Whitney Woelmer, Master’s Prospectus   
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**Overall Introduction**

Freshwater ecosystems provide crucial services to society. Whether it be naturally-formed lakes or human-built impoundments, freshwater ecosystems provide water for irrigation, industry, recreation, tourism, food production, and most importantly, drinking water. But as the human population has grown and our need for fresh water has increased, these resources have been degraded. My research interests combine the need to understand how water quality in freshwater ecosystems is changing and how we can better predict and adapt to improve the future state of freshwater ecosystems.

Climate change and land use change are two factors that have put the health of freshwater ecosystems in jeopardy (Smith, 2003; OTHERS). Eutrophication, excessive nutrient enrichment of a freshwater ecosystem, is increasing in both severity and occurrence (Smith, 2003), and is just one type of water quality impairment as a result of global change. Harmful algal blooms (HABs), a result of eutrophication, are known to produce unsightly water quality problems that can clog filters and produce deadly toxins, jeopardizing human health and costing millions of dollars to water treatment plants. The economic impact of HABs range from decreased tourism to public health to mitigation for water treatment plants, is estimated to be over $2 billion (Dodds et al. 2009). The short generation time of phytoplankton species further motivates their study because these negative impacts are often realized on a rapid time scale.

The influence of human activity can quickly cascade across landscapes through the transport of water through and among stream networks downstream to lakes and reservoirs. As precipitation patterns are expected to change, leading to pulses of rainfall through more frequent and intense storms, it is likely that we will see cascading effects of decreased water quality in freshwater ecosystems. For example, with increased storm frequency, we are likely to see rapid transport of sediment and nutrients from the landscape to downstream freshwater ecosystems, which can lead to increases in nutrient concentrations and turbidity and trigger blooms and anoxic events within lakes and reservoirs (REF). Consequently, we need to better understand these rapid temporal and spatial changes in nutrient and biological communities that can occur as a result of changing climate and land use. By studying nutrient and phytoplankton dynamics at a high-resolution temporal and spatial scale, we can gain an understanding of how our freshwater ecosystems are responding to global change.

Research to understand how systems are changing and developing efforts to anticipate their future response is more important than ever. In order for society to coexist with changing ecosystems and for managers to anticipate and mitigate poor water quality events before they happen, forecasting water quality is a critical tool. If water managers in Toledo, OH had known that a major HAB even in the western basin of Lake Erie in 2014 was going to cause water utilities to shut down water sources for nearly half a million people, perhaps preventative measures could have been taken that would have lessened the $65 million burden of economic damage and social trust that resulted from the shutdown (Bingham et al. 2013).

Together, my two chapters will better inform the scientific community on the drivers and dynamics of water quality in small, eutrophic drinking water reservoirs and produce forecasts of how water quality will respond to changing conditions in the future.

**Proposed Research**

*Chapter 1: Developing near-term forecasts of phytoplankton in a drinking water reservoir***Introduction**

Given the unprecedented level of anthropogenic degradation already experienced by freshwater lakes, reservoirs, restreams, and wetlands due to land use and climate change, (REFS), understanding not only the current state of our freshwater ecosystems, but predicting how they will respond tomorrow, next week, and next year is of utmost importance. In particular, knowing future water quality in advance would provide a substantial benefit to managers and freshwater ecologists by allowing them to make preventative measures when a poor water quality event is predicted, rather than managing an ecosystem after poor water quality has already occurred. Being able to anticipate water quality impairment could help save millions of dollars in water treatment costs, as well as protecting the trust required between a community and their water utility by avoiding a shutdown of water resources (Cvetkovich and Löfstedt, 1999; Ross et al. 2014). A recent survey has shown that less than half of Americans are confident in their water utility’s ability to treat their drinking water (AP-GfK, *Tap Water Confidence Poll*). Therefore, the ability to forecast the future state of our drinking water sources is of utmost importance to society and freshwater ecology as a discipline.

Forecasting as a technique outside of ecology has been developing for decades in many disciplines and has substantial breadth. Uses of forecasting can be found in many fields and applications, ranging from the well-known and widely-used weather forecasts to epidemiological forecasts of population mortality (Lee and Carter, 1992) and global Alzheimer’s trends (Brookmyer et al. 2007) to economic forecasts of bankruptcy declaration in the United States (Shumway et al. 2001). Many of these fields have been improving their forecasting abilities for decades (Shumway et al. 2001). For example, the accuracy of 36-hour weather forecasts has increased from ~25% in the 1950s to ~80% in the early 2000s (Dietze, 2017). This slow yet substantial increase in forecast accuracy over the past 50 years shows that progress cannot be expected to be immediate, and that there is merit in developing forecasts even when they have low accuracy.

Still, the development of forecasts of ecological systems and ecosystem services is still in its relative infancy (Dietze, 2017). The current shift in the scientific community towards publishing data in publicly accessible venues (cite FAIR here), as well as the development of high-frequency sensors which result in massive amounts of data (Hampton refs) have both enabled the field of ecological forecasting to recently expand. However, as the development of ecological forecasting is still in very early stages, there is not yet a consensus as to the best approach for making ecological forecasts. In particular, it is unclear if data-driven empirical models or numerical simulation process-based models yield higher accuracy forecasts (REFS). To better understand the current state of studies using ecological forecasting and their approaches, I conducted a high-level literature review. Studies were found using the Google Scholar database and the search terms ‘ecological forecasting’ and ‘forecasts.’ Studies which met the following requirements were selected as using ecological forecasting methods: they must 1) use models, 2) quantify uncertainty to make a probabilistic forecast or forecasts, and 3) run the model outside a specified training period (Table 1).

Empirical modeling methods were favored a majority of times (65%, n= 17, Table 1) in current forecasting studies selected in the literature review. Empirical time series modeling approaches were likely popular because of their data-driven nature; they are inherently developed for a single particular ecosystem because they are based on past trends within that ecosystem. Input time series data for empirical models are commonly available through routine monitoring and empirical models are generally simple and quick to develop and implement (REF). However, because empirical models are built on the historical conditions of a system, if future conditions are outside the realm of past conditions, these models may no longer be able to accurately make predictions (Dietze 2017). In contrast to empirical time series models, process-based models were favored in just over a third of the studies examined (35%, n=17, Table 1). It is not surprising that process-based models are currently less frequently used in the ecological forecasting literature given that they often require more input data, as well as more time and expertise to properly calibrate the multitude of parameters to accurately represent a specific waterbody. However, these models may be especially useful in the current era of global change given their ability to explain underlying mechanisms which cause a given response and are likely more generalizable to other systems because they are based on a set of fundamental equations rather than the historical pattern of a single system.

The studies examined in the literature review spanned the realm of basic and applied research, showing multiple motivations for ecological forecasting. While a majority of the studies in our literature review were conducted to inform the field of basic ecology (73%, n = 15), all of the studies whose forecasting products were directly tied to a management tool or product were focused on forecasting various aspects of aquatic ecosystems, including water quality variables as well as species distributions in marine environments and habitat quality (Table 1). This illustrates not only the interest in the scientific community to understand changing freshwater systems, but the need by managers and stakeholders for probabilistic forecasts in order to respond and adapt to changing conditions in freshwater ecosystems.

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| Table 1. Summary of literature review targeting studies using ecological forecasting methods. | | | | | |
| Authors & Year | Approach | Best Model | Ecosystem | Forecast Product | Use of forecast product in decision making (Y/N) |
| Araujo et al. 2005 |  | Empirical |  | Bird species ranges | N |
| Brown et al. 2013 | Model comparison?? | Process-based and empirical |  | Chesapeake Bay water quality | Y |
| Dean et al. 2004 |  | Process-based |  | Carbon sequestration in forests | N |
| Estes et al. 2013 |  | Empirical |  | Productivity and suitability of crops in South Africa | N |
| Gonzalez-Benecke et al. 2017 | Future projections | Process-based | Southern U.S. forest | Loblolly Pine projections | N |
| Hazen et al. 2017 |  | Empirical |  | Blue whale density | Y |
| Lindegren et al. 2013 |  | Process-based |  | Baltic cod dynamics | N |
| Liu et al. 2006 |  | Empirical |  | Coral Reef Bleaching | Y |
| Martinez-Meyer et al. 2004 |  | Empirical |  | Ecological niches of mammal species | N |
| Perretti et al. 2013 |  | Empirical |  | Species abundance | N |
| Stow et al. 2003 |  | Process-based and empirical |  | Estuarine water quality | Y |
| Thomas et al. 2018 |  | Empirical |  | Phytoplankton dynamics | N |
| Thuiller et al. 2004 |  | Empirical |  | Tree species distributions | N |
| White and Nemani 2004 |  | Process-based |  | Soil water | N |

My first chapter will focus on addressing the knowledge gap in ecological forecasting regarding how best to forecast water quality. We will focus on the dynamics of HABs (harmful algal blooms) as one metric of water quality in our system, which will be measured by changes in phytoplankton abundance. I will produce hindcasts and near-term iterative forecasts of phytoplankton in a drinking water reservoir using both an empirical and a process-based approach. Model performance will be assessed by a suite of metrics addressing both the ability of the model to capture overall phytoplankton dynamics, as well as extreme events (blooms). My work will specifically address the following questions:

* + Question 1: How well can an empirical model vs. a process-based model hindcast observed phytoplankton dynamics?
  + Question 2: How well can an empirical model and a process-based model forecast near-term phytoplankton dynamics over a 16-day period (assessed by comparing quantified uncertainties of a probabilistic forecast with observed dynamics)?
  + Question 3: How does an ensemble model approach improve 16-day forecasts of phytoplankton over a single model approach?

Chapter 1 will thus span the field of applied and basic forecasting science by**: 1) informing managers and decision-makers about which variables are most important for routine monitoring and management of water quality in the face of land use and climate change through the selection of variables within the empirical model, 2) providing essential information to the freshwater research community regarding modeling approaches to forecasting water quality.**

**Methods**

*Study Site*

Falling Creek Reservoir (FCR) is a small (~12 ha), shallow (maximum depth = ~9.3 m) dimictic drinking water reservoir located in southwestern Virginia. FCR is owned and operated by the Western Virginia Water Authority (WVWA). The watershed of FCR is almost entirely forested, although the reservoir continues to exhibit incidences of poor water quality as a result of historical eutrophication (Gerling et al.2016). The major water source to FCR comes from a single tributary which flows from Beaverdam Reservoir (BVR; Figure 1).

A close up of a logo

Description automatically generated

Figure 1. Map of Falling Creek Reservoir and Beaverdam Reservoir and their watersheds.

*Historical and sensor dataset*

An extensive, routine monitoring dataset of water quality in FCR has been collected since 2013 in collaboration with the WVWA and Virginia Tech. This dataset includes meteorological, physical, chemical, and biological data collected both at the deep hole of the reservoir and at the major inflow to FCR (EDI Portal: Carey et al. 2018, Carey et al. 2019). The inflow dataset also includes discharge to the reservoir measured every 15 minutes at a weir installed at the stream site. More recently, as part of the Smart and Connected Communities (SCC) project, FCR has been outfitted with numerous high-frequency sensors to capture real-time changes in water quality. These data are streamed wirelessly to a staging server and pushed to Github multiple times per day. Sensor data include multiple meteorological, physical, chemical, and biological variables.

*Model Development (Question 1)*

We will develop both an empirical and a process-based model to forecast chlorophyll-a in the surface water (1.0 m) at FCR during the summer stratified period (May-October), when phytoplankton populations are at their highest. The training period for both models will be 2013-2016 during which we have regularly, weekly coverage of both response and driver data. Both models will be validated using data from 2018.

Empirical: ARIMA

We chose an autoregressive integrated moving average (ARIMA) generalized linear model for our empirical approach to forecast chlorophyll-a in FCR. The autoregressive term in ARIMA was determined by selecting the previous timestep of chlorophyll-a with the highest Pearson’s r correlation coefficient with the current measurement of chlorophyll-a. From a pool of 53 potential meteorological, physical, chemical, and biological driver variables, we first focused on driver variables that have biological significance for phytoplankton growth and which are also predictable using physical models (e.g., temperature, discharge). We excluded variables that were correlated with each other through the use of a Pearson’s correlation analysis (r > 0.5 & r < -0.5). Using these variables, we developed all possible ARIMA combinations with the selected driver variables, and the best model was determined by AICc (corrected Akaike’s Information Criterion).

Process-based: GLM

We used the General Lake Model (Hipsey et al. 2017; Hipsey et al. 2019), coupled with Aquatic  
Ecodynamics (Hipsey et al. 2013) (GLM-AED) as our process-based model. GLM-AED is a 1-dimensional, open source lake ecosystem model. GLM-AED requires a number of input data driver files, including the hypsographic curve of the lake, initial physical, chemical, and biological conditions, daily stream inflow volume and water chemistry, and hourly weather. Hourly climate driver data from 2013-2017 were downloaded from the North American Land Data Assimilation System (NLDAS-2) website, and other driver data files were derived from the historical and sensor dataset for FCR.

GLM-AED was calibrated to best fit phytoplankton dynamics during the summer stratified period during 2013-2016. Parameters were systematically adjusted to improve the model fit with observational data, first for temperature, then for dissolved oxygen, nitrogen, phosphorus, and carbon, and finally for phytoplankton (following Bennett et al. 2013).

Model Assessment

Model performance will be assessed using a number of metrics currently being used in the ecological forecasting field. As one metric alone cannot determine if a model performs better than another, a holistic approach examining several model performance metrics will be used.

Comparisons of observed and model descriptors will include the mean, standard deviation, quantiles (Dietze 2017), and kurtosis (Bennett et al. 2013). Forecasts are said to be in consensus if they are insignificantly different from the sample mean (Gregory et al. 2001)

Model outputs will also be compared with each other using the following performance metrics: put these in Table 2?

* RMSE
* R2 (variation from the 1:1 line)
* Bias
  + SD(model)/SD(data)
  + Base R bias calc mean(observed – model)
* Slope of the regression btw model and OBS
* Pearson’s correlation between the model and OBS
* Area under the curve (Araujo, Thuiller, and Pearson 2006)

Lastly, model performance will be examined through visual assessment of the following diagnostic figures (Dietze 2017):

* Observed and model predictions over time
* Predicted vs. observed + 95% confidence interval

*Forecasting Framework: FLARE (Question 2)*

After addressing Question 1, both models will be integrated into an existing forecasting framework, Forecasting Lake and Reservoir Ecosystems (FLARE), to produce iterative near-term 16-day forecasts of chlorophyll-a (Thomas et al, in prep). FLARE is designed to pull 2-week weather predictions from the National Oceanic and Atmospheric Administration (NOAA) GEFS server to force both ARIMA and GLM-AED on a daily time step. Additionally, ARIMA’s autoregressive term will be determined from measured chlorophyll-a streamed via our sensor-cloud network to provide yesterday’s chlorophyll-a concentration as well as for comparison with the previous days’ forecasts. Lastly, inflow discharge data for both models will be estimated using an autoregressive linear model of discharge based on the previous day’s mean discharge at the major inflow to the reservoir. Driver uncertainty will be calculated for both ARIMA and GLM-AED forecasts by propagating the uncertainty associated with the NOAA weather forecasts. Parameter uncertainties for both ARIMA and GLM-AED will be calculated by sampling from a distribution of key parameters within each model. Forecast effectiveness will be assessed using a suite of performance metrics calculated by comparing the forecast model outputs to the observed high-frequency chlorophyll-a sensor in FCR (Table 2). Assessment metrics will be calculated for various conditions (summer stratified period, fall mixed period, winter ice period, and following storm events) to determine which approach is most robust under different reservoir and meteorological conditions.

*Integrated Model Averaging (Question 3)*

In order to develop the most informative forecast of chlorophyll-a, we will develop a weighted model including both empirical and process-based model outputs averaged to incorporate the strengths of multiple models and compare it with a single model approach. This will allow the ensemble forecast to capture as much variability as possible in chlorophyll-a and the different strengths of the two models**. If, for example, one model does a better job predicting chlorophyll-a at lower concentrations, while another model is more effective at capturing large bloom events, the goal is using the relative strengths of both models to improve overall chlorophyll prediction (or something like that!).** I anticipate that for low probability yet high impact events such as phytoplankton blooms, an ensemble approach may be necessary to capture these peaks in phytoplankton concentration that may operate under different mechanisms. Incorporating multiple models will enable us to develop an early-warning system which will alert users when conditions that indicate a peak in phytoplankton is likely to occur.

**Preliminary Results**

Question 1: Hindcasts of chlorophyll-a

Using the summer period of 2013-2017 as our training period, we developed and calibrated both an empirical model (ARIMA) and process-based model (GLM-AED). Our best-fitting ARIMA model over 2013-2016 included discharge to the reservoir and shortwave radiation. ARIMA hindcasted chlorophyll-a over 2013-2016 with an R2 = 0.44 and RMSE = 1.71 ug/L. The ARIMA model was able to successfully capture fluctuations at lower chlorophyll-a concentrations (<10 ug/L) (Figure 2). However, when chlorophyll-a reached values above ~10 ug/L, the model the model was unable to recreate these observed dynamics. GLM-AED was calibrated over 2013-2016 and hindcasted chlorophyll-a with R2 = XXX and RMSE = YYYY. While GLM-AED does not capture the same fluctuations in chlorophyll-a dynamics as the empirical model, it does capture some large peaks in chlorophyll-a that the ARIMA does not.

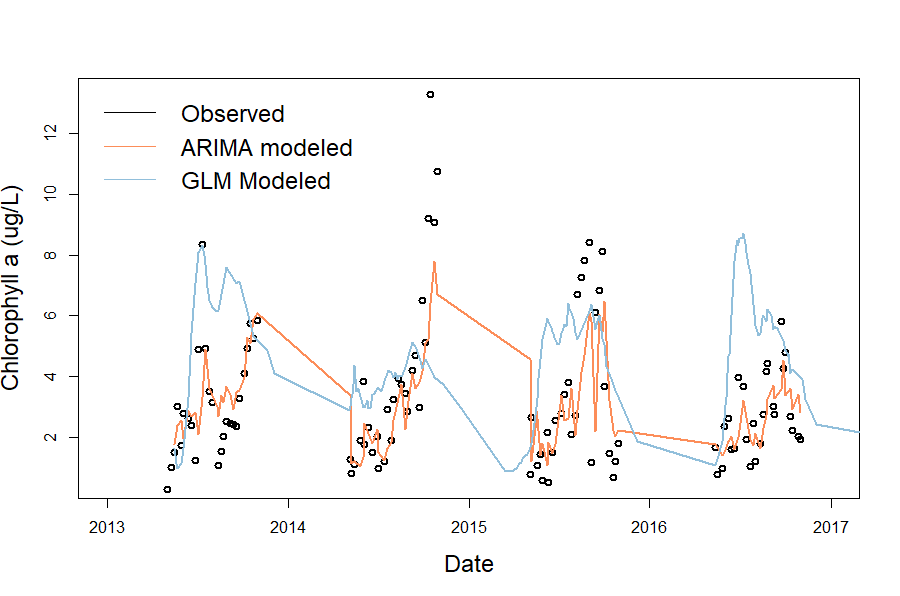


Figure 2. Observed and modeled chlorophyll-a data over 2013-2016.

Table 2 shows the proposed timeline of remaining steps to finish work required for Chapter 1 and to address the steps needed to address Questions 2 and 3.

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| **Table 2. Proposed timeline for Chapter 1** *Black boxes indicate completed tasks, gray boxes indicate proposed completion* | | | | | |
|  | Fall 2018 | Spring 2019 | Summer 2019 | Fall 2019 | Spring 2020 |
| Develop ARIMA GLM-AED |  |  |  |  |  |
| Calibrate GLM-AED |  |  |  |  |  |
| Produce hindcasts |  |  |  |  |  |
| Validate model (Q1) |  |  |  |  |  |
| Adapt FLARE code for ARIMA (Q2) |  |  |  |  |  |
| Create integrated model average (Q3) |  |  |  |  |  |
| Run forecasts in FLARE |  |  |  |  |  |
| Submit manuscript, target journal: *Ecological Applications* |  |  |  |  |  |

**Chapter 2. Spatial heterogeneity of nutrients and phytoplankton along a double reservoir continuum**

Reservoirs are ecosystems marked by physical heterogeneity and are classically defined as having a gradient of riverine, transitional, and lacustrine zones (Thornton et al. 1990). The nutrient chemistry and biological communities change substantially as water moves downstream along this gradient, as demonstrated by the large decrease in nutrient concentrations between the inflow and outflow of reservoirs (Harrison et al. 2009, Kling et al. 2000, Powers et al. 2015). However, studies examining how concentrations of nitrogen, phosphorus, and chlorophyll-a change along the reservoir gradient *at multiple sites* between the inflow and outflow are rare, and those that do measure nutrients and biology throughout the reservoir zones along the gradient report inconsistent patterns (see below). Further, because managers generally extract water from reservoirs for drinking from the deep hole only, most reservoir studies only focus on the lacustrine zone (cite lots of studies here), leading to a critical gap in the understanding of how these water quality variables change along a reservoir gradient.

For my second chapter, I am particularly interested in examining if there are sites along a reservoir gradient that disproportionally affect nutrient concentrations and chlorophyll-a, which has many implications for water quality in the lacustrine zone that is extracted for drinking. Many interacting biogeochemical processes occur along the reservoir gradient that need to be considered in order to understand the inconsistent patterns in nutrient and chlorophyll concentrations reported in previous studies. If the location of sampling sites is adjacent to reservoir “hot spots” of nutrient processing (*sensu* McClain et al. 2003) that may occur within and at the intersection between zones, snapshot sampling at the inflow and outflow alone may not reflect longitudinal trends of the reservoir continuum. Thus, finely-resolved spatial sampling is needed to fully understand longitudinal reservoir nutrient and chlorophyll-a dynamics.

My proposed work builds on past studies looking at nitrogen concentrations along a reservoir gradient that report a number of contradictory patterns. Some have found that nitrogen concentrations are highest in the riverine zone due to high nutrient inputs from the watershed (Soares et al. 2012), while others have found that the transitional zone, where turbulence is decreased yet nutrients are still abundant, is a hotspot for nitrogen fixation across reservoirs of varying trophic status, effectively increasing the concentration of NH4 (Scott et al. 2009). Additionally, when the hypolimnion of a reservoir becomes anoxic, it can lead to disproportionately high levels of ammonium (NH4) being released from the sediment while nitrate (NO3) is concurrently denitrified within the lacustrine zone (Gerling et al. 2016). These dynamics may lead to an effective increase in ammonium yet decrease in nitrate in the lacustrine zone of the reservoir.

Similar to nitrogen, patterns in chlorophyll-a heterogeneity are inconsistent between studies. There is some support to show that chlorophyll-a is highest in the riverine zone, decreasing along the downstream gradient (Scott et al. 2009). In contrast, others report the transitional zone as being an especially active zone for phytoplankton activity (Rychtecky & Znachor, 2011; Thornton 1990), and others still have found the lacustrine zone to have the highest chlorophyll-a in ecosystems that are not limited by nutrient availability (Soares et al. 2012). Further, Borges et al. (2008) found that the longitudinal pattern of heterogeneity of chlorophyll-a was variable among seasons in two tropical reservoirs in Brazil. This finding highlights the fact that patterns in reservoir chlorophyll-a are highly variable.

Trends in reservoir phosphorus concentrations are less reported than nitrogen or chlorophyll. One study of a large, deep reservoir in the Czech Republic showed that both soluble and total phosphorus decreased along the reservoir gradient (Rychtecky & Znachor, 2011). Borges et al. (2008) found contrasting patterns in two reservoirs in Brazil, one showing a decrease in phosphorus along the reservoir gradient, while another showed no clear longitudinal pattern. Sedimentation processes also influence longitudinal distributions of phosphorus, with classical reservoir theory positing that sedimentation should be highest in the transitional zone, which should lead to an overall decrease of nutrients along the reservoir gradient (Thornton 1990). However, internal loading of soluble phosphorus can play a substantial role in phosphorus concentrations during anoxic conditions in the hypolimnion, which may lead to increases in phosphorus in the lacustrine zone (Thornton 1990). While all of these studies agree that spatial heterogeneity of nutrients and phytoplankton exists along a reservoir gradient, the lack of consistency among studies necessitates additional research, especially in smaller reservoirs, which overall remain understudied relative to larger reservoirs. In smaller reservoirs, the transitions among zones may happen more rapidly, which could result in greater variability in nitrogen, phosphorus, and chlorophyll along the downstream gradient.

An important factor that can affect the heterogeneity of chemical and biological variables along reservoir gradients is hydrologic flow. Under low flow conditions, residence times of reservoirs and streams are increased, resulting in slower export of nutrients and more time for biotic processing (Saunders and Kalff, 2001). This can lead to an increase in chlorophyll concentrations while nutrient conditions remain high, but external loading of nutrients is low under this scenario and nutrients can become quickly depleted. In comparison, high flow conditions may result in less biotic uptake of nutrients by phytoplankton as water is flushed out more rapidly, but high flow also brings in high levels of external nutrients which are often limiting to phytoplankton. This can result in high nitrogen and phosphorus, but low chlorophyll concentrations. Low chlorophyll concentrations are typical of the deep hole of a reservoir, which often the only study site in reservoir surveys, and there is less known about how these varying hydrologic regimes affect nutrient and chlorophyll concentrations along the entire reservoir gradient. One study measured a direct decrease in spatial heterogeneity of phytoplankton with increases in residence time (Soares et al. 2012), illustrating the need to better understand how nutrient and chlorophyll vary not just at the lacustrine site but along the entire reservoir gradient. Further support for the importance of hydrologic flow in driving phytoplankton at the lacustrine site comes from preliminary results of Chapter 1. The empirical model from my forecasting chapter revealed the importance of upstream stream discharge and variability in hydrologic flow, to phytoplankton dynamics at the deepest site of a reservoir. This finding highlights the importance of gaining a better understanding of how upstream discharge can influence nutrient dynamics along the reservoir continuum before reaching the lacustrine zone.

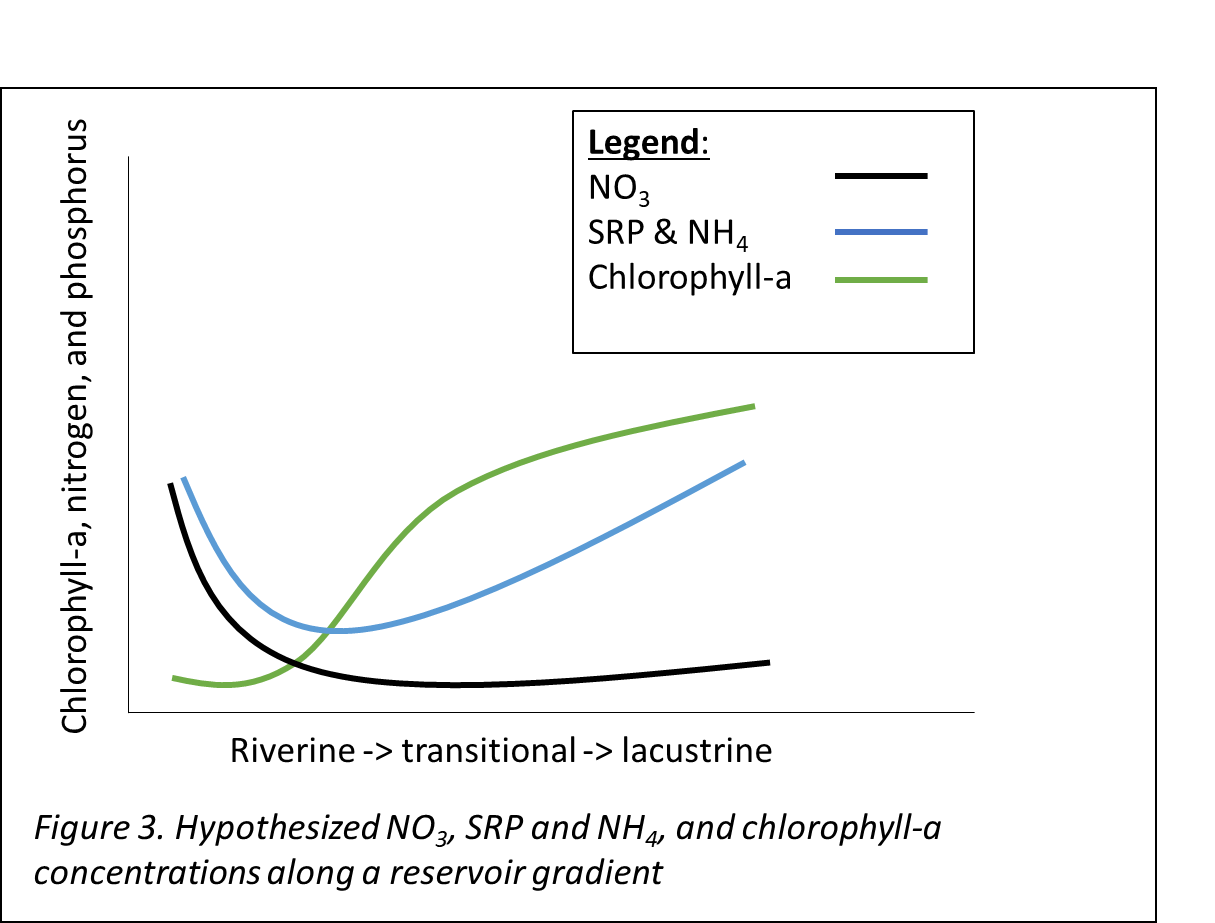
In the face of global change, understanding how water quality varies along the reservoir continuum is increasingly important. Large storms have already increased in frequency and severity and projected to continue to do so under future climate change (Prein et al. 2017). With these storms, we are likely to see increases in hydrologic flow which can increase external loading () and mixing regimes within reservoirs which can alter internal loading (). Both of these climate drivers may impact the heterogeneity of nutrients and chlorophyll along a reservoir continuum. This increased heterogeneity due to global change highlights the need to improve our understanding of how reservoir ecosystems function. Moreover, identifying areas within a reservoir where chemical or biological concentrations are disproportionately high can help prioritize management efforts to areas within freshwater systems that are more vulnerable to eutrophication or changes in trophic status.

**Proposed Work**

My second chapter will focus on the longitudinal spatial heterogeneity of nitrogen, phosphorus, and chlorophyll-a in Beaverdam Reservoir (BVR) and Falling Creek Reservoir (FCR) and the influence of hydrologic flow on this heterogeneity. This research will inform our understanding of how reservoirs will respond to global climate change, which is expected to include more variability in hydrologic flow and resultant residence times as a result of changing precipitation patterns.

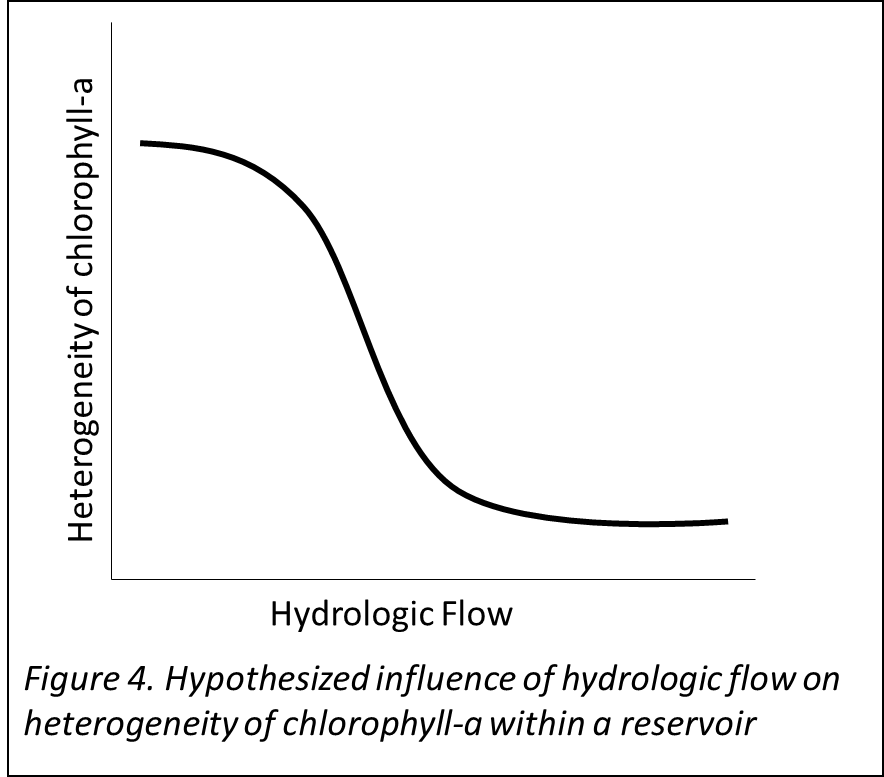
***Question 1****: What is the longitudinal heterogeneity of nitrogen, phosphorus, and chlorophyll-a along a double reservoir continuum?*

**Hypothesis 1**: I hypothesize that there will be substantial spatial heterogeneity in nitrogen, phosphorus, and chlorophyll-a within both BVR and FCR along a reservoir gradient of riverine to transitional to lacustrine (Figure 3). I expect nitrate (NO3) to follow the traditional view of nutrient decrease along the reservoir gradient due to both sedimentation and biotic uptake (Thornton 1990). In contrast, I expect to find a different pattern with soluble reactive phosphorus (SRP) and ammonium (NH4), due to the importance of internal loading in our shallow, eutrophic reservoirs which experience substantial anoxia during the summer stratified period (Gerling et al. 2016). I expect that both SRP and NH4 will enter the riverine zone at relatively high concentrations from stream inputs, decrease within the transitional zone due to sedimentation, and increase in the lacustrine zone as a result of internal loading under anoxic conditions. Lastly, I expect to find low chlorophyll concentrations in the riverine zone due to high flow and low nutrient conditions from stream inputs and increases in the transitional zone in response to increased nitrate, followed by a further increase in the lacustrine zone as internal phosphorus and ammonium becomes abundant. Testing these hypotheses requires intensive sampling along the reservoir continuum to determine if these patterns exist, which would not be discernable from snapshot inflow and outflow sampling.



***Question 2****: How does a gradient of hydrologic flow conditions influence longitudinal heterogeneity?*

**Hypothesis 2:** I hypothesize that increases in flow will increase spatial heterogeneity in both reservoirs (Figure 4). Spatial heterogeneity will be calculated as the coefficient of variation (CV) among sites within a reservoir.



**Methods**

*Study site*

Beaverdam Reservoir (BVR) is a small (39 ha), shallow (maximum depth < 13 m), dimictic reservoir owned and operated by the Western Virginia Water Authority (WVWA) and located in Vinton, VA. BVR has multiple inflow streams, but we have selected the major inflow in the western and the eastern arms for this study (Figure 1, above). BVR has an outflow pipe that flows to Falling Creek Reservoir (FCR), a smaller (~12 ha), shallower (maximum depth = ~9.3 m), dimictic reservoir, also owned and operated by WVWA.

*Proposed Field sampling, summer 2019*

We intend to sample the reservoir continuum once per month from May to September to capture a gradient in seasonal conditions. Additionally, we will add adaptive sampling events to capture a gradient of hydrologic flow conditions (n = ~8 total). We will collect nutrient chemistry (total and soluble nitrogen and phosphorus), chlorophyll-a, and physical characteristic using a YSI sonde (dissolved oxygen, conductivity, and water temperature) of the surface (~0.1m) at all sites. At stream sites, we will also measure discharge using a flowmeter.

*Sampling Sites*

Proposed sampling locations can be seen in Figure X. Sampling for spatial heterogeneity will begin at the two inflow sites to BVR (n = 2) to gauge nutrient and biological inputs to the reservoir. We will sample at 5 sites within BVR to capture a gradient of riverine, transitional, and lacustrine environments, including one site at the outflow pipe that feeds the stream that flows into FCR. Along the stream that flows from BVR to FCR, we will sample at 4 locations. The first location will be immediately after the surfacing of the pipe that flows out of BVR; the second location will be downstream of a confluence between a natural stream and the inflow stream created by BVR’s outflow pipe; the third location will be at a weir where historical sampling has taken place; the fourth location will be immediately before the stream enters into FCR. We will also sample a second inflow to FCR at a wetland site at the northern end of FCR. Within FCR, we will sample 4 sites along a gradient of riverine to lacustrine, as well as at the spillway outflow of FCR. In total, we propose 17 sites along the continuum from BVR to FCR.

*Data analysis*

To determine the heterogeneity of sites within BVR and FCR, we will calculate the coefficient of variation among the sites. We will also develop generalized linear models to analyze drivers of nutrient and phytoplankton dynamics along a stream-reservoir gradient, which will include potential driver variables of physical, chemical, and meteorological variables.

Table 3 outlines my proposed timeline for completing the steps required for Chapter 2.

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| **Table 3. Proposed timeline for Chapter 2**  *Black boxes indicate completed tasks, gray boxes indicate proposed completion* | | | | |
|  | Spring 2019 | Summer 2019 | Fall 2019 | Spring 2020 |
| Set up transects in BVR and FCR |  |  |  |  |
| Summer field sampling |  |  |  |  |
| Nutrient analyses |  |  |  |  |
| Nutrient statistical analyses |  |  |  |  |
| Manuscript writing and edits |  |  |  |  |
| Submit manuscript, target journal: ? |  |  |  |  |

CITATIONS

Bingham, M.; Sinha, S. K.; Lupi, F. Economic Benefits of Reducing Harmful Algal Blooms in Lake Erie; Environmental Consulting and Technology, Inc., 2015; p 66.

Carey C. C., A. B. Gerling, R. P. McClure, M. E. Lofton, B. J. Bookout. 2018. Discharge time series for the primary inflow tributary entering Falling Creek Reservoir, Vinton, Virginia, USA 2013-2018. Environmental Data Initiative.

Carey C. C., M. E. Lofton, A. B. Gerling, R. P. McClure, J. P. Doubek, B. R. Niederlehner, K. J. Farrell. 2018. Water chemistry time series for Beaverdam Reservoir, Carvins Cove Reservoir, Falling Creek Reservoir, Gatewood Reservoir, and Spring Hollow Reservoir in southwestern Virginia, USA 2013-2017. Environmental Data Initiative.

Carey C. C., R. P. McClure, A. B. Gerling, J. P. Doubek, S. Chen, M. E. Lofton, K. D. Hamre. 2019. Time series of high-frequency profiles of depth, temperature, dissolved oxygen, conductivity, specific conductivity, chlorophyll a, turbidity, pH, oxidation-reduction potential, photosynthetic active radiation, and descent rate for Beaverdam Reservoir, Carvins Cove Reservoir, Falling Creek Reservoir, Gatewood Reservoir, and Spring Hollow Reservoir in Southwestern Virginia, USA 2013-2018. Environmental Data Initiative.

Cvetkovich, G. and R. Löfstedt, eds. *Social trust and the management of risk*. 1999,

Earthscan: New York.

Ross, V.L., K.S. Fielding, and W.R. Louis, *Social trust, risk perceptions and public*

*acceptance of recycled water: Testing a social-psychological model.* Journal of

Environmental Management, 2014. **137**: p. 61-68.

AP-GfK, *Tap Water Confidence Poll*, in AP-GfK Poll 2016, Associated Press-GfK Public

Affairs & Corporate Communications.

Thornton, K. W., B. L. Kimmel & F. E. Payne (eds), 1990. Reservoir limnology: ecological perspectives. Wiley, New York.