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# Modeling Response of Water Quality to Land-use and Climate Change in Lake Auburn, Me

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MODELING RESPONSE OF WATER QUALITY TO LAND-USE AND CLIMATE CHANGE IN LAKE AUBURN, ME

By

Nicholas Messina

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Advisory Committee:

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By Nicholas Messina

Thesis Advisor: Dr. Aria Amirbahman

An Abstract of the Thesis Presented
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Lake Auburn, Maine, USA, is a historically unproductive lake that has experienced multiple algal blooms since 2011. The lake is the water supply source for a population of ~60,000. We modeled past temperature, and concentrations of dissolved oxygen (DO) and phosphorus (P) in Lake Auburn by considering the watershed and internal contributions of P as well as atmospheric factors, and predicted the change in lake water quality in response to future climate and land-use changes. A stream hydrology and P-loading model (SimplyP) was used to generate input from two major tributaries into a lake model (MyLake) to simulate physical mixing, chemical dynamics, and sediment geochemistry in Lake Auburn from 2013 to 2017. Simulations of future lake water quality were conducted using meteorological boundary conditions derived from recent historical data and climate model projections for high greenhouse-gas emission cases. The effect of future land development on lake water quality for the 2046 to 2055 time period under different land-use and climate change scenarios were also simulated. Our results indicate that lake P enrichment is more responsive to extreme storm events than increasing air temperatures, mean precipitation, or windstorms; loss of fish habitat is

driven by windstorms, and to a lesser extent an increasing water temperature; and watershed development further leads to water quality decline. All simulations also show that the lake is susceptible to both internal and external P loadings. Simulation of temperature, DO, and P proved to be an effective means for predicting the loss of water quality under changing land-use and climate scenarios.

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# CHAPTER 1

# INTRODUCTION

Phosphorus (P), the primary limiting nutrient of freshwater systems, is the leading cause of eutrophication and loss of water quality in lakes (Wetzel, 2001). Increased algal productivity leads to abnormal color and odor, growth of toxic species of cyanobacteria, increased turbidity, and anoxia in the water body. A prolonged anoxic zone in the hypolimnion of a stratified lake can lead to the die off of larger organisms.

Nutrient loading to lakes can be from external and internal sources. External loads originate from the watershed and precipitation, more so during precipitation events. Particulate P associated with iron (Fe) and aluminum (Al) hydroxides increases in stream water during high flow events. Upon entering the lake, metal hydroxides with adsorbed deposit as lake sediments (Kopáček et al., 2007).

External lake nutrient loading is highly influenced by land use and land cover. The future trophic states of some lakes can be as or more responsive to land-use change than to climate change (Chang et al., 1992). High percentages of impermeable surfaces due to urbanization and poor agricultural practices, such as overgrazing or excessive fertilization, reduce infiltration of water, increase surface runoff, and increase the nutrient flux (Fletcher et al., 2013). Higher runoff rates can cause significant stream bank erosion, consequently increasing export of suspended solids and other pollutants from the watershed (Aulenbach et al., 2017).

Internal loading, where anoxic lake sediment releases P into the water column, can also be a leading cause of eutrophication (Nurnberg et al., 1986; Christophoridis and Fytianos, 2006; Matisoff et al., 2017; Orihel et al., 2017). The exchange of P across the sediment-water interface is regulated by DO and other electron acceptor-dependent redox reactions (Wetzel, 2001; Katsev, 2016). Hypolimnetic anoxia causes the reductive dissolution of Fe (III) hydroxides, releasing adsorbed P (Loh et al., 2013). As such, P and DO have an inverse relationship in the hypolimnia of many temperate lakes (Nurnberg, 1998; Petticrew and Arocena, 2000).

Future climate change may significantly impact lake water quality in temperate regions (Meis et al., 2009; Foley et al., 2011; North et al., 2013; Ockenden et al., 2017). Numerical climate models predict higher temperatures, and more frequent and more intense storms in northeastern USA as the global climate continues to warm (Spierre and Wake, 2010; Madsen and Wilcox, 2012; Fernandez et al., 2015 Increased temperature and runoff lead to lake P enrichment that can lead to an increase in cyanobacteria population and a decrease in phytoplankton biodiversity (Przytulska et al., 2017). Further, an increased number of high wind events can alter lake thermal stability (Effler et al., 2004). Tropical storms, such as Hurricane Irene that impacted northeast USA in 2011, were shown to have a significant impact on lake physical and biological activities (Klug et al., 2012); lake thermal stability was reduced significantly in nine temperate lakes in the northeast after Hurricane Irene. Wind-induced mixing of the water column resuspends sediment, and mixes dissolved nutrients that can increase algal productivity and impact phytoplankton species composition (Carrick et al., 1993; Huisman et al., 2004).

Temperature and DO are the two most important water quality parameters pertaining to the health of fish in lakes (Fry, 1971). A warming climate is expected to reduce the habitat of cold water fish due to warming of the water column and decreased DO in the hypolimnion of lakes during late summer stratification (Schindler et al., 1996).

Linking process-based models that simulate lake and stream physical and biogeochemical processes can provide an effective means of both understanding past events and forecasting future scenarios. A mathematical model is an idealized formulation simulating the response of a system to given conditions (Chapra, 2008). Applied to water quality, such models can be calibrated for individual lakes, and subsequently used to predict pollutant loading under a changing environment in that lake. Catchment models have been established for simulating terrestrial and in-stream processes to model P loading from watersheds (e.g., Wade et al., 2002; Jackson-Blake et al., 2017). Lake models have also been thoroughly validated to simulate lake thermal stratification (Imberger and Patterson, 1981; Goudsmit et al., 2002; Tanentzap et al., 2007; Perroud et al., 2009; Thiery et al., 2014) and biological processes (Saloranta and Andersen, 2007; Hipsey et al., 2013; Hu et al., 2016). In parallel, recent developments in sediment diagenetic modeling (Katsev et al., 2006; Couture et al., 2010; McCulloch et al., 2013; Katsev and Dittrich, 2013; Torres et al., 2015; Gudimov et al., 2016; Couture et al., 2016; Doan et al., 2018) have enabled the use of such models in a better understanding of lake nutrient cycling processes. Here, we rely on the recent coupling by Markelov et al. (in press) of a lake model (MyLake; Saloranta and Andersen, 2007) with a diagenetic model (Couture et al., 2016; Akbarzadeh et al., 2018) aimed at internal P load predictions.

Several studies have linked a combination of catchment models, lake water quality models, and land-use and climate change models (Kaste et al., 2006; Weinberger and Vetter, 2012; Bayer et al., 2013; Couture et al., 2014; Couture et al., 2018; Yalew et al., 2018; Crossman and Elliott, 2018; Mueller et al., 2019). Sediment diagenetic (e.g., Doan et al., 2018) and lake water quality models (Bruce et al., 2018; Kiuru et al., 2018) have also been developed and their coupling explored (Smits and van Beek, 2013; Couture et al., 2015; Markelov et al., in press). Building on those approaches, we present a model chain that fully links physical and biogeochemical dynamics in the aquatic environment, lake sediment geochemistry, surface runoff from the terrestrial ecosystem, meteorological shifts in the atmosphere, and anthropogenic changes to land cover, and thus considers the roles of both external and internal nutrient inputs into a lake. This is critical for the management of lakes that receive significant contributions from both sources.

In this study, SimplyP (Jackson-Blake et al., 2017) - a catchment model for P dynamics, and MyLake-Sediment (Markelov et al., in press) - a one-dimensional lake model with a sediment diagenetic sub-module, were applied to Lake Auburn, Maine, USA. Lake Auburn has been an object of interest since 2011 due to its importance as a drinking water source for two cities in the area and its notable decline in water quality over the last decade (Doolittle et al., 2018; Norton et al., in press). It was necessary to first simulate the watershed hydrology as well as the nutrient loading using a catchment model. MyLake then used inputs from SimplyP, as well as feedback from its sediment diagenesis module, to hindcast in-lake processes relating to DO consumption and P dynamics in the lake for model calibration. Further, several climate change and land-use scenarios were used to project lake water quality for the 2046-55 period.

# CHAPTER 2

# METHODS

## 2.1 Study Site

Lake Auburn is located in southern Maine and serves as the water supply for ~60,000 people in the cities of Auburn and Lewiston. Lake and watershed physical characteristics are summarized in Table 2.1. Lake bathymetry is shown in Fig. A1. Detailed land cover information is in Table A1.

The two major inlets to Lake Auburn are Basin Brook and Townsend Brook, located in the northwest and northeast corners, respectively (Fig. 2.1). The land cover information for the two tributaries is in Tables A2 and A3. Watersheds for Lake Auburn, Basin Brook, and Townsend Brook were delineated, and the land use was determined using Model My Watershed (Tarboton et al., 2018). Basin and Townsend brooks have catchment areas of ~23 and 7 $km^2$, respectively. Basin Brook flows through a network of two ponds and a wetland (Fig. 2.1). Townsend Brook is largely fed from a sand and gravel aquifer (Doolittle et al., 2018). The single outlet of Lake Auburn is located on the eastern shore, and the intake to the water treatment plant is located near the southeastern corner. There are no known point sources in the sub-catchments of the two major inlets.

**Table 2.1**. Physical characteristics of Lake Auburn and its watershed.

| | |
|---|---|
| Lake Area | 8.98 $km^2$ |
| Perimeter | 19.6 km |
| Maximum depth | 36 m |
| Mean depth | 11 m |
| Latitude (deepest point) | 44.14° |
| Longitude (deepest point) | -70.25° |
| Watershed area | 41.37 $km^2$ |
| Watershed area:Lake area ratio | 4.61 |
| Forested land cover of watershed | 73% |
| Agricultural land cover of watershed | 9% |
| Developed land cover of watershed | 9% |
| Wetland land cover of watershed | 7% |
| Open water of watershed | 2% |

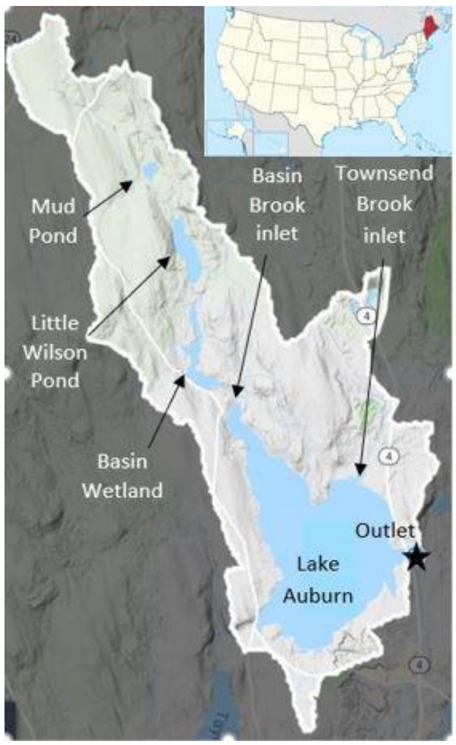


**Figure 2.1**. Lake Auburn location map (inset) and watershed map (modified from Wikipedia, 2019; Tarboton et al., 2018).

Lake Auburn is a historically unproductive lake that has seen multiple algal blooms since 2011. Epilimnetic total phosphorus (TP) concentrations have ranged from 6 to 16 μg $L^{-1}$ and epilimnetic chlorophyll-a (Chl a) concentrations have ranged from 1 to 17 μg $L^{-1}$ since 2000 (CDM Smith, 2013). This range of TP concentrations classifies

Lake Auburn as oligotrophic- to mesotrophic (Wetzel, 2001). Monthly mean Secchi disk measurements range from 6 to 8 m. The lake has experienced algal blooms in 2011, 2012, and 2018. In 2011, the lake experienced an unusually long period of anoxia in the hypolimnion, leading to internal P release, and was struck by Hurricane Irene nearly one month before the algal bloom. In 2012, the lake experienced a 15 cm 24 hr rainstorm, leading to watershed and shoreline erosion that possibly contributed to the algal bloom that year (CDM Smith, 2013). Hypolimnetic anoxia led to a large kill-off of lake trout in 2012 (Fleming, 2013). The 2018 bloom was preceded by intense rain events, but no hypolimnetic anoxia, suggesting an external input of nutrients into the lake.

**2.2 Lake, Watershed, and Climate Data**

Flow rate and TP concentrations from Basin Brook and Townsend Brook were provided by the Auburn Water District (AWD). Neither stream has ever been continuously gauged for Q or chemical species. Samples and measurements were taken directly at the inlets of the two streams to Lake Auburn (Fig. 2.1).

Temperature, DO, and TP profiles from Lake Auburn were also provided by AWD. Temperature and DO profiles at 1-meter intervals were taken nearly weekly during ice-free periods. P samples were taken monthly at a minimum during the ice-free season. Samples typically consisted of one core from the epilimnion and one sample grab from the hypolimnion, 1 m above the bottom at the deepest point, and some sampling dates included other depths.

Meteorological data were obtained from the nearest NOAA station at the Auburn/Lewiston Municipal Airport weather station, located ~9 km south of Lake

Auburn at 44.05°, -70.29° (NOAA, 2018). The data included daily air temperature, relative humidity, air pressure, wind speed, cloud cover, and precipitation.

The inflow temperature was estimated using an empirical relationship by Stefan and Preud'homme (1993). Inflow DO was assumed to be at saturation, a reasonable assumption in cold streams (Demars et al., 2011). Limited data on total organic carbon (TOC) concentrations from Basin Brook and Townsend Brook were available from Doolittle et al. (2018), enabling model estimation of particulate organic carbon (POC) and dissolved organic carbon (DOC).

### 2.3 Catchment and Lake Models

SimplyP, a catchment-scale nutrient model for the simulation of hydrology and P export, was used to simulate Q and TP in the tributary streams (Jackson-Blake et al., 2017). SimplyP is a process-based, spatially semi-distributed water quality model where catchments can be subdivided into subcatchments and land classes. The model considers three flowpaths for runoff: quick flow, soil water flow, and groundwater flow, representing overland flow that does not infiltrate, water that infiltrates the soil but does not reach the water table, and water that infiltrates to the water table, respectively. The model considers snow accumulation and melt, in-stream hydrology, land-phase and in-stream P transport, and transformation processes for Q and TP estimations. P is represented as dissolved P in soil water, labile soil P, inactive soil P, and particulate P in the stream bed. SimplyP uses air temperature, precipitation, and potential evapotranspiration as input data, and has parameters to define land use and catchment slope.

MyLake (Multi-year Lake simulation model) is a one-dimensional, process-based model for the simulation of vertical temperature distributions, ice cover, and P-phytoplankton dynamics (Saloranta and Andersen, 2007). One-dimensional lake models assume a mixed epilimnion and vertical gradients of temperature and concentrations in the hypolimnion (Perroud et al., 2009). These models work best for lakes with a uniform bowl-like bathymetry rather than lakes with multiple basins that creates horizontal gradients. Continuous, process-based models are superior to empirical models in lake modeling because many in-lake processes are dependent on daily weather-related events (Fang and Stefan, 2009). Two-and three-dimensional models have been applied to larger lakes but are computationally expensive (Zhang et al., 2008).

In this study, MyLake-Sediment was used to simulate temperature, DO, and TP at a 1-m vertical resolution and a daily time step. The model is available as an open-source MATLAB code. The model considers the lake at 1 m thick layers, from the surface to 36 m. Vertical diffusion and heat fluxes are evaluated at the layer interfaces, and diffusion coefficients and concentrations are assumed to be constant throughout each layer. Ice formation is triggered when the input air temperature for a day is below freezing; the model considers changing ice thickness and snow cover on the ice based on the weather data. Ice cover is an important process to model because it influences exchanges between the atmosphere and surface water and light penetration in the water column, both of which are important in predicting oxygen dynamics (Couture et al., 2015). The model considers the following biogeochemical processes related to P transformation and phytoplankton growth in the water column: mineralization of dissolved organic P (DOP) and particulate organic P (POP) to orthophosphate (ortho-P);

removal of ortho-P through phytoplankton growth or through adsorption onto suspended solids; and resuspension of Chl a and particulate inorganic P (PIP; Couture et al., 2014). The model takes meteorological data (air temperature, precipitation, cloud cover, wind speed, air pressure, and relative humidity) as well as inflow data as inputs.

In addition to processes in the water column and heat flux from the sediment, MyLake-Sediment uses a sediment diagenesis module. It also considers DOC degradation in the water column as a DO sink, and the DOC effect on light attenuation in the lake (Kiuru et al., 2018). However, Lake Auburn is not a humic lake (DOC ranges from 1.0 to 3.3 mg $L^{-1}$) and normally has low turbidity (~0.6 NTU; CDM Smith, 2013). Lake Auburn is known to be susceptible to significant internal P release due to sediment $Fe(OH)_3$ reduction (Doolittle et al., 2018). Therefore, MyLake-Sediment was used because its sediment diagenesis module simulates the coupled process of P release and $Fe(OH)_3$ reduction, and considers release of P from degradation of phytoplankton (Markelov et al., in press).

**2.4 Future Meteorological Inputs**

Lake simulations for the years 2046 to 2055 were produced using meteorological inputs from (1) recent historical data that can be used to establish analog climate, and (2) output from two different projective climate models.

Historical analog scenarios, where past climate experiences are used to simulate future responses to climate change, have been widely used in climate research (Lorenz, 1969; Zorita and von Storch, 1999; Ford et al., 2010; Veloz et al., 2012). Under one of the projective climate models, daily simulations of weather for this time span were extracted from projections of the climate model GFDL ESM2M under scenario RCP8.5

as part of the Coupled Model Intercomparison Project Phase 5 (CMIP5; NOAA, 2012; Dunne et al., 2012). The ESM2M model simulates air temperature, precipitation, cloud cover, air pressure, relative humidity, and wind speed, which are needed for MyLake. For simplicity, we refer to this climate forcing as RCP8.5. Under the other projective climate model, a range of projected increases in air temperature and precipitation by the year 2050 was generated using emissions scenario A2, computed by version 3 of the NCAR Community Climate System Model (CCSM3) as part of the CMIP Phase 3 (CMIP3; Collins et al., 2006; Solomon et al., 2007; Fernandez et al., 2015).

### 2.4.1 Modern Analog

Using observed data from the local NOAA weather station (NOAA, 2018), the recent warmest years in Maine (2006, 2010, 2012, and 2016) were selected and the simulated weather for the 2046-2055 period was cycled through these years in the Analog Warm scenario. An Analog Wet scenario was similarly produced using the recent wettest years in Maine (2005, 2008, 2009, 2010, and 2014). A scenario Analog Warm/Wet was also simulated, where the climate data for future years repeatedly looped through the year 2010 that was both one of the wettest and warmest in this time frame.

### 2.4.2 Projective Climate Models

The RCP8.5 scenario represents a target radiative forcing of 8.5 W $m^{-2}$ in 2100, very high greenhouse gas emissions, and the non-implementation of climate change policies (Riahi et al., 2011). Scenario A2 simulates Earth with a continuously increasing population, and slower economic and technological development than other scenarios simulated in the CMIP3 (Solomon et al., 2007), and atmospheric concentrations of $CO_2$ reaching 850 ppm by 2100 (Lehodey et al., 2010). Compared to the newer CCSM4 model, CCSM3 performed better in reanalysis for the modern control period in the northeastern USA (Fernandez et al., 2015). Thus, we chose to utilize output from CCSM3 for two scenarios, A2-lb and A2-ub. The A2-lb scenario applied an increase of 1.4 °C and 5% precipitation as a lower bound and the A2-ub scenario applied an increase of 1.7 °C and 6% precipitation as an upper bound to the weather data from 2006 to 2015 to simulate the years 2046-2055 (Fernandez et al., 2015).

### 2.4.3 Future Land-Use Changes

To simulate the effects of climate change on Lake Auburn, the forecasted meteorological inputs under each scenario were separately used as inputs to SimplyP and MyLake models. This method captures the impacts of climate change on the catchment, of altered external loads on the lake, and of climate change on internal processes in the lake. Increase in development in the watershed was simulated in SimplyP by increasing the impervious area by 50% at the expense of forested area. Every climate change scenario was also executed under a coupled climate change and development scenario.

The reduction in lake P loading was simulated by (a) eliminating external P loads from the tributaries to the lake (an analog for implementing best management practices; BMPs), and (b) inhibiting sediment P release via, for example, alum ($Al_2(SO_4)_3$) addition (Cooke et al., 1982; Huser et al., 2011).

## 2.5 Model Sensitivity and Calibration

SimplyP was calibrated manually for Basin Brook and Townsend Brook. Manual calibration of catchment models can better capture peak P events when calibrated against observations taken at lower frequency (Jackson-Blake and Starrfelt, 2015). Each parameter was varied individually to minimize RMSE between simulations and observations from 2014 to 2017.

Sensitivity analysis tests the impact of change in a parameter on the model outcome. A sensitivity analysis was first performed manually for all parameters in MyLake-Sediment before calibration. All parameters were individually varied from their original value (doubled or halved, depending on what physically made sense) and the changes in RMSE for temperature, DO, and TP were observed. Parameters with the greatest impact were used in calibration.

MyLake was calibrated using the MATLAB built-in Genetic Algorithm. Genetic Algorithms are a guided random process, in contrast to a strictly random process such as the Monte Carlo methods (Kramer, 2017). This optimization method has been applied to calibration of MyLake in a previous study (Couture et al., 2018). The Algorithm was executed by optimizing the model's fit for temperature, DO, and TP against observations from 2013 to 2017. The model was first calibrated with respect to lake temperature, because establishing values for parameters relevant to the physical mixing of the lake are essential for simulating DO and TP.

A goal of the calibration was to simplify the sediment diagenesis model such that only the most relevant diagenetic processes were considered. To eliminate the minimally influential secondary redox processes, such as sulfate and nitrate reduction, the concentrations of these constituents were set to zero. Concentrations of sulfate, nitrate, and sediment $Al(OH)_3$ are low in Lake Auburn (Doolittle et al., 2018). Only parameters pertinent to reductive dissolution of $Fe(OH)_3$ were calibrated, and they were the most influential parameters under these assumed conditions.

Numerical climate models, while internally consistent, tend to have solution biases that necessitate the application of factors to correct for biases at a more localized spatial resolution. Bias correction is a statistical downscaling method used in climate change modeling for applying global climate models to regional scales (von Storch et al., 1993; Themeßl et al., 2012; Manzanas et al., 2018). Global climate models can be validated and calibrated through climate reanalysis (Auger et al., 2018). The RCP8.5 model projects future meteorological values at a coarse horizontal grid cell resolution (2° × 2.5°). It was therefore necessary to calibrate the extracted model output to a more localized area. RCP8.5 model simulations from 2006 to 2015 were compared to the observed data from this time period, and the model parameters were adjusted by applying appropriate correction factors to correct for the bias.

## CHAPTER 3

## RESULTS AND DISCUSSION

### 3.1 Stream Simulations

SimplyP provided simulations of flow (Q) and TP for Basin Brook and Townsend Brook (Figs. 3.1 and 3.2). The calibrated parameters and the corresponding best fits used in SimplyP are summarized in Table A4.

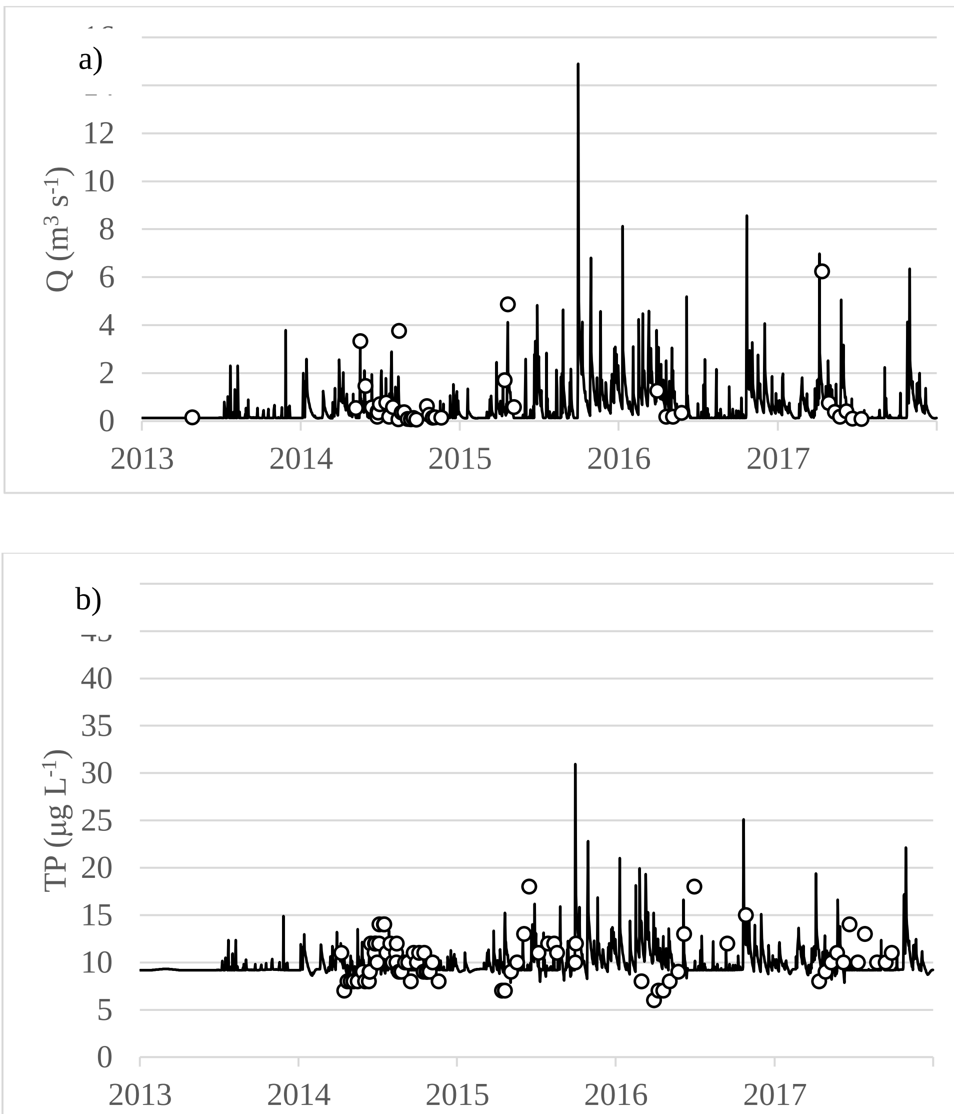


**Figure 3.1**. SimplyP simulations of (a) stream flow (Q), and (b) total phosphorus (TP) for Basin Brook. Points are observed values and lines are simulated values.

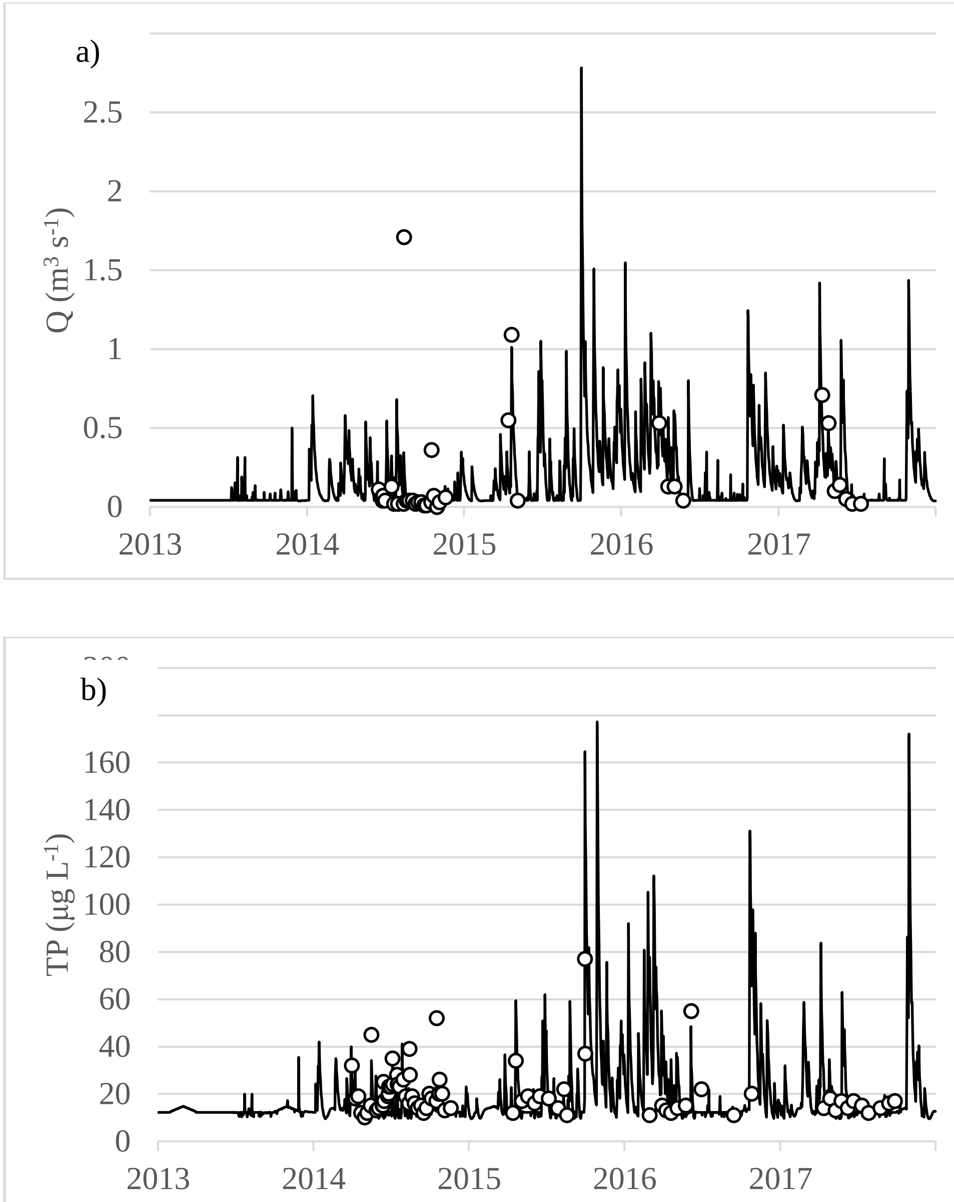


**Figure 3.2**. SimplyP simulations of (a) stream flow (Q), and (b) total phosphorus (TP) for Townsend Brook. Points are observed values and lines are simulated values.

Table 3.1 summarizes the performance statistics for Q in both streams. The Nash-Sutcliffe model efficiency (NSE) coefficients for both simulations were positive, indicating that the model predictions were more accurate than using the mean of the observed data (Jain and Sudheer, 2008).

**Table 3.1**. Summary of performance statistics for SimplyP and ice-out phenology in MyLake. The number of observations (n), root-mean-square-error (RMSE), coefficient of determination ($R^2$), and the Nash-Sutcliffe model efficiency (NSE; for Q) coefficient are shown.

| SimplyP | n | RMSE | $R^2$ | NSE |
|---|---|---|---|---|
| Q Basin Brook | 38 | 1.15 $m^3 s^{-1}$ | 0.33 | 0.30 |
| Q Townsend Brook | 38 | 0.29 $m^3 s^{-1}$ | 0.31 | 0.30 |
| TP Basin Brook | 77 | 3.77 µg $L^{-1}$ | 0.00 | |
| TP Townsend Brook | 77 | 20.20 µg $L^{-1}$ | 0.25 | |
| | | | | |
| MyLake | | | | |
| Ice-out date | 12 | 7.63 d | 0.85 | |

Table 3.1 also summarizes the performance statistics for TP in both streams. Basin Brook's modeling was complicated by the fact that the observed TP concentrations (average ~10 µg $L^{-1}$, standard deviation ~2 µg $L^{-1}$) did not correlate positively with Q, as expected in a small, mostly wooded watershed. The extensive Basin Brook wetland immediately upstream of the lake is a likely significant source of particulate P uptake (Knox et al., 2008; Doolittle et al., 2018), leading to a relatively constant TP concentration for export to the lake. More frequent sampling of stream water chemistry, even for just a short time period, can greatly increase performance of catchment models (Jackson-Blake and Starrfelt, 2015). Townsend Brook's Q and TP show a more positive correlation in peak events. Much of the runoff in Townsend Brook is transported vertically to groundwater flow, damping Q and removing P as adsorbed P in the porous and permeable soil (Doolittle et al., 2018).

MyLake takes, as external inputs, a single value for TP each day. The TP simulations from Townsend Brook typically had a smaller effect on TP flux to the lake because of its lower average flow rate than that of Basin Brook.

Base flow index, base flow recession constant, and groundwater total dissolved P (TDP) concentration were critical parameters for establishing the base flow conditions. Groundwater TDP concentration is set as a constant in SimplyP, and TP in the stream is set equal to groundwater TDP concentration under base flow conditions. The proportion of flow routed to quick flow ($f_{quick}$; Table A4) is influential for correctly simulating peak flow events; capturing these events was a goal of the calibration process. A compromise between strong overall statistical performance and capturing peak events was navigated.

### 3.2 Lake Simulations

Correctly simulating ice cover is critical due to the key role ice cover plays in lake DO dynamics (Terzhevik et al., 2010). In this study, MyLake simulated ice-out phenology for 2006 to 2018 period well (Fig. 3.3; Table 3.1). Performance statistics are within the range reported for other ice phenology modeling studies (Table 3.1; Gebre et al., 2014; Couture et al., 2015; Bueche et al., 2017), except for 2012 and 2016 where large discrepancies between observed and simulated ice-out dates were obtained. Those discrepancies did not appear to affect temperature simulations (Fig. 3.4a).

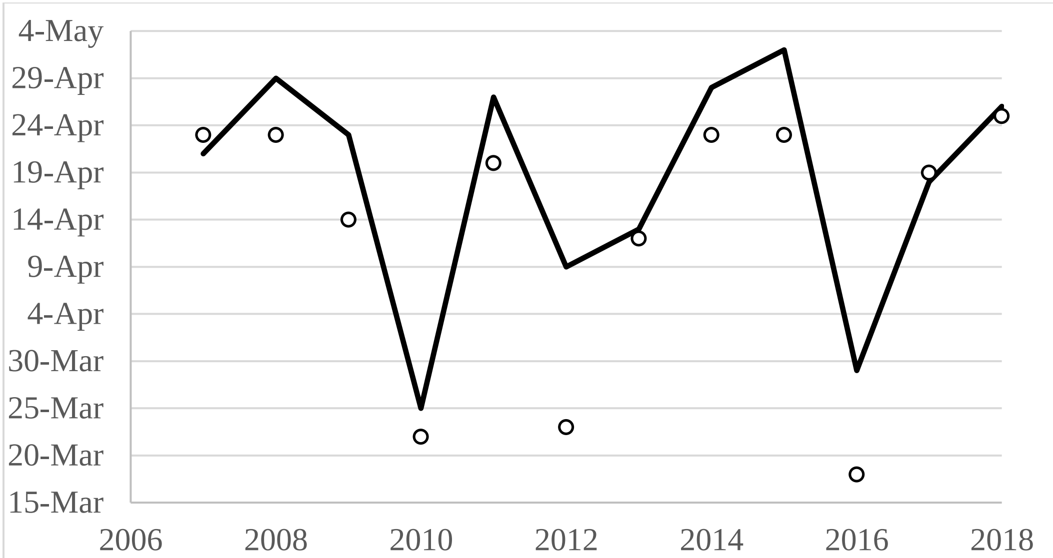


**Figure 3.3**. Ice-out phenology, observed (circles) and simulated (line), from 2007 to 2018.

The observed data and model simulations of temperature, DO, and TP for the 2013-2017 period are shown in Fig. 3.4. The calibrated parameters and the resulting values in MyLake-Sediment are summarized in Table A5. The plots for temperature, DO, and TP show three depths representing the epilimnion, metalimnion, and hypolimnion. A more detailed statistical analysis showing model performance for each depth range is in Table 3.2. Using the ratio of RMSE to standard deviation of observations (RSR), and percent bias (PBIAS), variables at every depth were simulated as “satisfactory”, at a minimum, and mostly as “very good” (Table 3.2; Moriasi et al., 2007). Although $R^2$ is commonly used as a metric for model evaluation, this statistic is sensitive to outliers and insensitive to systematic differences between simulations and observations, allowing for strong bias under high values of $R^2$ (Legates and McCabe, 1999).

**Table 3.2**. Model performance evaluation for MyLake. Statistics shown are number of observations (n), root-mean-square-error (RMSE), coefficient of determination ($R^2$), RSR, and PBIAS. Criteria for qualitative parameter classification (Moriasi et al., 2007) are listed at the bottom.

| | n | RMSE | $R^2$ | RSR | PBIAS |
|---|---|---|---|---|---|
| Temp. 0 m | 157 | 1.50 | 0.95 | 0.25: Very good | 1.66: Very good |
| Temp. 9 m | 157 | 1.58 | 0.86 | 0.38: Very good | 4.43: Very good |
| Temp. 33 m | 155 | 0.94 | 0.40 | 0.66: Satisfactory | 26.98: Good |
| DO 0 m | 151 | 0.57 | 0.66 | 0.42: Very good | 3.37: Very good |
| DO 9 m | 150 | 0.70 | 0.43 | 0.35: Very good | 4.06: Very good |
| DO 33 m | 148 | 1.24 | 0.62 | 0.36: Very good | 13.12: Very good |
| TP 0-8 m | 87 | 2.22 | 0.00 | 0.48: Very good | 21.22: Very good |
| TP 9-16 m | 40 | 2.36 | 0.27 | 0.64: Satisfactory | -8.91: Very good |
| TP 32-34 m | 64 | 4.09 | 0.34 | 0.25: Very good | 4.74: Very good |

| Parameter | Very Good | Good | Satisfactory | Poor |
|---|---|---|---|---|
| RSR | 0-0.5 | 0.5-0.6 | 0.6-0.7 | >0.7 |
| PBIAS | 0-25 | 25-40 | 40-70 | >70 |

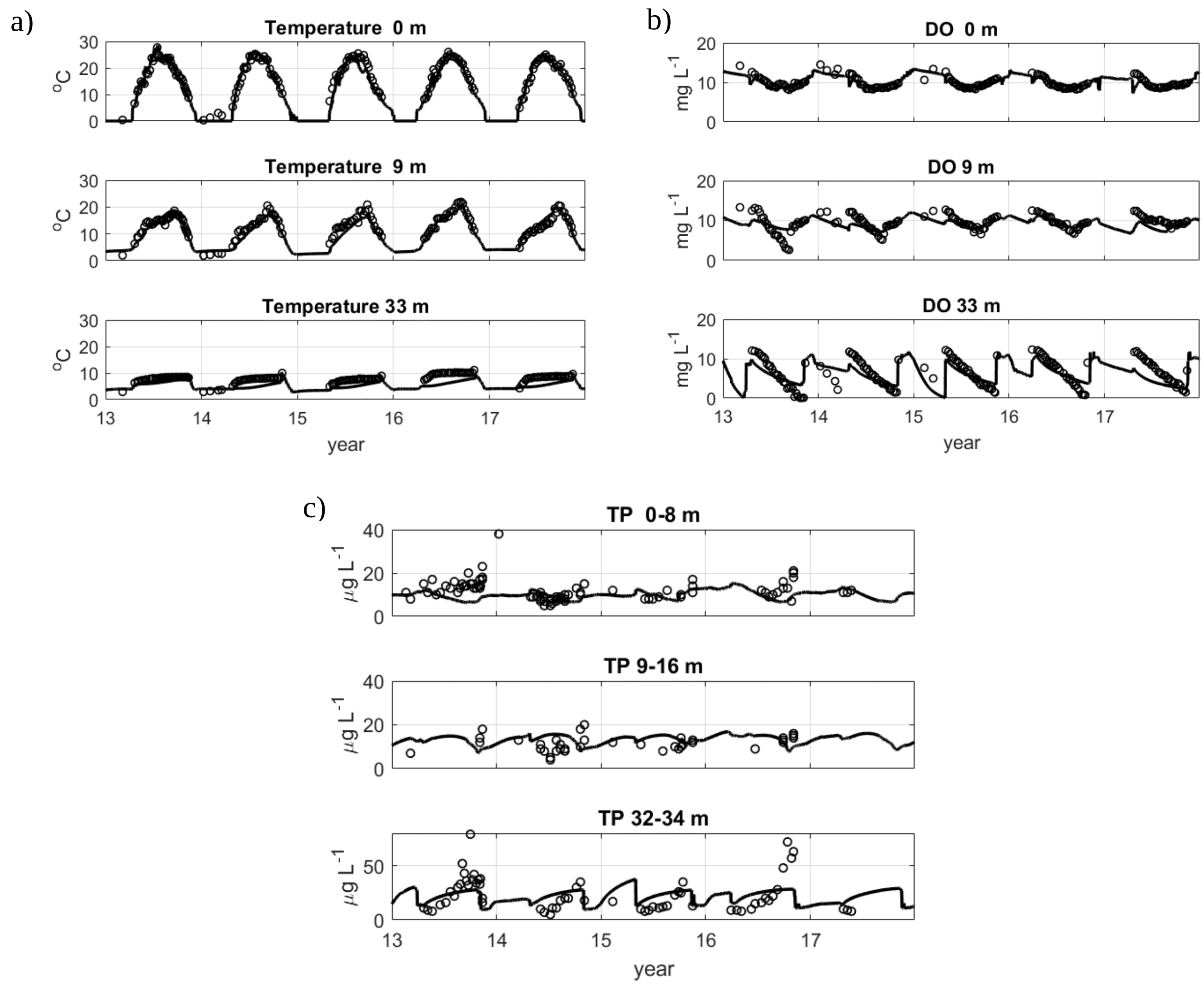


**Figure 3.4**. Simulation of Lake Auburn temperature (a), DO (b), and TP (c) for the 2013-2017 period. Observed data are points. Simulations are lines. Tick marks on the x-axis indicate January 1 of the corresponding year.

The goodness of fits for temperature decreased with depth, which is expected of one-dimensional lake models that rely on surface-atmosphere interactions (Thiery et al., 2014), and is consistent with a previous application of this model (Markelov et al., in press). The goodness of fits for DO is consistent with model performance in previous applications of MyLake (Couture et al., 2015; Markelov et al., in press), although in this application the simulation commonly underestimated the hypolimnetic DO depletion rate. Features of the lake bathymetry may explain this discrepancy (see section 3.6). Winters in which DO was depleted (2013 and 2015) correspond to winters with a low Q. Lake water under ice cover behaves as a closed system with respect to DO, and depletion occurs more quickly in the absence of surface inflow as an oxygen source (Fang and Stefan, 2000). Finally, the model's predictive power for simulating P increased with depth, capturing the increasing trend in hypolimnetic P by late summer each year (Fig. 3.4). Previous applications of MyLake and MyLake-Sediment did not analyze model performance for hypolimnetic P.

Simulating DO and P for 2013 in the metalimnion and hypolimnion was particularly challenging, possibly as a consequence of the relatively high sedimentation rate in Lake Auburn. Typical boreal lakes in the northeastern USA have a sedimentation rate of $\leq$1-2 mm $yr^{-1}$ (Davis et al., 1986). A recent study estimated the sedimentation rate of Lake Auburn at $\geq$6 mm $yr^{-1}$ at the deepest point of the lake using $^{210}Pb$ isotope possibly due to substantial shoreline erosion (Norton et al., in press). Algal blooms in one year provide excess POC at the sediment-water interface (SWI) that enhances hypolimnetic anoxia and fuels lake P enrichment through its degradation for succeeding years; however, a large input of un-weathered shoreline material could bury the POC layer at the SWI preventing sediment P release. In 2013, the lake experienced especially extensive anoxia and high internal P release that should have added excess POC and POP to the sediment. But the high sedimentation rate may have buried this excess POC and reduced the P release rate in 2014. This could account for the abrupt shift in observed DO depletion and TP from 2013 to 2014 that is not captured in model simulations.

The parameters presented in Table A5 were the most sensitive parameters during model calibration. Open water diffusion parameter and wind sheltering coefficient, a parameter that is a function of lake surface area and is used in the calculation of total kinetic energy available for wind-induced mixing (Saloranta and Andersen, 2007), are influential for temperature distribution as they control lake physical mixing (Hondzo and Stefan, 1993). Other influential parameters for simulating the temperature distribution relate to the growth of phytoplankton. Decreasing water clarity from algal growth decreases light penetration, enhancing warming and cooling of the hypolimnion. DO and TP simulations were both affected by the parameters related to the reaction rates involving the consumption of POC and P, and reduction of DO and $Fe(OH)_3$ (Table A5). Therefore, DO and TP were calibrated simultaneously. The effective depth parameter, representing the depth below which the sediment may release species into the water column, is an influential and adjustable parameter for correctly simulating effluxes from the sediment, as it approximates the area of sediment that is effectively exchanging with the bottom water (Markelov et al., in press).

### 3.3 Land-Use Changes and Climate Change Scenarios

Figures A2-A4 compare the observed mean air temperature, precipitation, and wind speed from 2006 to 2015 to each of the climate change scenarios for the 2046-2055 period. Results from the RCP8.5 model indicate a projected increase of ~2 °C in mean air temperature, the greatest increase among all models. Analog Wet produced the lowest mean air temperature as a result of the selection of the wettest years including years with heavy snowfall, thus including years with long, cold winters. Analog Warm/Wet had the highest overall mean precipitation. Fig. A4 excludes the A2 scenarios because their mean annual wind speeds are identical to those observed in the 2006-2015 period.

The extracted data from the RCP8.5 model demonstrated a consistent increase in both air temperature and precipitation but did not produce peak storm events that have been observed in the past (Table 3.3). An extreme precipitation event was defined as one in which ≥50 mm of precipitation falls in a 24-hour period (Fernandez et al., 2015). The RCP8.5 forcing affords a modest decrease in the number of extreme events, but not a single hyper-extreme event, which we define as an event in which ≥100 mm of precipitation falls in a 24-hour period. Even though these events are defined within a 24-hour period, the analysis in Table 3.3 includes 24-hour days because the model operates at, and the weather is input at, a daily time step.

**Table 3.3**. Average number of days of extreme and hyper-extreme precipitation events per year. Climate change scenarios are for the 2046–2055 period.

| | Observed 2005-15 | RCP8.5 | A2-lb | A2-ub | Analog Warm | Analog Wet | Analog Warm/Wet |
|---|---|---|---|---|---|---|---|
| Days/yr ≥ 50 mm | 10.3 | 8.0 | 11.9 | 12.0 | 15.3 | 6.4 | 14.0 |
| Days/yr ≥ 100 mm | 7.4 | 0.0 | 8.1 | 8.1 | 10.4 | 2.8 | 3.0 |

### 3.4 Impacts of Land-Use and Climate Change on Streams

Mean Q increased across every climate change scenario (Fig. S3.5a). Most scenarios also simulated an increase in maximum Q. Every climate change-development scenario simulated an increase in mean and maximum Q from its corresponding climate change scenario, indicating that an increase in impervious area in the catchment increases both total and peak runoff events from the watershed.

Increases in stream TP correspond to increases in Q due to surface runoff and erosion from overland flow, the stream bed, and embankments (Likens et al., 2013). This is reflected in the correspondence between Figs. S3.5a and S3.5b. There was a greater difference between changes in maximum TP in corresponding climate change and land-use scenarios than between changes in mean P, indicating that development of the watershed had a greater influence on the maximum compared to the mean nutrient loading.

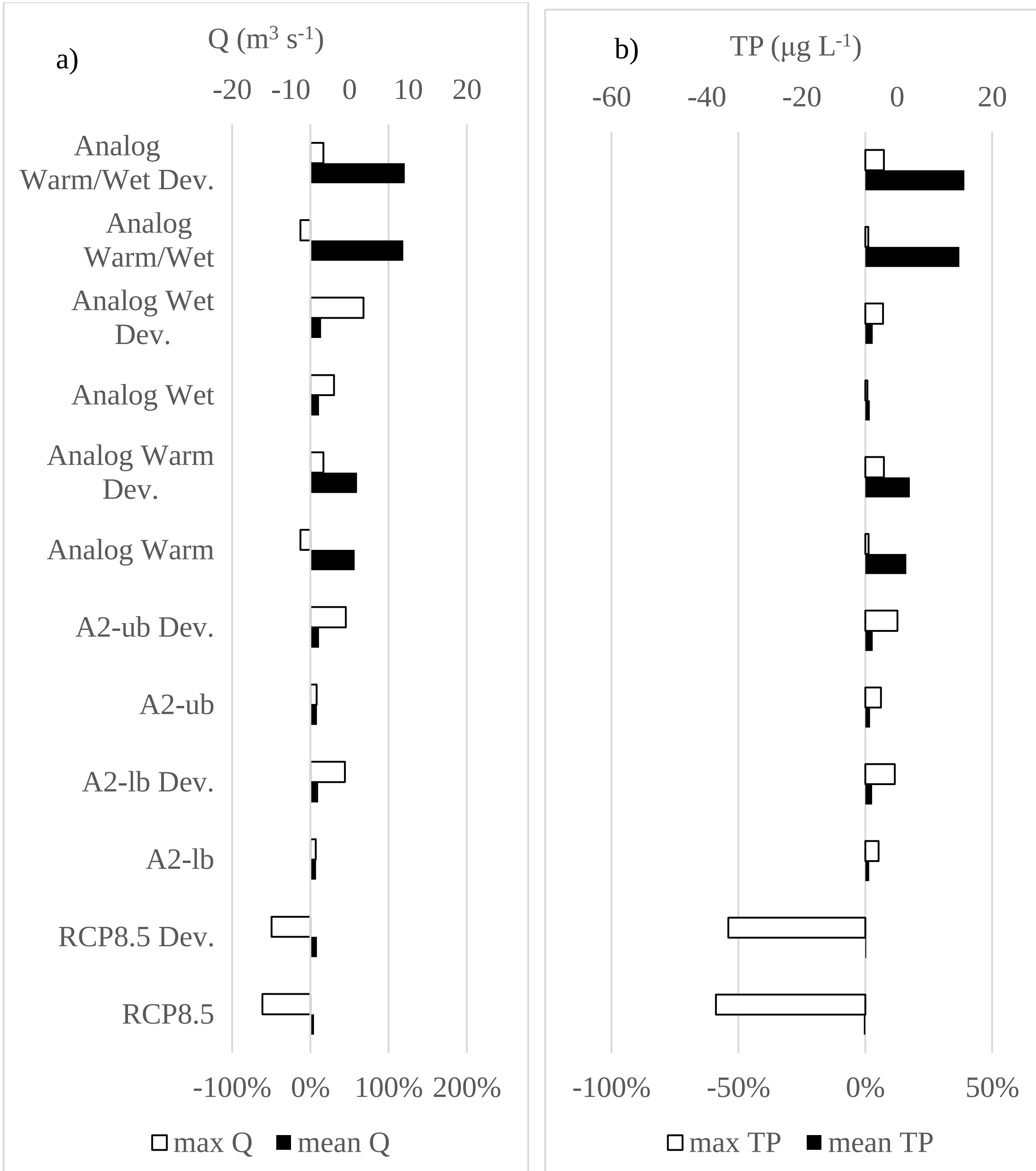


**Figure 3.5**. Maximum and mean absolute and percent change in Q and TP in stream flow from past simulations (2010 to 2015) to future scenarios (2050 to 2055)

### 3.5 Impacts of Land-Use and Climate Change on Lake

The simulated mean ice-out dates for 2047-2055 for the historical analog, RCP8.5, and A2 experiments were earlier than that observed 2007-2015 for every year except 2010 (Fig. 3.6). March ice-outs occurred three times from 2007 to 2018 (Fig. 3.3), while four out of six climate change scenarios simulated more than two March ice-outs for all years from 2047 to 2055. The RCP8.5 scenario simulated a record ice-out in the year 2054. Early ice-out dates impact the timing and increase the magnitude of certain plankton groups (Adrian et al., 1999) and decrease DO availability during the late summer (Couture et al., 2015), although this is also driven by changes in DOC (see section 3.6). Early ice-out in Lake Auburn has statewide implications because synchrony in the past earliest ice-out years among Maine lakes indicates a coherence in ice-out dates (Beyene and Jain, 2015).

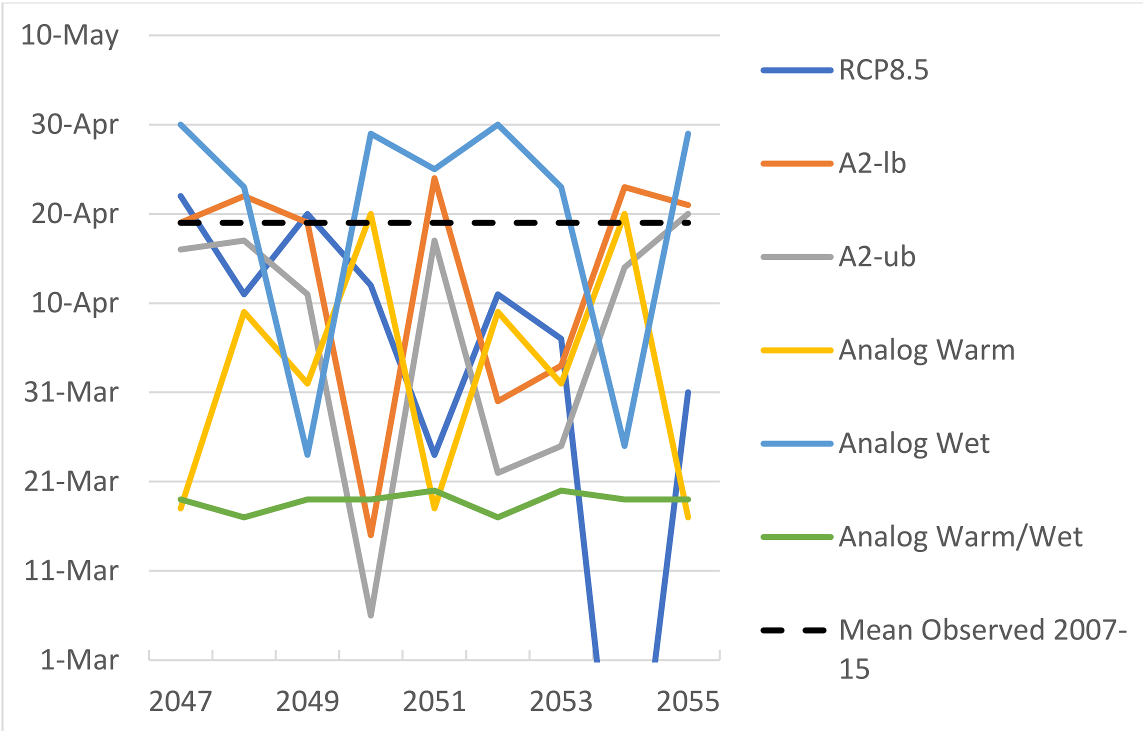


**Figure 3.6**. Ice-out phenology under climate change scenarios (2047-2055). The RCP8.5 model simulated ice-out for February 1, 2054 is not shown.

The optimum habitat for lake trout, a game fish in Lake Auburn, are temperatures <10° C and DO concentrations >6 mg $L^{-1}$ (MacLean et al., 1990). Most climate change scenarios simulated a reduction in the numbers of days of optimum trout habitat (Table 5), suggesting a potential for the increase of trout kill-offs. Lake Auburn has experienced a recent increase in the populations of warm water fish species (largemouth bass and chain pickerel), and the changing conditions in the lake could have an impact on the competition between warm water and cold water fish species. Depletion of hypolimnetic DO and warming of the water column have been linked to decline in habitat in other cold water species (Hansen et al., 2019).

**Table 3.4**. Percent change in number of days of optimum habitat for lake trout from past (2010 to 2015) to future scenarios (2050 to 2055).

| RCP8.5 | A2-lb | A2-ub | Analog Warm | Analog Wet | Analog Warm/Wet |
|---|---|---|---|---|---|
| 0.69% | -0.59% | -0.98% | -7.85% | -0.29% | -2.06% |

Most scenarios simulated an increase in epilimnetic temperature (Fig. 7). The Analog Wet scenario simulated a small decrease because the selection of the wettest years included years with high snowfall, thus including harsh winters with colder temperatures.

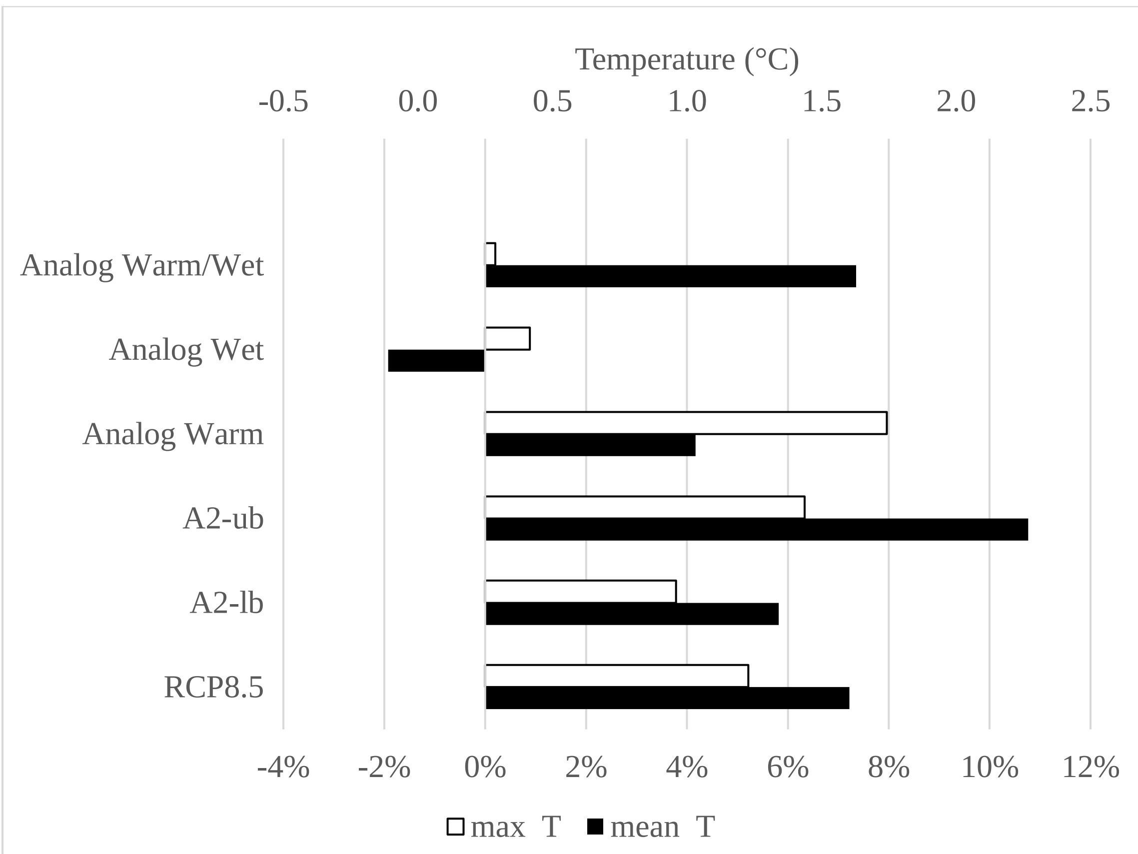


**Figure 3.7**. Maximum and mean absolute and percent change in epilimnetic temperature (0-8 m) from past simulations (2010-2015) to climate change scenarios (2050-2055).

All scenarios, except the RCP8.5, predicted increases in the epilimnetic and hypolimnetic P concentrations (Figs. 3.8). The epilimnetic P increased in both mean and magnitude of the outlier events (Fig. 3.8a). The Analog Warm/Wet was the worst-case scenario for the lake, as repeated cycling through one of the warmest and wettest years the lake has seen in recent history resulted in a mean increase of ~81% in epilimnetic P and a mean increase of ~7% in epilimnetic temperature. The Analog Warm scenario projected a greater increase in epilimnetic P than hypolimnetic P because the water column fully mixed in multiple years, bringing P released from the sediment to the surface. The greatest change in the hypolimnetic P was projected in the Analog Warm/Wet scenario (Fig. 3.8b).

The RCP8.5 scenario was the only scenario that did not project an P increase in the water column, despite projecting a climate with the highest mean air temperature and a relatively high number of extreme events. The RCP8.5 was also the only scenario that did not project a single hyper-extreme event in the 2050-2055 period. Together, this suggests that P enrichment of Lake Auburn is more responsive to hyper-extreme events than an increase in air temperature, mean precipitation, or windstorms.

Every land development scenario projected a greater increase in the epilimnetic P than its corresponding climate change scenario (Fig. 3.8a). Increase in the impervious area in the catchment led to increases in overall and peak concentrations of P in the runoff. This resulted in greater mean and peak epilimnetic P concentrations. The future trophic state of Lake Auburn will depend, in part, on human activities and changes made to the land cover of the watershed.

a)

b)

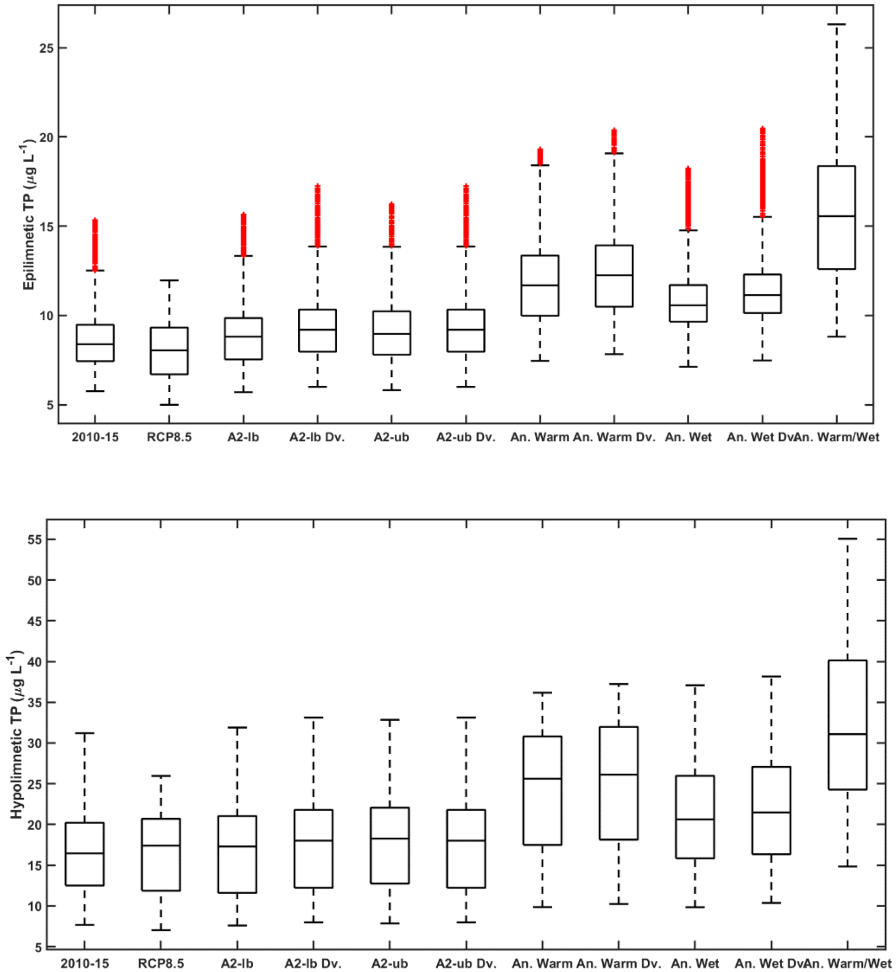


**Figure 3.8**. Box plot comparing distributions of mean daily (a) epilimnetic TP (0-8 m) and (b) hypolimnetic TP (32-34 m) from 2050 to 2055 for all future scenarios. Outlier events are indicated with dashed red lines.

Differences in the hypolimnetic TP between different climate change scenarios and their corresponding development scenarios are minimal (Fig. 3.8b). This indicates that hypolimnetic P is not strongly affected by changes in peak runoff but is responsive to increases in overall internal plus external loading. Inactivation of sediment P release, and P elimination in the runoff from the watershed are simulated in Fig. 3.9. Even with external loads set to zero, the internal loading was simulated as a significant source of P for the water column, but internal loading gradually decreased after five years (Fig. 3.9). This suggests that internal recycling of legacy P in sediment can maintain P enrichment of the water column long after exports from the watershed are reduced.

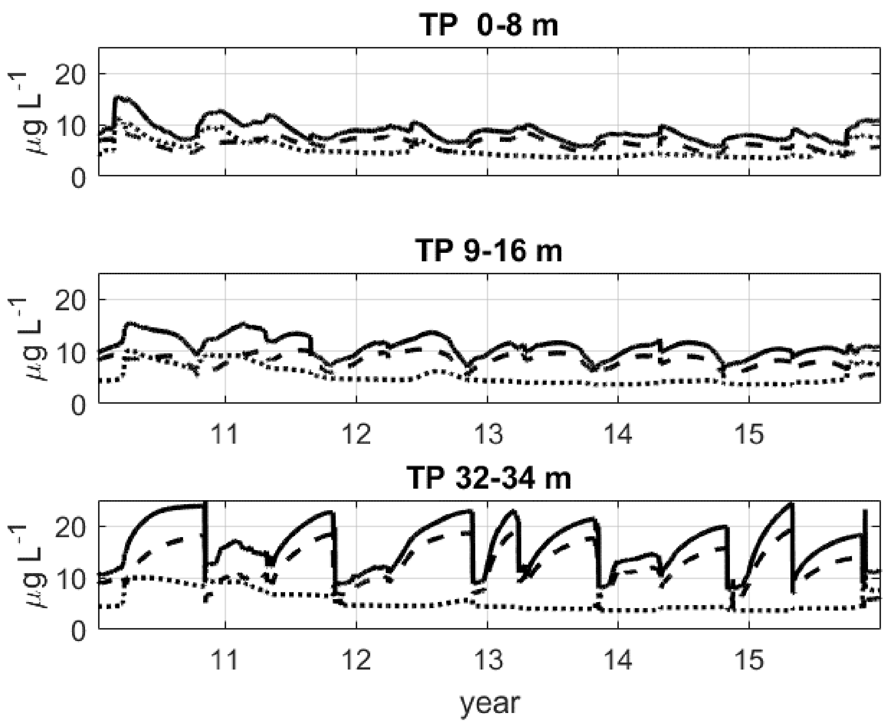


**Figure 3.9**. Modeled daily total P (solid) and its internal and external sources for 2010-2015. Dashed line simulates internal P only and dotted line simulates external P only (sediment inactivation).

An investigation on the effects of P sources revealed that the lake is susceptible to both internal and external loading (Fig. 3.9-3.10). In 2010, one of the warmest and wettest years on record for Lake Auburn, external loading accounted for ~65% of P in the water column. After a few years of moderate weather, external loading accounted for ~43% of P in the water column in 2013 but was the dominant P source again in 2016. Therefore, to maintain water quality in Lake Auburn, the roles of both the watershed and lake sediment should be considered in any effort to minimize P loading in the lake.

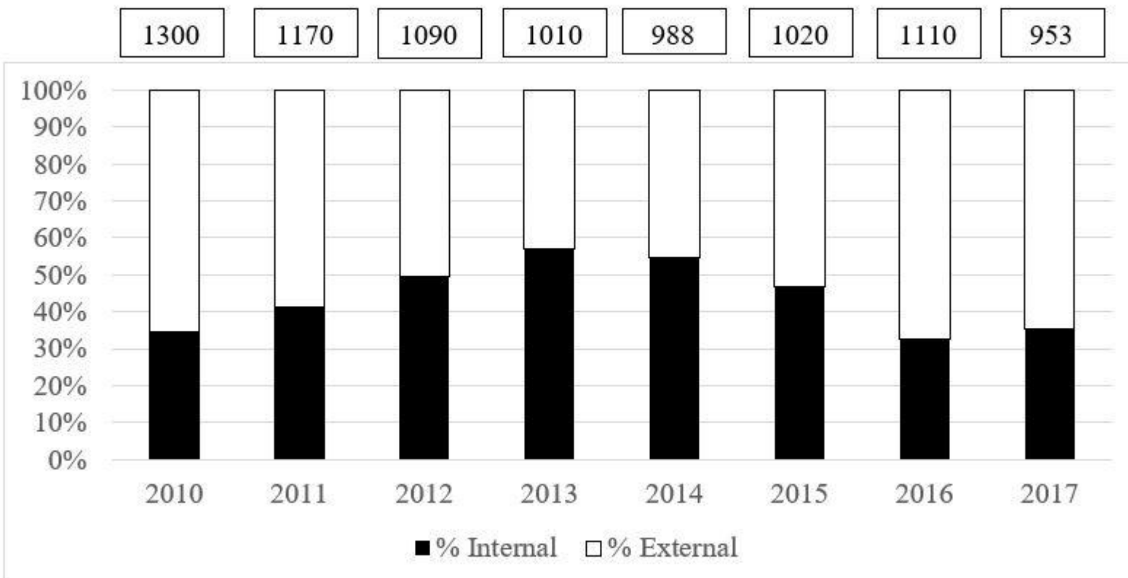


**Figure 3.10**. Percentage of internal and external mean loading as sources of P in the lake 2010-15. Mean daily mass of total P in the lake is at the top of each year (kg).

### 3.6 Sources of Uncertainty

One-dimensional lake models are best-suited for lakes with a bowl-like bathymetry because they assume horizontal homogeneity within layers. Bathymetric data indicates that most of Lake Auburn is no deeper than 27 m. However, the deepest point, where all of the sampling data were collected, has a maximum depth of 36 m, creating an isolated area that can at times be separated from the dynamics of the rest of the lake (CDM Smith, 2013). The effect of the isolated deepest point may account for the challenges in our simulations.

MyLake utilizes a simplified approach to algal dynamics that contributes to uncertainty in simulating P. The model assumptions include phytoplankton species homogeneity, absence of zooplankton grazing, and a simplification that all algal cells follow the Redfield ratio. Lake Auburn has diverse cyanobacteria species, including *Gloeotrichia echinulata* (CDM Smith, 2013). This organism occurs in remote, oligotrophic lakes, including several low nutrient lakes in the northeastern USA (Carey et al., 2012). Colony growth is controlled by light and temperature in shallow sediments (Karlsson-Elfgren et al., 2004). The unresponsiveness of this particular algal species to nutrient loading is not captured by the model, and as such, the contribution of this species to the POC and POP are not represented.

The DOC concentration has increased in many temperate and boreal lakes in the northeastern USA in response to declines in acid deposition since the implementation of Clean Air Act legislation of 1970 and 1990 (Evans et al., 2005; Monteith et al., 2007). Studies suggest that increases in DOC leads to faster DO consumption in boreal lakes (Couture et al., 2015). An increase in DOC for Lake Auburn was not simulated due to (a) its relatively low concentration and (b) a lack of long-term DOC monitoring data. However, any potential increase in the DOC would lead to faster depletion of DO (Knoll et al., 2018) and thus a greater potential for an increase in internal P release. Additionally, long-term decreases in acid deposition results in increased P export from wooded watersheds to lakes (Kopáček et al., 2015) due to P mobilization promoted by increased pH, and potential association with DOC via cation bridging (Saunders, 1965; Borie and Zunino, 1983; Guppy et al., 2005). The role of decreasing acid deposition on increasing P exports was also not captured by the models.

Limitations in climate change models include the spatial and temporal resolutions. Many modern, third generation climate models perform computation at a 1° × 1° resolution (Auger et al., 2018), that covers an area of ~9325 $km^2$ at Lake Auburn's latitude. Bias correction through reanalysis helps account for more localized weather (Themeßl et al., 2012). MyLake operates at a daily time step and consequently requires future climate simulations at the same frequency. Given the natural climate variability, daily simulations of weather 30 years in the future are subject to a great deal of uncertainty (Fernandez et al., 2015).

MyLake does not have a mechanism to account for groundwater input into the lake. Flow and P contributions from groundwater can be approximated by modifying inflow and P scaling factors; however, this would also affect the contributions from the overland runoff. The water budget for groundwater in Lake Auburn has been crudely estimated as minimal compared to stream flow (Dudley, 2004).

## CHAPTER 4

## CONCLUSIONS

The goal of this research was to demonstrate the application of a system of models to assessing the vulnerability of a temperate mesotrophic lake to future climate and land-use scenarios. The application of various future climate change scenarios to the catchment and lake models predicts an increase in lake epilimnetic warming and P enrichment, conditions favoring eutrophication, and a loss of habitat for cold water fish. Simulations of future land development worsened the lake water quality.

Where internal loading is a significant source of P to the lake, watershed BMP's alone are insufficient lake restoration methods, especially if external loads originate from nonpoint sources (Welch and Jacoby, 2009). Instead, sediment P release inactivation, as simulated in this study, can be achieved through addition of Al-containing salts, such as alum, or hypolimnetic oxygenation. Lake sediment with significantly higher concentrations of $Al(OH)_3$ than Fe(OH) effectively sequester P, even under anoxic conditions, and prevent internal loading (Kopáček et al., 2005; Lake et al., 2007; Wilson et al., 2010). Excess $Al(OH)_3$ from alum treatment will be slowly covered by P-rich sediment from external loads if high external P input to the lake continues, and the effectiveness of the treatment will be lost with time (Rydin et al., 2000). Treatment longevity is highly variable for Al salt addition and adequate monitoring of the lake is still needed to evaluate the effectiveness of a treatment dose for possible future treatments (Huser et al., 2015).

Even minor improvements in the quality of water source tend to lead to modest savings in treatment costs (Price and Herberling, 2018). In light of the threat of eutrophication, costly upgrades will have to be implemented by the water treatment plant to maintain Lake Auburn as a sustainable drinking water source (Fleming, 2013). In this lake, P as the limiting nutrient can originate from either internal or external loads. The importance of each can vary depending on the weather. Accordingly, any lake restoration plans should include both watershed management and in-lake remediation schemes. This framework of models can be applied to other lakes appropriately fitting the necessary assumptions of the models for similar vulnerability analysis.

## REFERENCES


Adrian, R., Walz, N., Hintze, T., Hoeg, S., Rusche, R., 1999. Effects of ice duration on plankton succession during spring in a shallow polymictic lake. Freshw. Biol. 41, 621-634.

Akbarzadeh, Z., Laverman, A.M., Rezanezhad, F., Raimonet, M., Viollier, E., Shafei, B., Van Cappellen, P., 2018. Benthic nitrate exchanges in the Seine River (France): An early diagenetic modeling analysis. Sci. Total Environ. 628-629, 580-593.

Auger, J.D., Birkel, S.D., Maasch, K.A., Mayewski, P.A., Schuenemann, K.C., 2018. An Ensemble Mean and Evaluation of third Generation Global Climate Reanalysis Models. Atmos. 9, 236-248.

Aulenbach, B.T., Landers, M.N., Musser, J.W., Painter, J.A., 2017. Effects of Impervious Area and BMP Implementation and Design on Storm Runoff and Water Quality in Eight Small Watersheds. J. Am. Water Resour. Assoc. 53, 382-399.

Bayer, T., Brusn, C.W., Schallenberg, M., 2013. Application of a numerical model to predict impacts of climate change on water temperatures in two deep, oligotrophic lakes in New Zealand. Hydrobiologia 713, 53-71.

Beyene, M.T., Jain, S., 2015. Wintertime weather-climate variability and its link to early spring ice-out in Maine lakes. Limnol. Oceanogr. 60, 1890-1905.

Borie, F., Zunino, H., 1983. Organic matter-phosphorus associations as a sink in P-fixation processes in allophonic soils of Chile. Soil Biol Biochem. 15, 599-603.

Bruce, L.C., Frassi, M.A., Arhonditsis, G.B., Gal, G., Hamilton, D.P., Hanson, P.C., Hetherington, A.L., Melack, J.M., Read, J.S., Rinke, K., Rigosi, A., Trolle, D., Winslow, L., Adrian, R., Ayala, A.I., Bocaniov, S.A., Boehrer, B., Boon, C., Brookes, J.D., Bueche, T., Busch, B.D., Copetti, D., Cortes, A., de Eyto, E., Elliott, J.A., Gallina, N., Gilboa, Y., Guyennon, N., Huang, L., Kerimoglu, O., Lenters, J.D., MacIntyre, S., Makler-Pick, V., McBride, C.G., Moreira, S., Ozkundakci, D., Pilotti, M., Rueda, F.J., Rusak, J.A., Samal, N.R., Schmid, M., Shatwell, T., Snorthheim, C., Soulignac, F., Valerio, G., van der Linden, L., Vetter, M., Vincon-Leite, B., Wang, J., Weber, M., Wickramaratne, C., Woolway, R.I., Yao, H., Hipsey, M.R., 2018. A multi-lake comparative analysis of the General Lake Model (GLM): Stress-testing across a global observatory network. Environ. Modell. Software 102, 274-291.

Bueche, T., Hamilton, D.P., Vetter, M., 2017. Using the General Lake Model (GLM) to simulate water temperatures and ice cover of a medium-sized lake: a case study of Lake Ammersee, Germany. Environ. Earth Sci. 76, 1-14.

Carey, C.C., Ewing, H.A., Cottingham, K.L., Weathers, K.C., Thomas, R.Q., Haney, J.F., 2012. Occurrence and toxicity of the cyanobacterium *Gloeotrichia echinulata* in low-nutrient lakes in the northeastern United States. Aquat. Ecol. 46, 395-409.

Carrick, H.J., Aldridge, F.J., Schelske, C.L., 1993. Wind influences biomass and composition in a shallow, productive lake. Limnol. Oceanogr. 38, 1179-1192.

CDM Smith. (2013). Lake Auburn Watershed Commission Consultant Report.

Chang, L.H., Railsback, S.F., Brown, R.T., 1992. Use of a reservoir water quality model to simulate global climate effects on fish habitat. Clim. Change 20, 277-296.

Chapra, S., 2008. Surface Water-Quality Modeling. Long Grove, Illinois. Waveland Press, Inc.

Christophoridis, C., Fytianos, K., 2006. Conditions Affecting the Release of Phosphorus from Surface Lake Sediments. J. Environ. Qual. 35, 1181-1192.

Collins, W.D., Bitz, C.M., Blackmon, M.L., Bonan, G.B., Bretherton, C.S., Carton J.A., Chang, P. Doney, S.C., Hack, J.J., Henderson, T.B., Kiehl, J.T., Large, W.G., McKenna, D.S., Santer, B.D., Smith, R.D., 2006. The Community Climate System Model Version 3 (CCSM3). J. Clim. 19, 2122-2143.

Cooke, G.D., Heath, R.T., Kennedy, R.T., McComos, M.R., 1982. Change in lake trophic state and internal phosphorus release after aluminum sulfate application. J. Am. Water Resour. Assoc. 18, 699-705.

Couture, R.M., de Wit, H.A., Tominaga, K., Kiuru, P., Markelov, I., 2015. Oxygen dynamics in a boreal lake responds to long-term changes in climate, ice phenology, and DOC inputs. J. Geophys. Res.: Biogeosci. 120, 2441-2456.

Couture, R.M., Fischer, R., Van Cappellen, P., Gobeil, C., 2016. Non-steady state diagenesis of organic and inorganic sulfur in lake sediments. Geochim. Cosmochim. Acta 194, 15-33.

Couture, R.M., Moe, S.J., Lin, Y., Kaste, Ø., Haande, S., Solheim, A.L., 2018. Simulating water quality and ecological status of Lake Vansjø, Norway, under land-use and climate change by linking process-oriented models with a Bayesian network. Sci. Total Environ. 621, 713-724.

Couture, R.M., Shafei, B., Van Cappellen, P., Tessier, A., Gobeil, C., 2010. Non-steady state modeling of arsenic diagenesis in lake sediments. Environ. Sci. Technol. 44, 197-203.

Couture, R.M., Tominaga, K., Starrfelt, J., Moe, S.J., Kaste, O., Wright, R.F., 2014. Modelling phosphorus loading and algal blooms in a Nordic agricultural catchment-lake system under changing land-use and climate. Environ. Sci.-Proc. Imp. 16, 1588-1599.

Crossman, J., Elliott, J.A., 2018. Bridging the gap between terrestrial, riverine and limnological research: An application of a model chain to a mesotrophic lake in North America. Sci. Total Environ. 622-623, 1363-1378.

Davis, R.B., Norton, S.A., Kahl, J.S., Anderson, D.S., Bacon, L.C., Blake, G.M., Morrison, M.M., Patterson, B.P., Whiting, M.C., Hites, R.A., Roll, L.A., Mitchell, M.J., Smol, J.P., Dixit, S.S., 1986. A comparative paleolimnological study of the impacts of air pollution on three northern New England Lakes: Preliminary Results. 7-1 to 7-60. *in* Charles DF, Whitehead DR. 1986. Paleoecological Investigation of Recent Lake Acidification (PIRLA): Interim Report. Electric Power Research Institute.

Demars, B.O.L., Manson, J.R., Olafsson, J.S., Gislason, G.M., Gudmundsdottir, R., Woodward, G.U.Y., Reiss, J., Pichler, D.E., Rasmussen, J.J., Friberg, N., 2011. Temperature and the metabolic balance of streams. Freshw. Biol. 56, 1106-1121.

Doan, P.T.K., Watson, S.B., Markovic, S., Liang, A., Guo, J., Mugalingam, S., Stokes, J., Morley, A., Zhang, W., Arhonditsis, G.B., Dittrich, M., 2018. Phosphorus retention and internal loading in the Bay of Quinte, Lake Ontario, using diagenetic modelling. Sci. Total Environ. 636, 39-51.

Doolittle, H., Norton, S.A., Bacon, L.C., Ewing, H.A., Amirbahman, A., 2018. The internal and watershed controls on hypolimnetic sediment phosphorus release in Lake Auburn, Maine, USA. Lake Reserv. Manage. 34, 258-269.

Dudley, R.W., 2004. Water budget for Lake Auburn, Maine, May 1, 2000 through April 30, 2003.United States Geologic Society Scientific Investigations Report 2004–5106.

Dunne, J.P., John, J.G., Adcroft, A.J., Griffies, S.M., Hallberg, R.W., Shevliakova, E., Stouffer, R.J., Cooke, W., Dunne, K.A., Harrison, M.J., Krasting, J.P., Malyshev, S.L., Milly, P.C.D., Phillips, P.J., Sentman, L.T., Samuels, B.L., Spelman, M.J., Winton, M., Wittenberg, A.T., Zadeh, N., 2012. RCP8.5's ESM2 Global Coupled Climate-Carbon Earth System Models. Part I: Physical Formulation and Baseline Simulation Characteristics. J. Clim. 25, 6646-6665.

Effler, S.W., Wagner, B.A., O'Donnell, S.M., Matthews, D.A., O'Donnell, D.M., Gelda, R.K. Matthews, C.M., Cowen, E.A., 2004. An upwelling event at Onondaga Lake, NY: characterization, impact and recurrence. Hydrobiologia. 511, 185-199.

Evans, C.D., Monteith, D.T., Cooper, D.M., 2005. Long-term increases in surface water dissolved organic carbon: Observations, possible causes and environmental impacts. Environ. Pollut. 137, 55-71.

Fang, X., Stefan, H.G., 2000. Projected Climate Change Effects on Winterkill in Shallow Lakes in the Northern United States. Environ. Manage. 25, 291-304.

Fang, X., Stefan, H.G., 2009. Simulations of climate effects on water temperature, dissolved oxygen, and ice and snow covers in lakes of the contiguous United States under past and future climate scenarios. Limnol. Oceanogr. 54, 2359-2370.

Fernandez, I.J., Schmitt, C., Stancioff, E., Birkel, S.D., Pershing, A., Runge, J., Jacobson, G.L., Mayewski, P.A., 2015. Maine's Climate Future: 2015 Update. Climate Change Institute Faculty Scholarship. University of Maine. 5.

Fleming, D. (2013). Lake Auburn: Good fishing in troubled waters. Portland Press Herald. Retrieved from https://www.pressherald.com/.

Fletcher, T.D., Andrieu, H., Hamel, P., 2013. Understanding management and modelling of urban hydrology and its consequences for receiving waters: A state of the art. Advances in Water Res. 51, 261-279.

Foley, B., Jones, I.D., Maberly, S.C., Rippey, B., 2011. Long-term changes in oxygen depletion in a small temperate lake: effects of climate change and eutrophication. Freshw. Biol. 57, 2011.

Ford, J.D., Keskitalo, E.C.H., Smith, T., Pearce, T., Berrang-Ford, L., Duerden, F., Smit, B., 2010. Cast study and analogue methodologies in climate change vulnerability research. WIREs Climate Change 1, 374-392.

Fry, E.F.J., 1971. The Effect of Environmental Factors on the Physiology of Fish. New York, New York. Academic Press.

Gebre, S., Boissy, T., Alfredsen, K., 2014. Sensitivity to climate change of the thermal structure and ice cover regime of three hydropower reservoirs. J. Hydrol. 510, 208-227.

Goudsmit, G.H., Burchard, H., Peeters, F., Wueest, A., 2002. Application of k-turbulence models to enclosed basins: The role of internal seiches. J. Geophys. Res.: Oceans 107, 23-1-23-13.

Gudimov, A., McCulloch, J., Chen, J., Doan, P., Arhonditsis, G., Dittrich, M., 2016. Modeling the interplay between deepwater oxygen dynamics and sediment diagenesis in a hard-water mesotrophic lake. Ecol. Inform. 31, 59-69.

Guppy, C.N., Menzies, N.W., Moody, P.W., Blamey, F.P.C., 2005. Competitive sorption reactions between phosphorus and organic matter in soil: a review. Austral. J. Soil Res. 43, 189+.

Hansen, G.J.A., Winslow, L.A., Read, J.S., Treml, M., Schmalz, P.J., Carpenter, S.R., 2019. Water clarity and temperature effects on walleye safe harvest: an empirical test of the safe operating space concept. Ecosphere 10, e02737.

Hipsey, M.R., Bruce, L.C., Hamilton, D.P., 2013. Aquatic EcoDynamics (AED) model library: science manual. The University of Western Australia.

Hondzo, M., Stefan, H.G., 1993. Lake Water Temperature Simulation Model. J. Hydraul. Engin. 119, 1251-1273.

Hu, F., Bolding, K., Bruggeman, J., Jeppessen, E., Flindt, M.R., van Gerven, L., 2016. FABM-PCLake – linking aquatic ecology with hydrodynamics. Geosci. Model Dev. 9, 2271.

Huisman, J., Sharples, J., Stroom, J.M., Visser, P.M., Kardinaal, W.E.A, Verspagen, J.M.H., Sommeijer, B., 2004. Changes in Turbulent Mixing Shift Competition for Light Between Phytoplankton Species. Ecol. 85, 2960-2970.

Huser, B., Brezonik, P., Newman, R., 2011. Effects of alum treatment on water quality and sediment in the Minneapolis Chain of Lakes, Minnesota, USA. Lake Reserv. Manage. 27, 220-228.

Huser, B.J., Egemose, S., Harper, H., Hupfer, M., Jensen, H., Pilgrim, K.M., Reitzel, K., Rydin, E., Futter, M., 2015. Longevity and effectiveness of aluminum addition to reduce sediment phosphorus release and restore lake water quality. Water Research 97, 122-132.

Imberger, J., Parker, G., 1981. A Dynamic Reservoir Simulation Model – DYRESM. Transport models for inland and coastal waters, 310-361.

Jackson-Blake, L.A., Sample, J.E., Wade, A.J., Helliwell, R.C., Skeffington, R.A., 2017. Are our dynamic water quality models too complex? A comparison of a new parsimonious phosphorus model, SimplyP, and INCA-P. Water Resour. Res. 53, 5382-5399.

Jackson-Blake, L.A., Starrfelt, J., 2015. Do higher data and Bayesian auto-calibration lead to better model calibration? Insights from an application of INCA-P, a process-based river phosphorus model. J. Hydrol. 527, 641-655.

Jain, S.K., Sudheer, K.P., 2008. Fitting of hydrologic model: A close look at the Nash-Sutcliffe Index. J. Hydrol. Engin. 13, 981-986.

Karlsson-Elfgren, I., Rengefors, K., Gustafsson, S., 2004. Factors regulating recruitment from the sediment to the water column in the bloom-forming cyanobacterium *Gloeotrichia echinulata*. Freshw. Biol. 49, 265-273.

Kaste, Ø, Wright, R.F., Barkved, L.J., Bjerkeng, B., Engen-Skaugen, T., Magnusson, J., Sælthun, N.R., 2006. Linked models to assess the impacts of climate change on nitrogen in a Norwegian river basin and fjord system. Sci. Total Environ. 365, 200-222.

Katsev, S., 2016. Phosphorus effluxes from lake sediments. In R. Lal and B.A. Stewart (Eds.), Soil phosphorus, CRC Press, Taylor and Francis.

Katsev, S., Dittrich, M., 2013. Modeling of decal scale phosphorus retention in lake sediment under varying redox conditions. Ecol. Model. 251, 246-259.

Katsev, S., Tsandev, I., L'Heureux, I., Rancourt, D.G., 2006. Factors controlling long-term phosphorus efflux from lake sediments: Exploratory reactive-transport modeling. Chem. Geol. 234, 127-147.

Kiuru, P., Ojala, A., Mammarella, I., Heiskanen, J., Kamarainen, M., Vesala, T., Huttula, T., 2018. Effect of Climate Change on CO2 Concentration and Efflux in a Humic Boreal Lake: A Modeling Study. J. Geophys. Res. 123, 2212-2233.

Klug, J.L., Richardson D.C., Ewing, H.A., Hargreaves, B.R., Samal, N.R., Vachon, D., Person, D.C., Lindsey, A.M., O'Donnell, D.M., Effler, S.W., Weathers, K.C., 2012. Ecosystem Effect of a Tropical Cyclone on a Network of Lakes in Northeastern North America. Environ. Sci. Technol. 46, 11693-11701.

Knoll, L.B., Williamson, C.E., Pilla, R.M., Leach, T.H., Brentrup, J.A., Fisher, T.J., 2018. Browning-related oxygen depletion in an oligotrophic lake. Inland Waters 8, 255- 263.

Knox, A.K., Dahlgren, R.A., Tate, K.W., Atwill, E.R., 2008. Efficacy of Natural Wetlands to Retain Nutrient, Sediment, and Microbial Pollutants. J. Environ. Qual. 37, 1837-1846.

Kopáček, J., Borovec, J., Hejzlar, J., Ulrich, K.U., Norton, S.A., Amirbahman, A., 2005. Aluminum Control of Phosphorus Sorption by Lake Sediments. Environ. Sci. Technol. 29, 8784-8789.

Kopáček, J., Hejzlar, J., Kaňa, J., Norton, S.A., Stuchlík, E., 2015. Effects of Acid Deposition on in-Lake Phosphorus Availability: A Lesson from Lakes Recovering from Acidification. Environ. Sci. & Technol. 49, 2895-2903.

Kopáček, J., Marešová, M., Hejzlar, J., Norton. S.A., 2007. Natural inactivation of phosphorus by aluminum in pre-industrial lake sediments. Limnol. Oceanogr. 52, 1147-1155.

Kramer, O., 2017. Genetic Algorithm Essentials. Cham, Switzerland. Springer.

Lake, B.A., Coolidge, K.M., Norton, S.A., Amirbahman, A., 2007. Factors contributing to the internal loading of phosphorus from anoxic sediments n six Maine, USA, lakes. Sci. Total Environ. 373, 534-541.

Legates, D.R., McCabe, G.J., 1999. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. Water Resourc. Res. 35, 233-241.

Lehodey, P., Senina, I., Sibert, J., Bopp, L., Calmettes, B., Hampton, J., Murtugudde, R., 2010. Preliminary forecasts of Pacific bigeye tuna population trends under the A2 IPCC scenario. Prog. Oceanogr. 86, 302-315.

Likens, G.E., Bormann, F.H., Pierce, R.S., Eton, J.S., Johnson, N.M., 2013. Biogeochemistry of a Forested Ecosystem. New York, New York. Springer-Verlag.

Loh, P.S., Molot, L.A., Nurnberg, G.K., Watson, S.B., Ginn, B., 2013. Evaluating relationships between sediment chemistry and anoxic phosphorus and iron release across three different water bodies. Inland Waters, 3, 105-118.

Lorenz, E.N., 1969. Atmospheric Predictability as Revealed by Naturally Occurring Analogues. J. Atmos. Sci. 26.

MacLean, N.G., Gunn, J.M., Hicks, F.J., Ihsan, P.E., Malhbot, M., Mosindy, T.E., Wilson, W., 1990. Genetic and environmental factors affecting the physiology and ecology of lake trout. Lake Trout Synthesis. Toronto, Ont. Ontario Ministry of Natural Resources.

Madsen, T., Wilcox, W., 2012. When It Rains, It Pours: Global Warming and the Increase in Extreme Precipitation from 1948 to 2011. Environment America: Research & Policy Center.

Manzanas, R., Lucero, A., Weisheimer, A., Gutiérrez, J.M., 2018. Can bias correction and statistical downscaling methods improve the skill of seasonal precipitation forecasts? Clim. Dyn. 50, 1161-1176.

Markelov, I., Couture, R.M., Fisher, R., Haande, S., Cappellen, P.V., 2019, in press. Coupling Water Column and Sediment Biogeochemical Dynamics: Modeling Internal Phosphorus Loading Climate Chang Responses and Mitigation Measures in Lake Vansjø, Norway. J. Geophys. Res.: Biogeosci.

Matisoff, G., Watson, S.B., Guo, J., Duewiger, A., Steely, R., 2017. Sediment and nutrient distribution and resuspension in Lake Winnipeg. Sci. Total Environ. 575, 173-186.

McCulloch, J., Gudimov, A., Arthonditsis, G., Chesnyuk, A., Dittrich, M. (2013). Dynamics of P-binding forms in sediments of a mesotrophic hard-water lake: Insights from non-steady state reactive-transport modeling, sensitivity and identifiability analysis. Chem. Geol. 354, 216-232.

Meis, S., Thackeray, S.J., Jones, I.D., 2009. Effects of recent climate change on phytoplankton phenology in a temperate lake. Freshw. Biol. 54 (9), 1888-1898.

Monteith, D.T., Stoddard, J.L., Evans, C.D., de Wit, H.A., Forsius, M., Hogasen, T., 2007. Dissolved organic carbon trends resulting from changes in atmospheric deposition chemistry. Nature 450, 537-541.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations, Am. Soc. Agr. Biol. Engin. 50, 885-900.

Mueller, H., Hamilton, D., Doole, G., Abell, J., McBride, C., 2019. Economic and ecosystem costs and benefits of alternative land use and management scenarios in the Lake Rotorua, New Zealand, catchment. Glob. Environ. Change 54, 102-112.

National Oceanic and Atmospheric Administration., 2018. Data Tools: Local Climatological Data (LCD). Retrieved from https://www.ncdc.noaa.gov/cdo-web/datatools/lcd.

National Oceanic and Atmospheric Administration., 2012. Index of CMIP5. Retrieved from ftp://nomads.RCP8.5.noaa.gov/CMIP5/.

Norton S., A. Amirbahman, A., Bacon, L., Ewing, H., Novak, M., Nurse, A., Retelle, M., Stager, C., Yates, M., 2019, in press. Chemical, biological, and trophic status of temperate lakes can be strongly influenced by the presence of late-glacial marine sediments. Lake Reserv. Manage.

North, R.P., North, R.L., Livingstone, D.M., Koster, O., Kipfer, R., 2013. Long-term changes in hypoxia and soluble reactive phosphorus in the hypolimnion of a large temperate lake: consequences of a climate regime shift. Global Change Biol. 20, 811-823.

Nurnberg, G.K., Shaw, M., Dillon, P.J., McQueen, D.J., 1986. Internal phosphorus load in an oligotrophic Precambrian shield lake with an anoxic hypolimnion. Can. J. Fish. Aquat. Sci. 43, 574-580.

Nurnberg, G.K., 1998. Prediction of annual and seasonal phosphorus concentrations in stratified and polymictic lakes. Limnol. Oceanogr. 43, 1544-1552.

Ockenden, M.C., Hollaway, M.J., Beven, K.J., Collins, A.L., Evans, R., Falloon, P.D., Forber, K.J., Hiscock, K.M., Kahana, R., Macleod, C.J.A., Tych, W., Villamizer, M.L., Wearing, C., Withers, P.J.A., Zhou, J.G., Barker, P.A., Burke, S., Freer, J.E., Johnes, P.J., Snell, M.A., Surridge, B.W.J., Haygarth, P.M., 2017. Major agricultural changes required to mitigate phosphorus losses under climate change. Nat. Commun. 8: 161.

Orihel, D.M., Baulch, H.M., Casson, N.J., North, R.L., Parsons, C.T., Seckar, D.C.M., 2017. Internal phosphorus loading in Canadian fresh waters: a critical review and data analysis. Can. J. Fish. Aquat. Sci. 74, 2005-2029.

Perroud, M., Goyette, S., Martynov, A., Beniston, M., Anneville, O., 2009. Simulation of multiannual thermal profiles in deep Lake Geneva: A comparison of one-dimensional lake models. Limnol. Oceanogr. 54, 1574-1594.

Petticrew, E.L., Arocena, J.M., 2000. Evaluation of iron-phosphate as a source of internal lake phosphorus loadings. Sci. Total Environ. 266, 87-93.

Price, J.I., Herberling, M.T., 2018. The Effects of Source Water Quality on Drinking Water Treatment Costs: A Review and Synthesis of Empirical Literature. Ecol. Econ. 151, 195-209.

Przytulska, A., Bartosiewicz, M., Vincent, W.F., 2017. Increased risk of cyanobacterial blooms in northern high-latitude lakes through climate change and phosphorus enrichment. Freshw. Biol. 62, 1986-1996.

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., Rafaj, P., 2011. RCP 8.5 – A scenario of comparatively high greenhouse gas emissions. Clim. Change 109, 33-57.

Rydin, E., Huser, B., Welch, E.B., 2000. Amount of phosphorus inactivated by alum treatments in Washington lakes. Limnol. Oceanogr. 45, 226-230.

Saloranta, T.M., Andersen, T., 2007. MyLake – A multi-year simulation model code suitable for uncertainty and sensitivity analysis simulations. Ecol. Model. 207, 45-60.

Saunders, W.M.H., 1965. Phosphate retention by New Zealand soils and its relationship to free sesquioxides, organic matter and other soil constituents. New Zeal. J. Agr. Res. 8, 30-57.

Schindler, D.W., Bayley, S.E., Parker, B.R., Beaty, K.G., Cruikshank, D.R., Fee, E.J., Schindler, E.U., Stainton, M.P., 1996. The effects of climate warming on the properties of boreal lakes and streams at the experimental lakes area, northwestern Ontario. Limnol. Oceanogr. 41, 1004-1017.

Smits, J.G.C., van Beek, J.K.L., 2013. ECO: A Generic Eutrophication Model Including Comprehensive Sediment-Water Interaction. PLoS ONE 8, e68104.

Solomon, S., Quin, D., Manning, M., Marquis, M., Averyt, K., Tigner, M.M.B., Miller, H.L., Jr., Chen, Z., 2007. Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK and New York, New York. Cambridge University Press.

Spierre, S.G., Wake, C.P., 2010. Trends in Extreme Precipitation Events for the Northeastern United States 1948-2007. The Sustainability Institute, 21.

Stefan, H.G., Preud'homme, E.B., 1993. Stream Temperature Estimation from Air Temperature. Water Resour. Bull. 29, 27-45.

Tanentzap, A.J., Hamilton, D.P., Yan, N.D., 2007. Calibrating the Dynamic Reservoir Simulation Model (DYRESM) and filling required data gaps for one-dimensional thermal profile predictions in a boreal lake. Limnol. Oceanogr.: Methods 5, 484-494.

Tarboton, D.N., Sazib, N., Aufdenkampe, A.K., 2018. The Model My Watershed Rapid Watershed Delineation Tool. Retrieved from https://modelmywatershed.org/.

Terzhevik, A.Y., Pal'shin, N.I., Golosov, S.D., Zdorovennov, R.E., Zdorovennova, G.E., Mitrokhov, A.V., Potakhin, M.S., Shipunova, E.A., Zverev, I.S., 2010. Hydrophysical aspects of oxygen regime formation in a shallow ice-covered lake. Water Resour. 37, 662-673.

Themeßl, M.J., Gobiet, A., Heinrich, G., 2012. Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. Clim. Change 112, 449-468.

Thiery, W., Stepaneko, V. M., Fang, X., Johnk, K. D., Li, Z., Martynov, A., Perroud, M., Subin, Z. M., Darchambeau, F., Mironov, D., Van Lipzig, N. P. M., 2014. LakeMIP Kivu: evaluating the representation of a large, deep tropical lake by a set of one-dimensional lake models. Tellus: Ser. A, Dyn. Meteorol. Oceanogr. 66, 1-18.

Torres, E., Couture, R.M., Shafei, B., Nardi, A., Ayora, C., van Cappellan, P., 2013. Reactive transport modeling of early diagenesis in a reservoir lake affected by acid mine drainage: Trace metals, lake overturn, benthic fluxes remediation. Chem. Geol. 419, 75-91.

Veloz, S., Williams, J.W., Lorenz, D., Notaro, M., Vavrus, S., Vimont, D.J., 2012. Identifying climatic analogs for Wisconsin under 21st-century climate-change scenarios. Clim. Change 112, 1037-1058.

von Storch, H. Zorita, E., Cubasch, U., 1993. Downscaling of global climate change estimates to regional scales: an application to Iberian rainfall in wintertime. J. Clim. 6, 1161-1171.

Wade, A. J., Whitehead, P. G., Butterfield, D., 2002. The Integrated Catchments model of Phosphorous dynamics (INCA-P), a new approach for multiple source assessments in heterogeneous river systems: model structure and equations. Hydrol. Earth Sys. Sci. 6, 583-606.

Weinberger, S., Vetter, M., 2012. Using the hydrodynamic model DYRESM based on results of a regional climate model to estimate water temperature changes at Lake Ammersee. Ecol. Model. 244, 38-48.

Welch, E.B., Jacoby, J.M., 2009. On Determining the Principal Source of Phosphorus Causing Summer Algal Blooms in Western Washington Lakes. Lake Reserv. Manage. 17, 55-65.

Wetzel, R., 2001. Limnology: Lake and River Ecosystems. San Diego, California. Academic Press.

Wilson, T.A., Amirbahman, A., Norton, S.A., Voytek, M.A., 2010. A record of phosphorus dynamics in oligotrophic lake sediment. J. Paleolim. 44, 279-294.

Yalew, S.G., Pilz, T., Schweitzer, C., Liersch, S., van der Kwast, J., van Griensven, A., Mul, M.L., Dickens, C., van der Zaag, P., 2018. Coupling land-use change and hydrologic models for quantification of catchment ecosystem services. Environ. Model. Softw. 109, 315-328.

Zhang, H., Culver, D. A., Boegman, L., 2008. A two-dimensional ecological model of Lake Erie: Application to estimate dreissenid impacts on large lake plankton species. Ecol. Model. 214, 219-241.

Zorita, E., von Storch, H., 1999. The analog method as a simple statistical downscaling technique: Comparison with more complicated methods. J. Climate 12, 2474-2489.

## APPENDIX: SUPPLEMENTARY DATA

**Table A.1**. Land cover information for Lake Auburn.

| Type | Area (km²) | Coverage (%) |
|---|---|---|
| Open Water | 1.20 | 0.03% |
| Perennial Ice/Snow | 0.00 | 0.00% |
| Developed, Open Space | 2.35 | 5.70% |
| Developed, Low Intensity | 0.92 | 2.20% |
| Developed, Medium Intensity | 0.42 | 1.00% |
| Developed, High Intensity | 0.07 | 0.20% |
| Barren Land (Rock/Sand/Clay) | 0.92 | 2.20% |
| Deciduous Forest | 8.69 | 21.00% |
| Evergreen Forest | 4.48 | 10.80% |
| Mixed Forest | 14.37 | 34.70% |
| Shrub/Scrub | 1.28 | 3.10% |
| Grassland/Herbaceous | 0.37 | 0.90% |
| Pasture/Hay | 3.23 | 7.80% |
| Cultivated Crops | 0.33 | 0.80% |
| Woody Wetlands | 2.34 | 5.70% |
| Emergent Herbaceous Wetlands | 0.39 | 0.90% |
| Sum | 41.37 | |

**Table A.2**. Land cover information for Basin Brook watershed.

| Type | Area (km²) | Coverage (%) |
|---|---|---|
| Open Water | 0.86 | 3.7 |
| Perennial Ice/Snow | 0 | 0 |
| Developed, Open Space | 1.02 | 4.4 |
| Developed, Low Intensity | 0.23 | 1 |
| Developed, Medium Intensity | 0.04 | 0.2 |
| Developed, High Intensity | 0 | 0 |
| Barren Land (Rock/Sand/Clay) | 0 | 0 |
| Deciduous Forest | 4.5 | 19.5 |
| Evergreen Forest | 2.25 | 9.8 |
| Mixed Forest | 9.38 | 40.7 |
| Shrub/Scrub | 0.72 | 3.1 |
| Grassland/Herbaceous | 0.23 | 1 |
| Pasture/Hay | 1.52 | 6.6 |
| Cultivated Crops | 0.14 | 0.6 |
| Woody Wetlands | 1.87 | 8.1 |
| Emergent Herbaceous Wetlands | 0.26 | 1.1 |
| Sum | 23.02 | |

**Table A.3**. Land cover information for Townsend Brook.

| Type | Area ($km^2$) | Coverage (%) |
|---|---|---|
| Open Water | 0.08 | 1.1 |
| Perennial Ice/Snow | 0 | 0 |
| Developed, Open Space | 0.4 | 5.5 |
| Developed, Low Intensity | 0.33 | 4.6 |
| Developed, Medium Intensity | 0.17 | 2.4 |
| Developed, High Intensity | 0.03 | 0.4 |
| Barren Land (Rock/Sand/Clay) | 0.37 | 5.1 |
| Deciduous Forest | 2 | 27.6 |
| Evergreen Forest | 0.78 | 10.8 |
| Mixed Forest | 1.78 | 24.5 |
| Shrub/Scrub | 0.32 | 4.5 |
| Grassland/Herbaceous | 0.02 | 0.2 |
| Pasture/Hay | 0.69 | 9.6 |
| Cultivated Crops | 0 | 0 |
| Woody Wetlands | 0.22 | 3.1 |
| Emergent Herbaceous Wetlands | 0.05 | 0.7 |
| Sum | 7.24 | |

**Table A.4**. Parameters calibrated in SimplyP model for Basin Brook and Townsend Brook. The last column is the range of accepted values from Jackson-Blake et al. (2017).

| | | | | | |
|---|---|---|---|---|---|
| <u>Basin Brook</u> | | | | | |
| Parameter | Units | Description | Value | | Range |
| $T_s$ | d | Soil water time constant | Arable land | Semi-Natural | |
| | | | 7.0 | 7.5 | 0–30 |
| $f_{quick}$ | N/A | Proportion of precipitation routed to quick flow | 0.200 | | 0-0.2 |
| FC | mm | Soil field capacity | 100 | | 100-400 |
| beta | N/A | Base flow index | 0.15 | | 0-1 |
| $T_g$ | d | Base flow recession constant | 25 | | 0-100 |
| $P_{soilConc}$ | mg $kg^{-1}$ | Initial Soil P concentration | 1500 | 873 | 0-3000 |
| $P_{netinput}$ | kg $ha^{-1}$ $yr^{-1}$ | Net annual P input to the soil | 10.0 | | -30-30 |
| $EPC_{o,init}$ | mg $L^{-1}$ | Initial soil water TDP concentration on agricultural land | 0.08 | | 0-2 |
| $M_{soil,m2}$ | kg $m^{-2}$ | Soil areal mass | 500 | | 0-800 |
| $TDP_g$ | mg $L^{-1}$ | Groundwater TDP concentration | 0.009 | | 0-2 |
| <u>Townsend Brook</u> | | | | | |
| Parameter | Units | Description | Value | | |
| $T_s$ | d | Soil water time constant | Arable land | Semi-Natural | |
| | | | 3.0 | 8.0 | 0-30 |
| $f_{quick}$ | N/A | Proportion of precipitation routed to quick flow | 0.080 | | 0-0.2 |
| FC | mm | Soil field capacity | 100 | | 100-400 |
| beta | N/A | Base flow index | 0.10 | | 0-1 |
| $T_g$ | d | Base flow recession constant | 25 | | 0-100 |
| $P_{soilConc}$ | mg $kg^{-1}$ | Initial Soil P concentration | 250 | 150 | 0-3000 |
| $P_{netinput}$ | kg $ha^{-1}$ $yr^{-1}$ | Net annual P input to the soil | 1.0 | | -30-30 |
| $EPC_{o,init}$ | mg $L^{-1}$ | Initial soil water TDP concentration on agricultural land | 0.010 | | 0-2 |
| $M_{soil,m2}$ | kg $m^{-2}$ | Soil areal mass | 500 | | 0-800 |
| $TDP_g$ | mg $L^{-1}$ | Groundwater TDP concentration | 0.010 | | 0-2 |

**Table A.5**. Parameters calibrated in MyLake for DO and TP. The range of accepted values are from Markelov et al. (in press).

| Parameter | Unit | Description | Value | Range |
|---|---|---|---|---|
| Kz_K1 | $m^2 d^{-1}$ | open water diffusion parameter | 0.012 | - |
| C_shelter | N/A | Wind shelter parameter | 0.887 | - |
| I_scV | N/A | Scaling factor for inflow volume | 1.991 | - |
| I_scT | N/A | Adjusting delta for inflow temperature | 3.624 | - |
| Swa_b0 | $m^{-1}$ | Non-PAR light attenuation coefficient | 0.299 | - |
| Swa_b1 | $m^{-1}$ | PAR light attenuation coefficient for water | 1.167 | 0.8-1.3 |
| wc_factor | N/A | scaling factor for rates in WC | $10^{-4}$ | - |
| k_POP | $y^{-1}$ | first order reaction rate for particulate organic phosphorus | $2.30\times10^{-2}$ | $1\times10^{-2}$-$4\times10^{1}$ |
| k_POC | $y^{-1}$ | first order reaction rate for particulate organic carbon | $4.19\times10^{-2}$ | $2\times10^{-3}$-$1.5\times10^{-1}$ |
| km_O2 | mM | Michaelis-Menten constant for $O_2$ | $8.00\times10^{-4}$ | $8\times10^{-4}$-$2\times10^{1}$ |
| k_Feox | $mM^{-1} y^{-1}$ | first order reaction rate for iron oxides | $6.78\times10^{5}$ | $3.5\times10^{2}$-$1.6\times10^{7}$ |
| k_pdesorb_a | $mM^{-1} y^{-1}$ | first order reaction rate for phosphorus adsorption to iron hydroxides | $3.09\times10^{2}$ | - |
| effective depth | m | depth of lake to which water column is affected by sediment | -1 | -1 to max. depth |

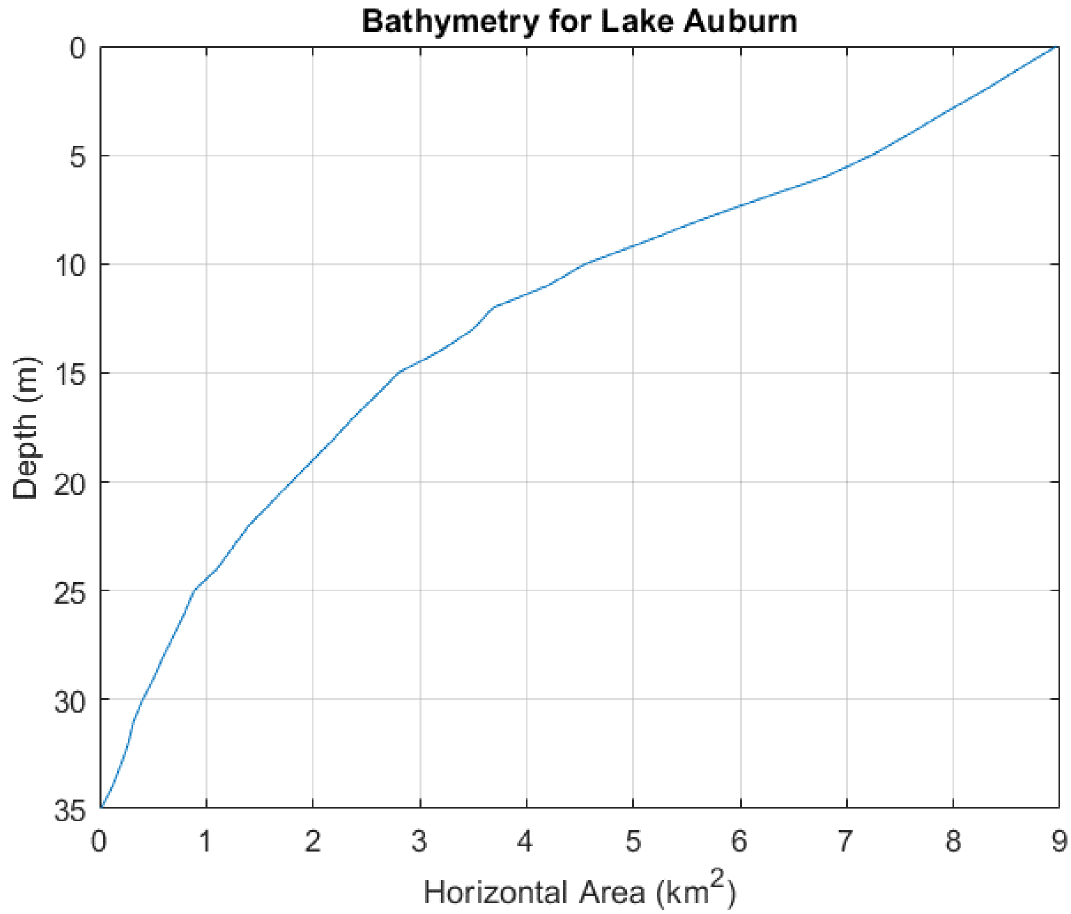


**Figure A.1**. Bathymetry for Lake Auburn.

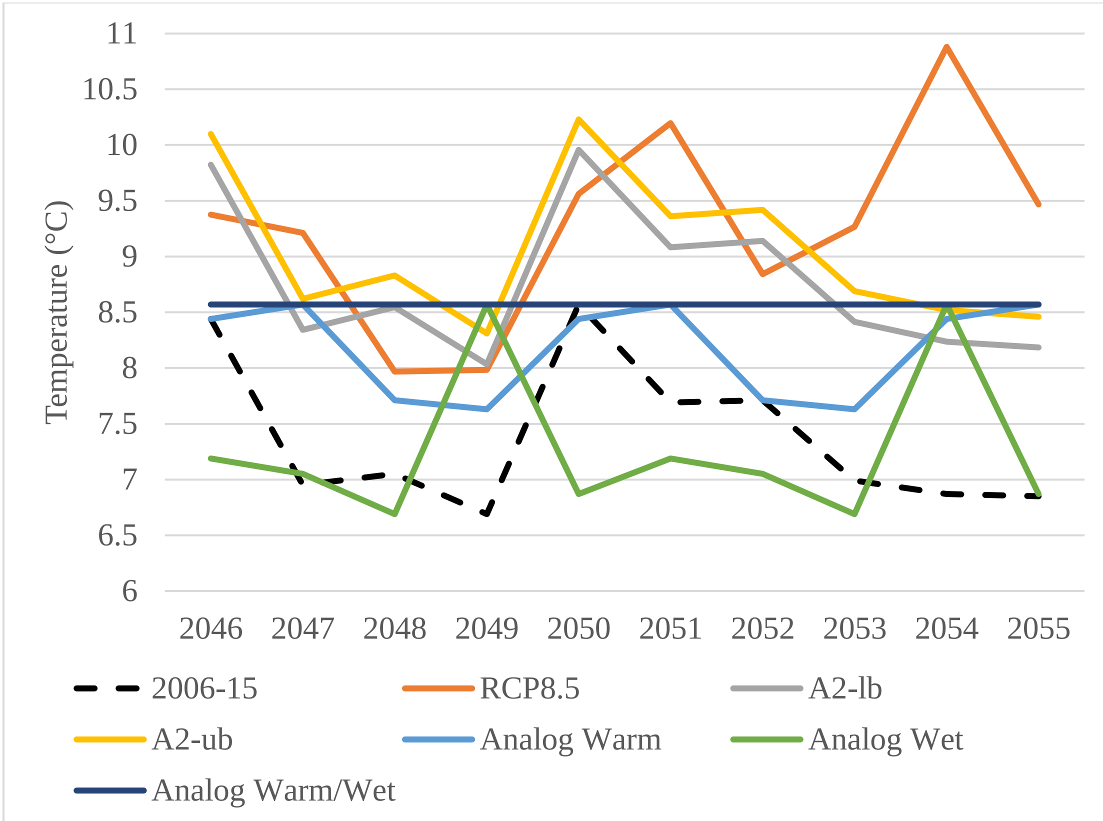


**Figure A.2**. Time series of mean annual daily air temperature for 2006-15 and future (2046-2055) climate scenarios.

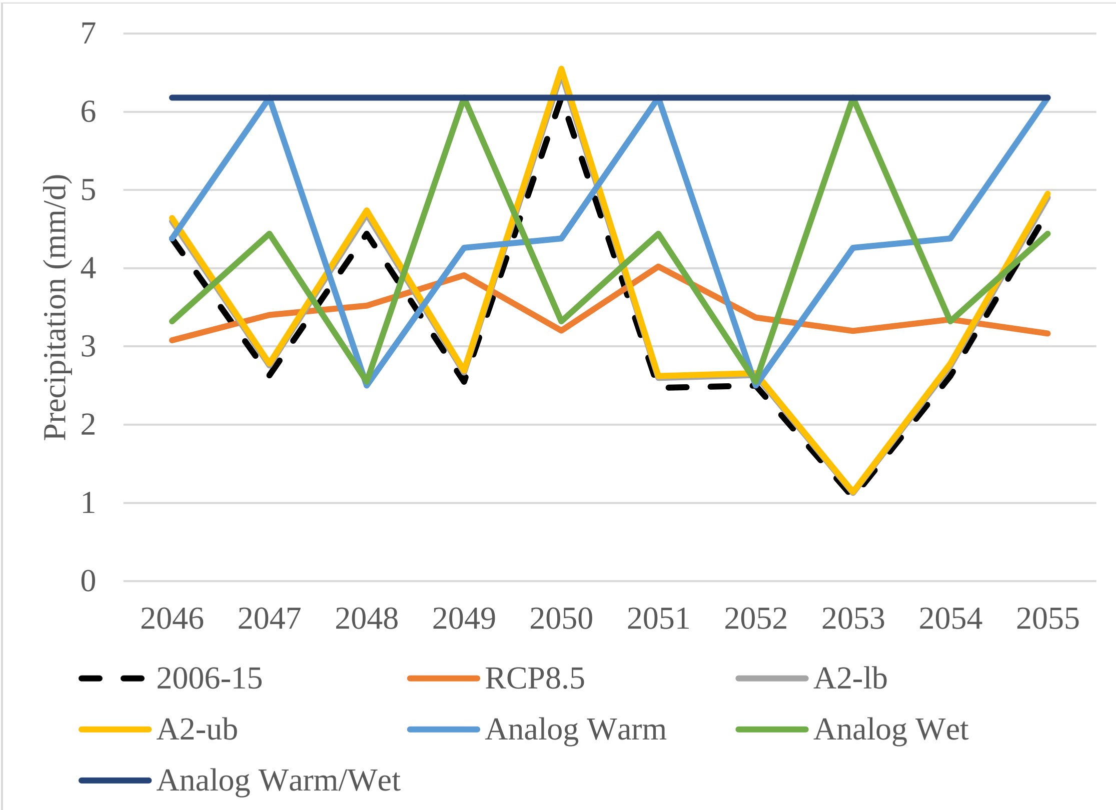


**Figure A.3**. Time series of mean annual daily precipitation for 2006-15 and future (2046-2055) climate scenarios.

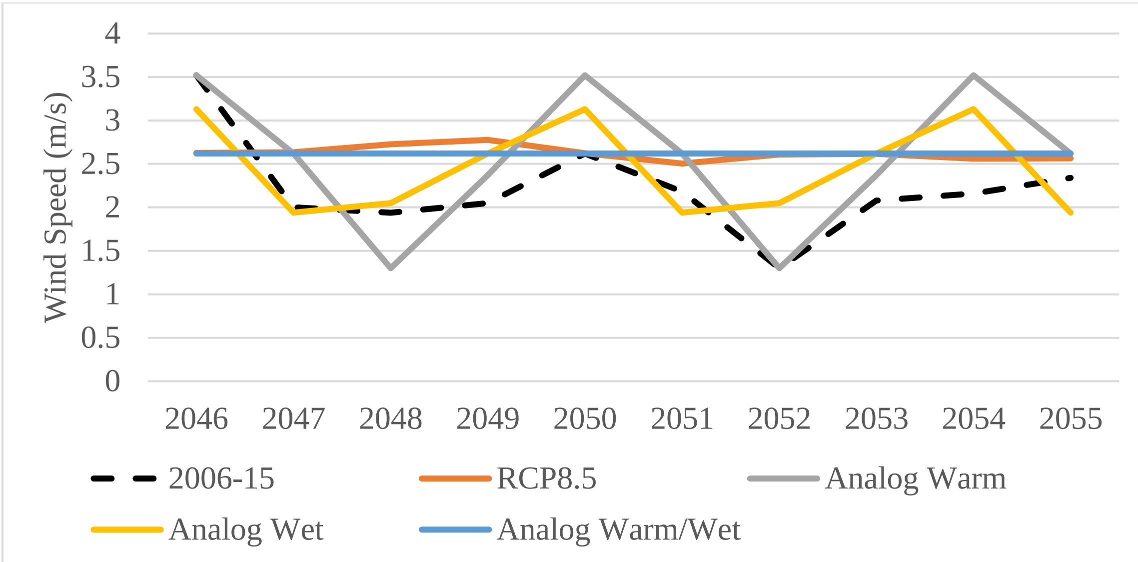


**Figure A.4**. Time series of mean annual daily wind speed for 2006-15 and future (2046-2055) climate scenarios.

## BIOGRAPHY OF THE AUTHOR

Nicholas Messina was born in Trenton, New Jersey on April 1, 1996. He was raised in Derry, New Hampshire and graduated from Pinkerton Academy in 2014. He attended the University of Maine and graduated in 2018 with a B.S. in Civil and Environmental Engineering. After receiving his degree, Nick will begin working for CMA Engineers in Portsmouth, NH. Nick is a candidate for Master of Science degree in Civil and Environmental Engineering from the University of Maine in December 2019.