audio-based indicator species recognition (Sprengel et al) and prevalence estimation. However, audio-based methods for ecosystem state estimation have not yet been implemented within the context of a wireless sensor network. This would only work for species that use characteristic vocalizations such as songbirds or mammals, but not fishes or aquatic invertebrates.

As real-time data informs better understanding of systems models should be equipped to automatically assimilate this data to improve their representation of the system as in Bartos and Kerkez 2021<sup>12</sup>.

### *Application of traditional control theory tools to wetland systems*



**Figure 5.** State estimate feedback for real-time natural resource management. Command input (typically denoted “r”) not included for simpler representation.

### Observer (state estimator) design

Given some filtered output of the system (typically represented as  $y = Cx$ ) an estimate of the internal state of a system can be estimated and used to inform control decisions.<sup>13</sup> An observer could be constructed that takes the estimated prevalence of vocalizing indicator species (songbirds, birds of prey, mammals) and uses these to estimate the presence and density of other life (vegetation, invertebrates) in the wetland. These estimates could be linked to more human comprehensible outputs such as ecosystem type. As an example, if vocalizations of Kirtland's

<sup>11</sup> [The Effects of Dissolved Oxygen on Steelhead Trout, Coho Salmon, and Chinook Salmon Biology and Function by Life Stage](#)

<sup>12</sup> [Pipedream: An interactive digital twin model for natural and urban drainage systems - ScienceDirect](#)

<sup>13</sup> [https://en.wikipedia.org/wiki/State\\_observer](https://en.wikipedia.org/wiki/State_observer)

warblers, black bears, and whitetail deer are heard, an automated algorithm could predict that the microphone is placed in a northern Michigan forest dominated by young jackpines.

### Multiple input systems

Generally, multiple inputs offer increased flexibility in the manipulation of a system. However, in this study the frequency inputs are functions of the immediate water level and so do not create additional degrees of freedom. There may be a better way of representing the natural system's frequency-based dependencies.

Furthermore, the water level is not completely controllable. System operators would generally have the ability to dictate the discharge through valves or the height of a weir but disturbances (precipitation and uncontrolled streamflows) will also affect the water level in an asset.

### Approaches other than control theory

Completely autonomous control algorithms are unlikely to be a fruitful avenue of exploration in the near future (unless low-cost surrogates are developed for stormwater modeling) due to the high computational complexity of these models, even in a very small system. Furthermore, AI agents can be very slow learners and pursue unexpected and undesirable strategies (such as pulsing flows through a stream in [Mullapudi et al 2020<sup>14</sup>](#)). However, there is likely utility for some machine learning tools within a control theoretic framework.

Rule-based strategies leverage existing expertise to direct the system in human comprehensible ways. They often yield good results for predictable cases and may be simplest to implement in many cases. All the strategies used in this study were rule-based. However, as the number, complexity, and spatial scale of systems to be controlled increases the enumeration of rule-based controls will become onerous. Further, how to balance competing goals may be unclear.

### *Multi-parameter optimization*

If the effects on quality, quantity, and ecological objectives could be forecast at the time a control decision (open/close a valve or raise/lower a weir) is made, heuristic strategies (approximations of gradient descent) could optimize a weighted combination of these factors. The weights of these factors would provide an accessible way for non-technical decision makers to dictate their priorities and feel that they are in control of their assets, even when control is automated.

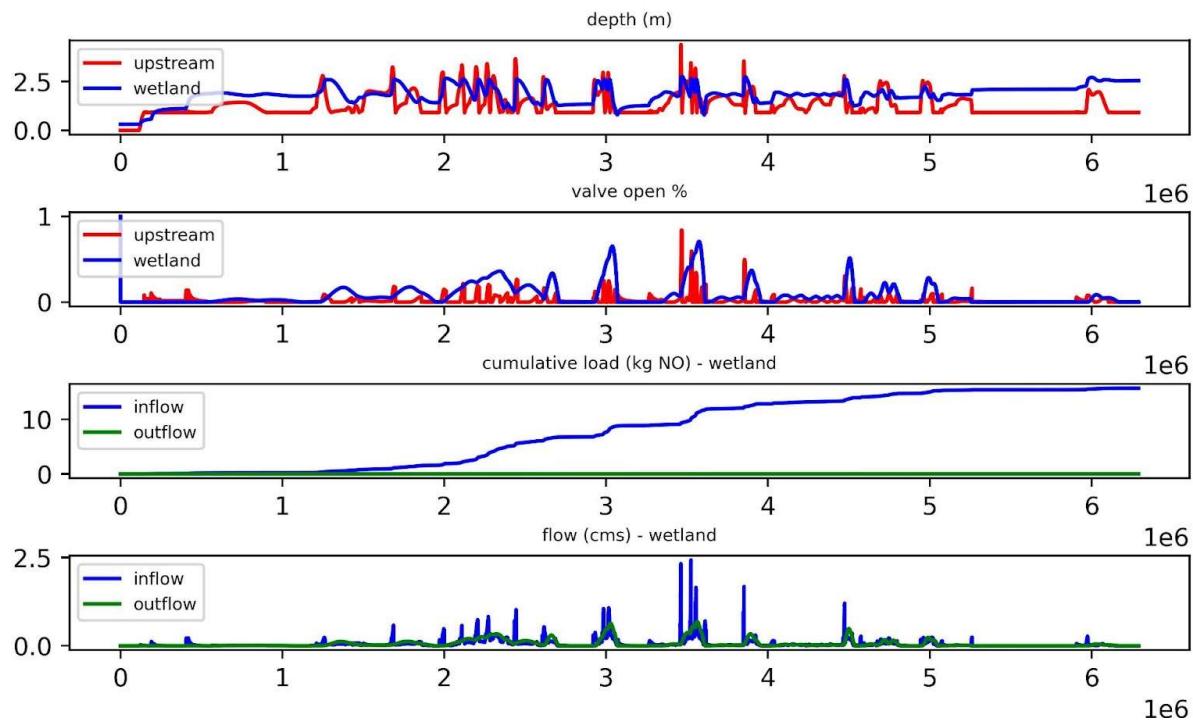
Rule-based prioritizations may be more effective than weighting. For a stormwater system that approach may look like:

- when there's a large storm forecasted, minimize flooding
- during a smaller event, try to maximize treatment
- when there's little or no precipitation, manipulate water levels within the system to create better habitats for desired species.

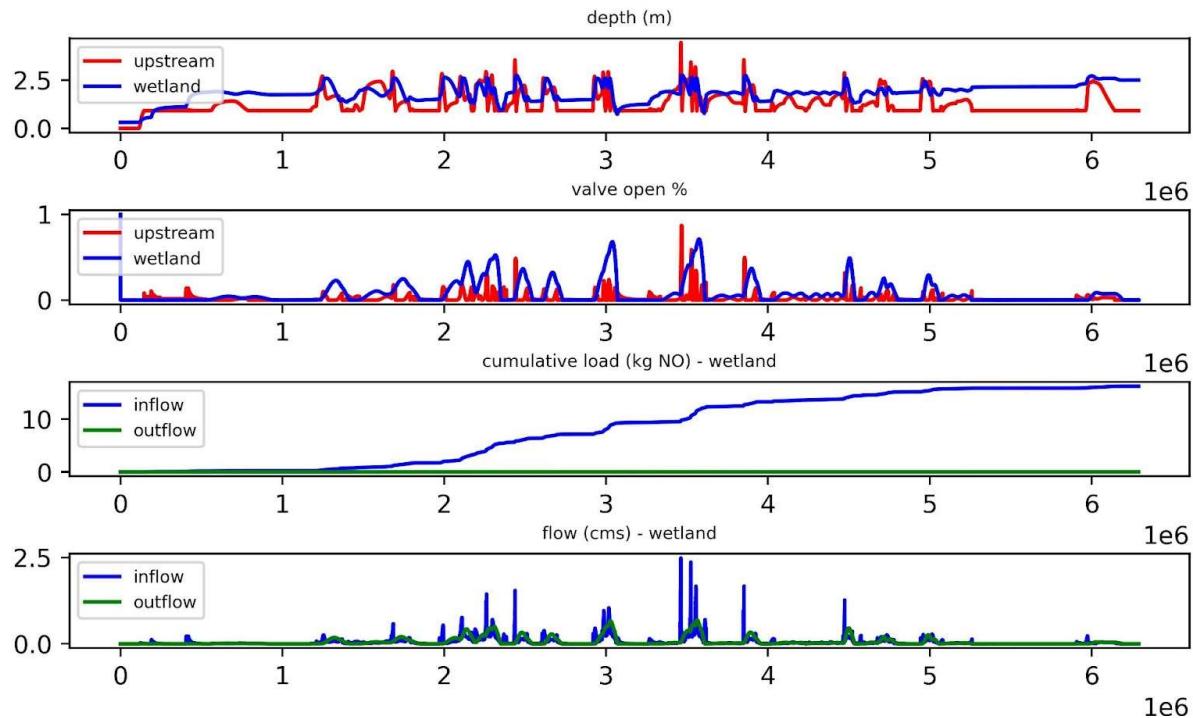
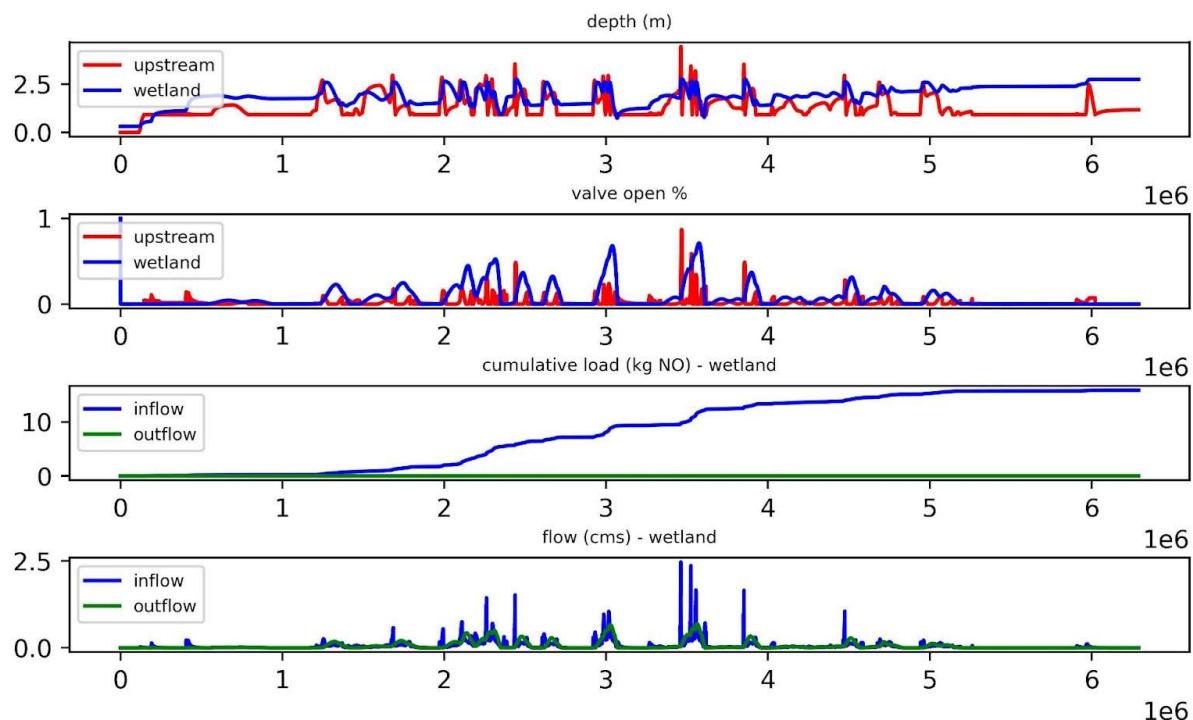
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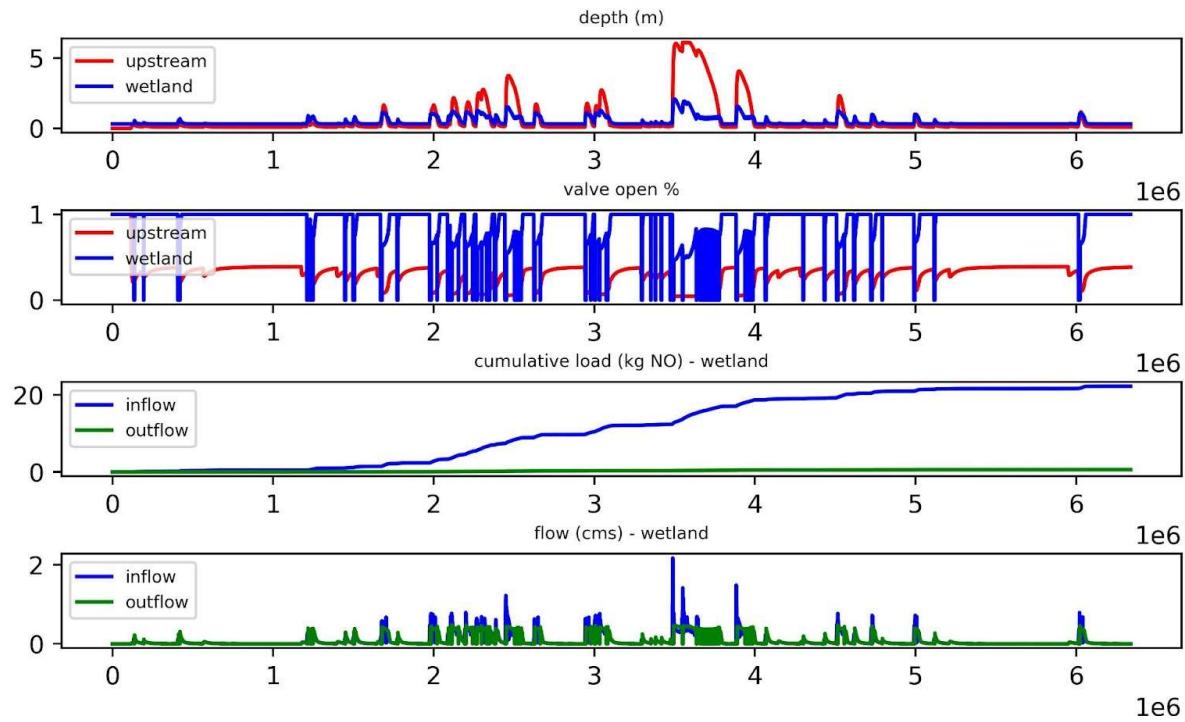
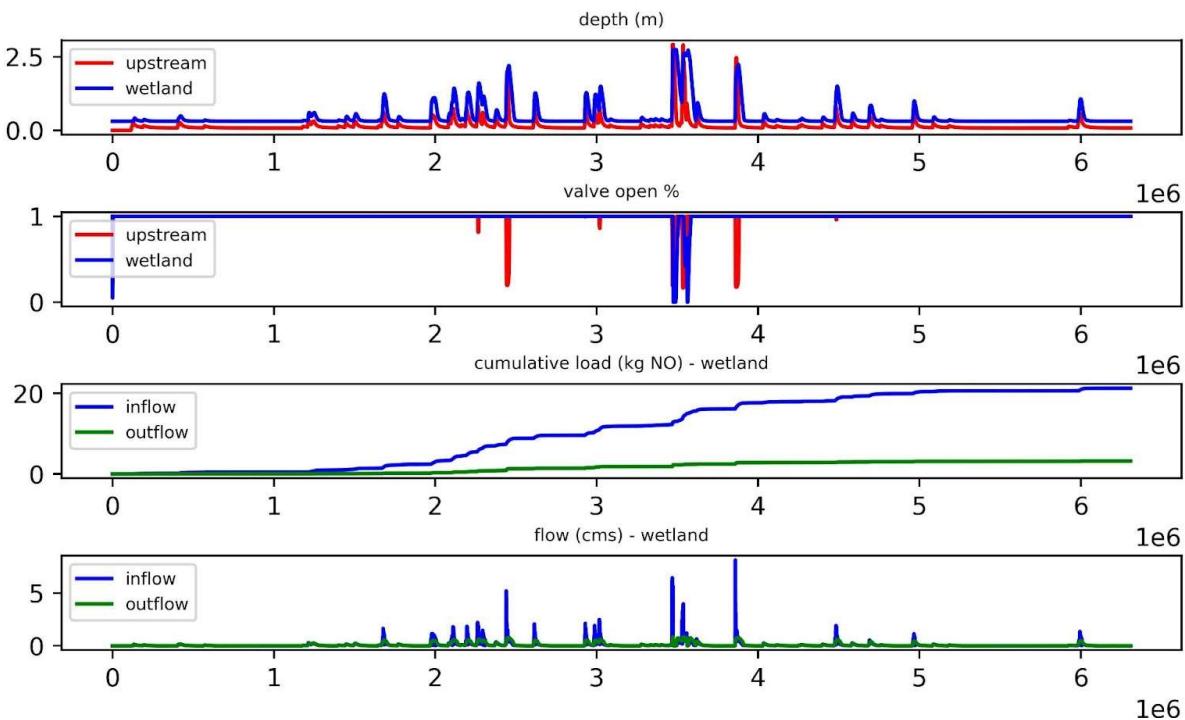
<sup>14</sup> [Deep reinforcement learning for the real time control of stormwater systems Abhiram Mullapudi, Matthew J. Lewis, Cyndee L.Gruden, Branko Kerkez](#)

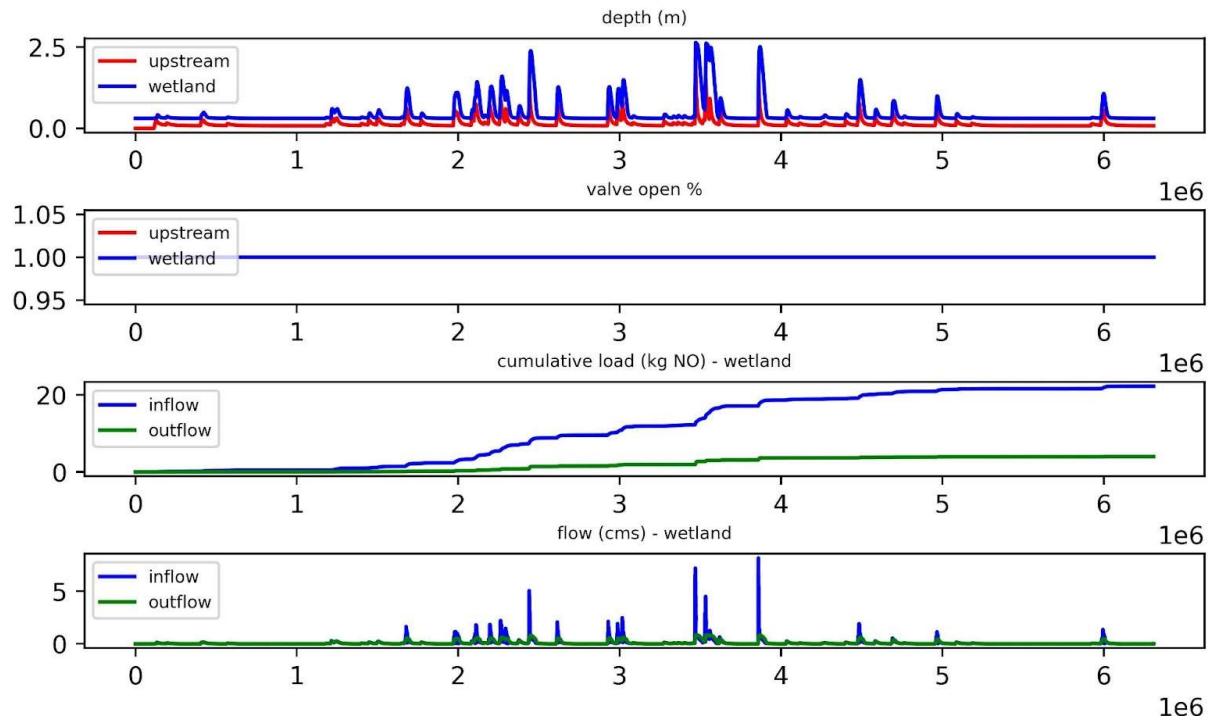
## Appendix A: Stormwater system simulation results



FWS\_A\_results

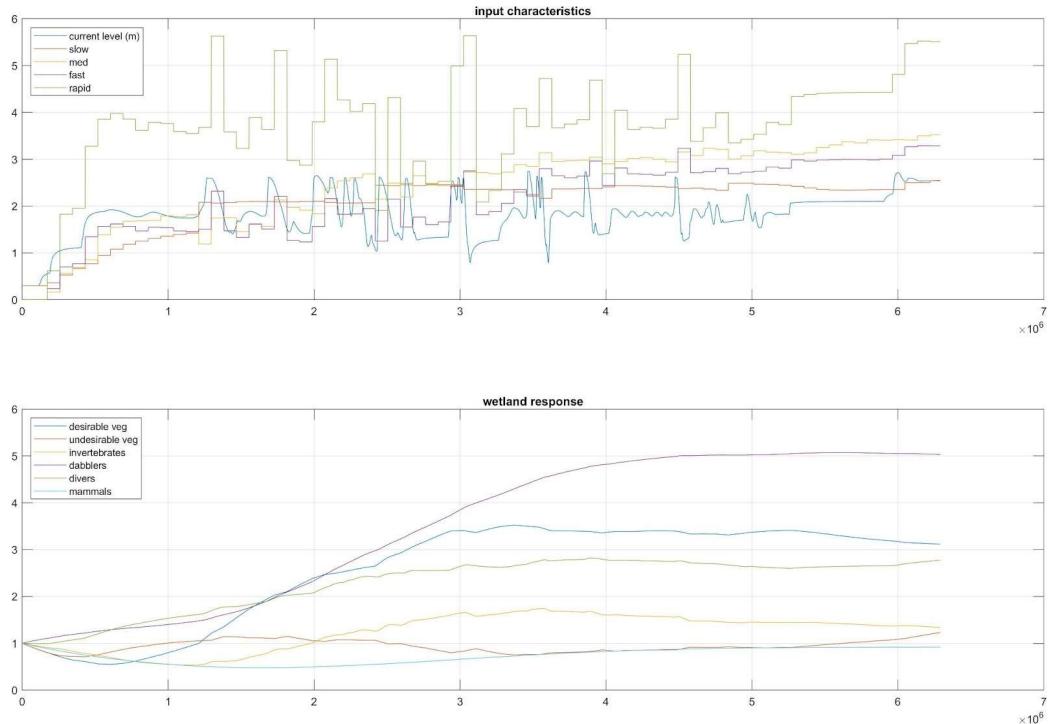
**FWS\_B\_results****FWS\_C\_results**

**nitrate\_removal\_results****quantity\_control\_results**

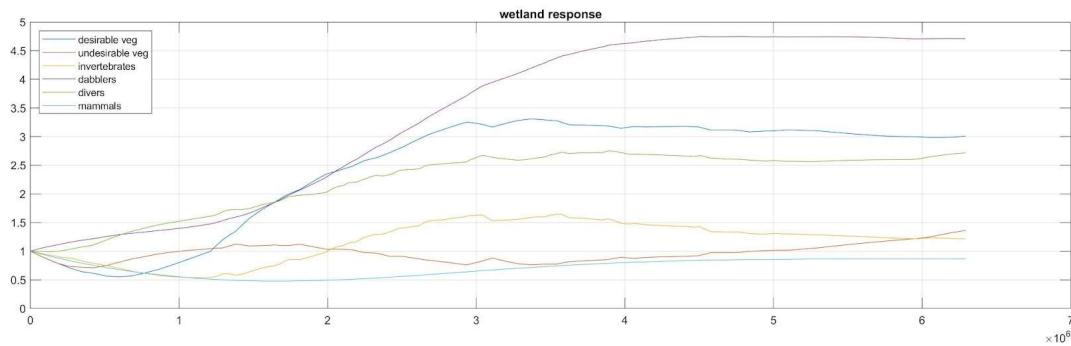
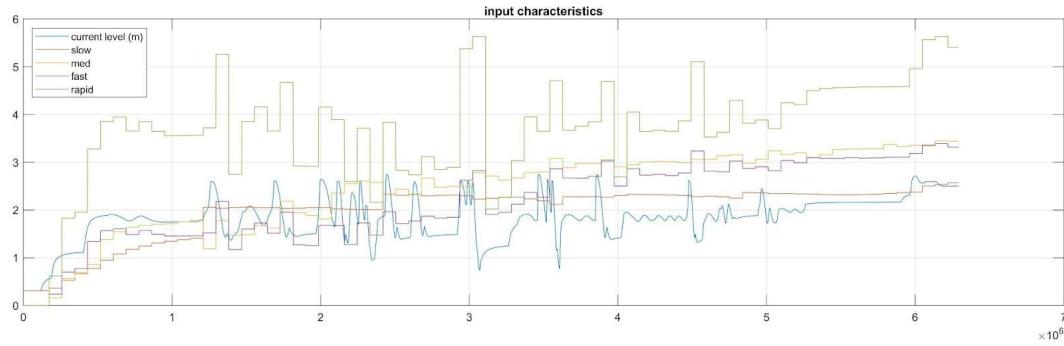


**uncontrolled\_results**

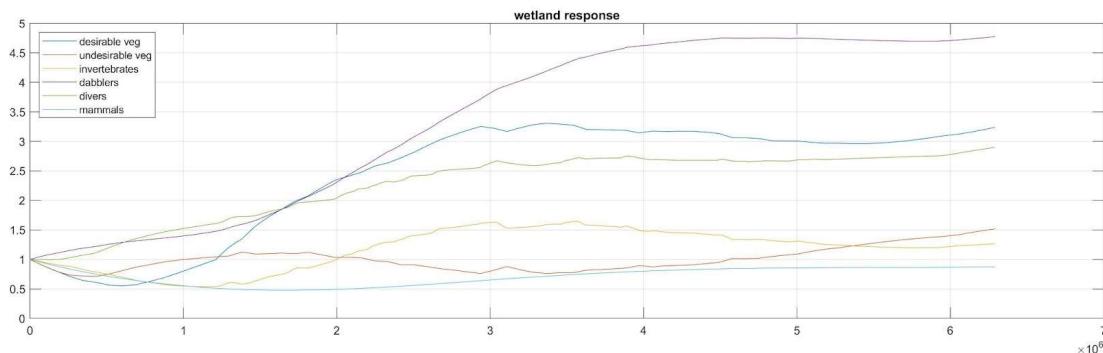
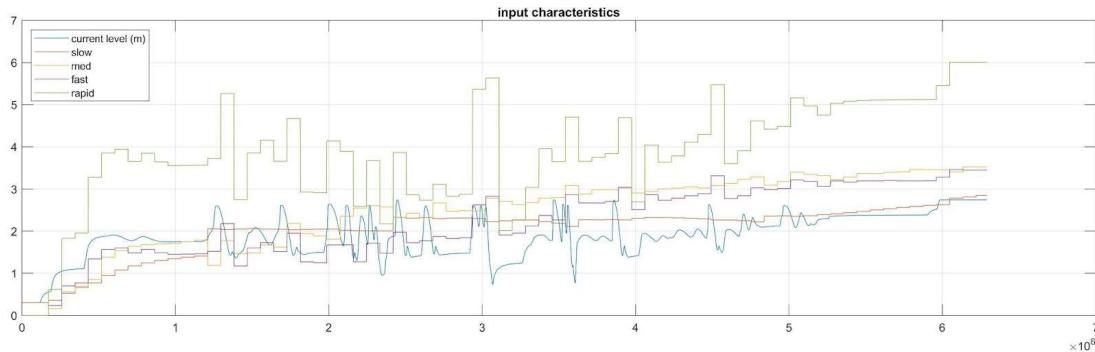
## Appendix B: Wetland simulation results



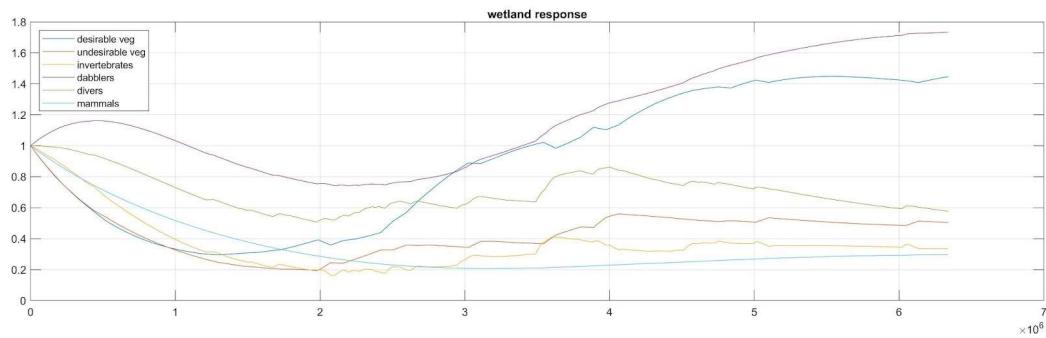
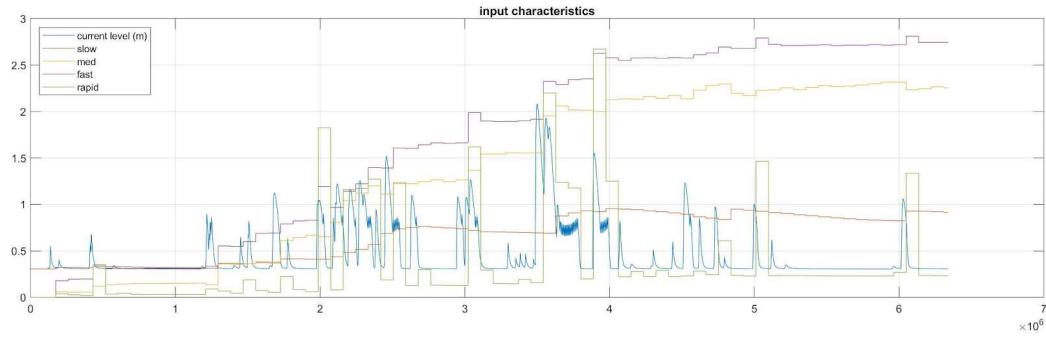
**FWS\_A\_results**



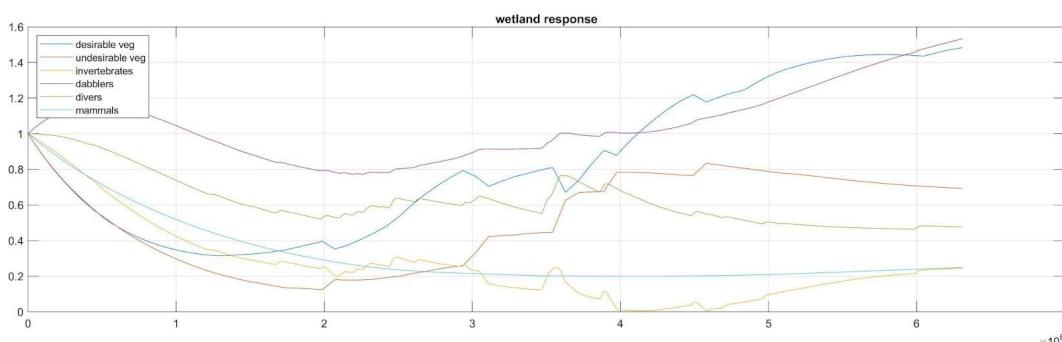
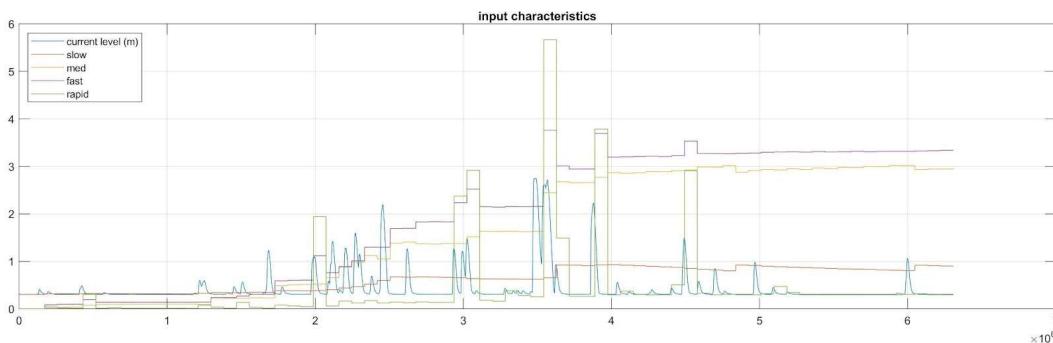
### FWS\_B\_results



### FWS\_C\_results



### **nitrate\_removal\_results**



### **quantity\_control\_results**

