2022 LSPA-Virginia Tech Calhoun Fellowship Final Report

Coupling modeling scenarios and a forecasting framework to inform water quality management in Lake Sunapee

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1. Executive Summary

Climate change and land use change threatens freshwater ecosystems around the globe, especially clear water lakes such as Lake Sunapee. In response to this increased variability, there is an urgent need to understand how lakes will respond to multiple stressors. Using multiple modeling approaches that harness both high-frequency buoy data and long-term datasets from the Lake Sunapee Protective Association's monitoring program, we produced long-term projections of how lake thermal dynamics (i.e., water temperatures, ice cover, and stratification metrics) will change through the end of the 21st century using an ensemble of models and climate scenarios. Building off of this work, we conducted a watershed modeling experiment to simulate the effects of nutrient loading scenarios on streams throughout the Lake Sunapee watershed on within-lake water quality. Our LSPA-Virginia Tech Calhoun Fellowship-sponsored research provides valuable information on prioritizing conservation and land management efforts within key sub-watersheds of the Lake Sunapee region, while also quantifying the uncertainty around future climate change effects on the lake. Altogether, this research has set the framework for expanding our forecasts to additional water quality variables, and informs freshwater forecasting research more broadly, which together benefits both Lake Sunapee and lakes around the world.

2. Introduction

Clear water, or oligotrophic, lakes such as Lake Sunapee provide many important ecosystem services, such as habitat for aquatic organisms, drinking water, aesthetic enjoyment, and recreational opportunities (Schallenberg et al. 2013). However, many oligotrophic lakes are experiencing abrupt and severe water quality problems attributed to climate change and land development (Stoddard et al. 2016). In particular, Lake Sunapee, an oligotrophic lake located in central New Hampshire, USA, has experienced increased air temperatures and nutrient loading over the past several decades, resulting in cyanobacterial blooms that have decreased its water quality (Carey et al. 2014, Richardson et al. 2017, Ward et al. 2020). Given the ongoing development occurring in Lake Sunapee's watershed, new tools to predict future water quality are vital to anticipate and combat water quality degradation and improve the management of Lake Sunapee.

To react in a timely manner, new ecosystem modeling tools for predicting future water quality are vital to improving the management of lakes (Carey et al., 2022; Thomas et al., 2020). These modeling tools to date have primarily focused on short-term predictions (daily to weekly scales) for aiding near-term decision-making for freshwater management (e.g., Carey et al., 2022; Thomas et al., 2020). To complement short-term forecasting, long-term projections (i.e., year to century scale) and scenario-based simulations provide longer lead times for managing water quality, as well as providing alternate scenarios to guide decision-making and policy. However, there is considerable uncertainty in long-term projections of future lake water quality, which is likely to increase into the future over long periods of time (Petchey et al., 2015). Sources of uncertainty at this time scale range from socioeconomic and political trends which dictate how humans will continue to impact the climate, to how the climate will change in response to human-induced drivers, as well as how lake ecosystems will respond to climate change. Fully examining the influence of these different sources of uncertainty is critical to accurately informing our understanding of future lake ecosystems.

Lake thermal dynamics (e.g., water temperatures, duration of ice coverage) which are critical to overall lake ecosystem health are already changing in response to altered climate (Woolway & Merchant, 2018). For example, thermal stratification (i.e., the presence of a strong temperature gradient from the surface to bottom of the lake) directly influences the timing of fall mixing, which is when the surface and bottom of the lake become the same temperature, and spring mixing, when ice melts from the lake and temperatures again become uniform from the surface to the bottom (Lewis Jr., 1983; Wetzel, 2001). These stratification and mixing patterns are expected to shift in lakes under most climate change scenarios (Woolway & Merchant, 2019a).

In temperate lakes like Sunapee, Woolway & Merchant (2019a) projected stronger thermal stratification in the summer, shorter mixing times, and a loss of ice cover. Mixing and stratification patterns have major implications for lake ecological processes such as primary productivity (i.e., algal activity), availability of fish habitat, and the exchange of greenhouse gasses with the atmosphere by altering physical mixing processes which impact thermal habitat and nutrient availability (Kirillin, 2010, Wetzel 2001). On average, the duration of ice cover is expected to decrease in lakes by 29 ± 8 days globally under future climate change scenarios

(Woolway & Merchant, 2019a). Changes to ice cover can impact lake hydrodynamics and both summer and winter lake ecology, leading to changes in available habitat of microorganisms and fish (Salonen et al., 2009, Hampton et al., 2017). Overall, quantifying the ecological impact of changing thermal dynamics requires accurate predictions of future lake thermal regimes.

One way to estimate uncertainty in long-term lake thermal projections is to use an ensemble (multiple alternate simulation) modeling approach. In lake projections, this approach uses a suite of climate scenarios, fed into numerous climate models, that are coupled with multiple lake models to produce an ensemble projection (e.g., Golub et al., 2022; Her et al., 2019; Kobler & Schmid, 2019). Comparing ensemble members provides a more realistic representation of the diverse spread of possible model outcomes as well as an opportunity to examine the contributions of model selection uncertainty on projections. By predicting lake thermal dynamics using multiple lake models and climate scenarios coupled to climate models, we can better quantify the uncertainty in future lake responses to climate change. Further, aggregate ensemble predictions have been shown to outperform individual models in predictions of both phytoplankton concentration and ice dynamics (Kobler & Schmid, 2019; Trolle et al., 2014).

In addition to climate change impacts on lake thermal dynamics, changes in watershed land use can also greatly impact other metrics of within-lake water quality. Ward et al. (2020)'s findings demonstrate the synergistic impact that nutrient loading via land use change can have on lake water quality, showing that climate change alone had a minimal impact on within-lake water quality, but climate change coupled with nutrient loading scenarios significantly decreased within-lake water quality. However, it remains unknown which regions within the Lake Sunapee watershed might contribute most to overall within-lake water quality. Building on this study, as well as our own long-term projections of thermal dynamics, we selected a single lake model to simulate land use change within each of the 11 sub-watersheds in the Lake Sunapee region. By partitioning the nutrient loading into individual watersheds, we can assess the relative impact of each sub-watershed on overall within-lake water quality.

To protect the long-term resilience of Lake Sunapee's water quality, we collaborated with the Lake Sunapee Protective Association to develop predictive frameworks for quantifying how Lake Sunapee's water quality may change due to both climate and land use change in the future with the support of the Calhoun Fellowship. Coupling Lake Sunapee's >30-year long-term monitoring dataset with lake ecosystem models and state-of-the-art cyberinfrastructure, we developed projections of multiple lake thermal metrics over the next 100 years with a full uncertainty analysis. In addition, we used a single lake model coupled with nutrient loading scenarios to determine the relative impact of 11 individual sub-watersheds to overall water quality in Lake Sunapee. Our project aimed to answer the following questions:

1. How will thermal dynamics in Lake Sunapee change over the next century?
2. How does the contribution of uncertainty sources vary with the thermal metric being projected (e.g., lake ice cover, surface temperature, etc.)?
3. How do increases in inflow nutrient concentrations and inflow discharge rates in 11 different sub-catchments of Lake Sunapee affect overall within-lake nutrient concentrations?

3. Methods

Data Sources

Lake Sunapee has been monitored by the LSPA and its members for decades, resulting in an invaluable monthly dataset of summer water temperature and oxygen from the surface (0.1 m) to the bottom of Lake Sunapee (33 m) at the deepest site of the lake (Steele et al. 2021). In 2007, the lake was outfitted with a buoy which measures high-frequency temperature observations every meter from the surface down to 10.0 m. In addition, the buoy measures dissolved oxygen (DO) at the surface (~1.0 m) and below the thermocline (10.0 m, LSPA et al. 2022). In addition to the automated sensors on the buoy, we used a long-term LSPA dataset of total phosphorus (TP) at the deepest site of the lake (Steele et al. 2021) to compare modeled and observed TP, an important indicator of water quality.

We coupled the long-term within-lake Sunapee dataset with measurements of TP collected in streams draining 11 different sub-catchments around the lake (Steele et al. 2021, Fig. 1). These stream sites integrate all of the sub-catchments of Lake Sunapee, and provide a good representation of the near-total discharge of both water and nutrients into the lake. Because these data were collected approximately monthly, we used a land-use and precipitation run-off model to estimate daily estimates of discharge, TP, and total nitrogen (TN) in the streams draining each sub-watershed.

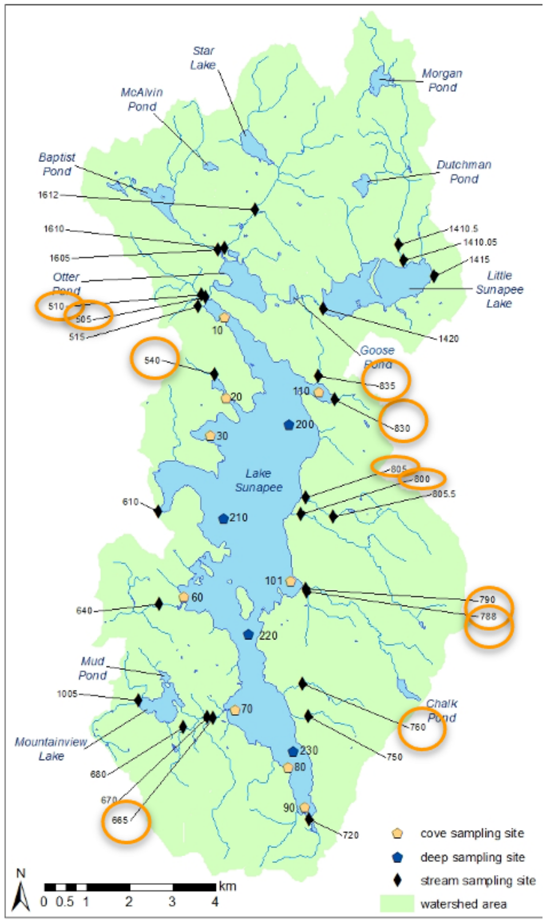

Figure 1. Lake Sunapee and its surrounding watershed area. The orange circles represent the inflows used in this study. Map Source: Lake Sunapee Protective Association (LSPA)'s Lake Management Program (LMP)

Long-term projections using ensemble modeling

To create ensemble projections of lake thermal dynamics, we used three Representative Concentration Pathways (RCP's) climate scenarios coupled to four General Circulation Models (GCMs), which simulate global climate, to drive five vertical one-dimensional (1-D) hydrodynamic lake models. Coupled output from each RCP and GCM was obtained from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), which is an international effort to better understand climate projections and their uncertainties using ensemble modeling (Frieler et al. 2017; Golub et al., 2022). Each lake model was calibrated with ten years (2005-2015) of historical water temperature data using standard methods to a minimum Root Mean Square Error (RMSE) for six lake thermal metrics (described below). The relative performance of each model following calibration was evaluated using five years of validation data (from 2015-2020). After calibration and validation, projections were run from 1938 to 2099, including a spin-up period (1938-1974) to minimize the impact of initial conditions on the simulations, a historical period used to calculate a baseline representing 'normal' historical conditions (1975-2005), and a future climate projection period (2006-2099). Anomalies from the historical baseline were calculated for all future projections based on the difference between the historical and projection periods to determine the change in each thermal metric. To determine the influence of GCM and lake model on projection uncertainty, we partitioned the relative contributions of lake model and GCM uncertainty over the projection period for all thermal metrics across the paired GCM and lake model combinations for RCP 8.5, which is the most severe RCP and is representative of the current global emissions trajectory (Schwalm et al., 2020).

We chose six ecologically important thermal metrics for our long-term projections: summer mean surface and bottom temperatures, Schimdt stability, thermocline depth, summer stratification duration, and total ice duration. Schmidt stability (the stability of a water body's thermal stratification and its resistance to mixing, in J/m^2) and thermocline depth (the depth of greatest density change in the water column due to water temperature changes) were calculated using the package rLakeAnalyzer (Read et al., 2011). In addition to these metrics, the summer (June-August) mean surface and bottom temperatures, summer stratification duration (length of time stratified over the whole year not including inverse stratification, or ice cover), as well as total length of ice duration were calculated using the LakeEnsemblR R package (Moore et al., 2021).

Watershed nutrient scenarios

To test the sensitivity of Lake Sunapee's water quality to changes in watershed nutrient conditions, we ran multiple scenarios which simulated altered land-use across 11 individual sub-catchments. We first calibrated and validated the coupled General Lake Model and Aquatic Ecodynamics (GLM-AED) modeling workflow, which models the physical, chemical, and biological characteristics of lakes (Hipsey et al. 2019, Hipsey 2022). GLM-AED was calibrated from 2000-2010 with a spin-up from 2000-2005 to reduce initial condition uncertainty. Validation was performed from 2010-2020 using a spin-up from 2010-2015. During calibration and validation, we compared whole water column temperature and surface total phosphorus to observations for goodness of fit calculations.

Following calibration and validation, we ran GLM-AED under a number of scenarios which simulated altered land-use within sub-catchments of the watershed. These scenarios were by design simplistic to highlight the relative contributions of different sub-catchments to overall within-lake water quality and did not include important factors such as climate change, hydrological/land use coupling, or groundwater. We tested two different types of scenarios which represented changes in land-use: 1) Nutrients x2, in which we doubled the baseline estimated inflow nutrient concentrations (TN and TP) in each of the 11 sub-watersheds individually, and 2) Discharge x2, in which we doubled the baseline estimated discharge rates in each of the 11 sub-watersheds individually. Both of these scenarios simulated increased nutrient loading into Lake Sunapee through different pathways (following Ward et al. 2020). We ran our simulations from 2005-2020 with a five year spin-up (2005-2010) to reduce the influence of initial conditions. We successively doubled the nutrients of each individual inflow and ran GLM-AED with only one altered inflow at a time (all other inflows were unaltered), resulting in 11 total simulations for each nutrient loading scenario. These outputs from each scenario were compared with one another as well as with a reference simulation which included no changes to baseline estimated inflow discharge rates and nutrient concentrations. Over the entire simulation period (2010-2020), we calculated the annual median and range of within-lake concentrations of TN and TP to estimate the change from the reference simulation due to changes in each of the 11 sub-watersheds. Ultimately, this approach provided a first opportunity for us to examine the sensitivity of Lake Sunapee's overall water quality to changes in each of these inflow sites' nutrient input and provides a framework for future studies to expand upon with greater detail and complexity.

4. Results

Q1. How will thermal dynamics in Lake Sunapee change over the next century?

Throughout the calibration and validation period, all lake models generally reproduced observed Sunapee dynamics for all thermal metrics (Table 1). The ensemble mean aggregated across all lake models performed as good or better for multiple metrics during calibration and validation compared to the best performing individual model, with an RMSE of whole water temperature of 1.29 °C, and bias of -0.12 °C (Table 1). This result emphasizes the importance of using an ensemble of models rather than a single model.

Our projections show that all six thermal metrics of Lake Sunapee will change substantially in response to climate change over the next century (Fig. 2). Mean summer surface water temperature is projected to increase by 2-5 °C above historical conditions by 2099 (Fig. 2A). Similarly, mean summer bottom water temperature is also projected to increase, but to a slightly lesser extent, by 0.5-3 °C (Fig. 2B). Metrics of stratification indicate a longer and stronger summer stratification period within the lake annually, with total summer stratification duration increasing by 20-40 days (Fig. 2E). In addition, the strength of thermal stratification, Schmidt stability, is projected to increase by 50-150 J/m^2 (Fig. 2C). In contrast, total ice duration is projected to decrease by 25-75 days (Fig. 2F). Interestingly, thermocline depth is projected to stay the same over the course of the century, with increased variability by the end of the century (Fig. 2D). As a result of longer summer stratification and less ice cover, Lake Sunapee's mixing dynamics will be altered, with up to 50 additional days spent stratified in the summer months and up to 75 fewer days spent stratified due to ice cover in the winter months.

Total forecast uncertainty in each lake metric increased over time and with Representative Concentration Pathway (RCP) scenario, with the largest uncertainty at end-century under RCP 8.5. The magnitude of anomalies for each metric were largely driven by RCP scenario, with the smallest range projected by RCP 2.6, followed by RCP 6.0, and the highest ranges projected by RCP 8.5 (Fig. 2F), which largely follow expected patterns corresponding to the socioeconomic trajectories represented by each RCP scenario. For example, under RCP 2.6, which includes reduced carbon emissions by mid-century (van Vuuren et al., 2011), anomalies decreased from mid- to end-century, with lower predicted temperatures, less change in stratification, and lower Schmidt stability values at end-century compared to mid-century, in line with the socioeconomic trajectory of this scenario.

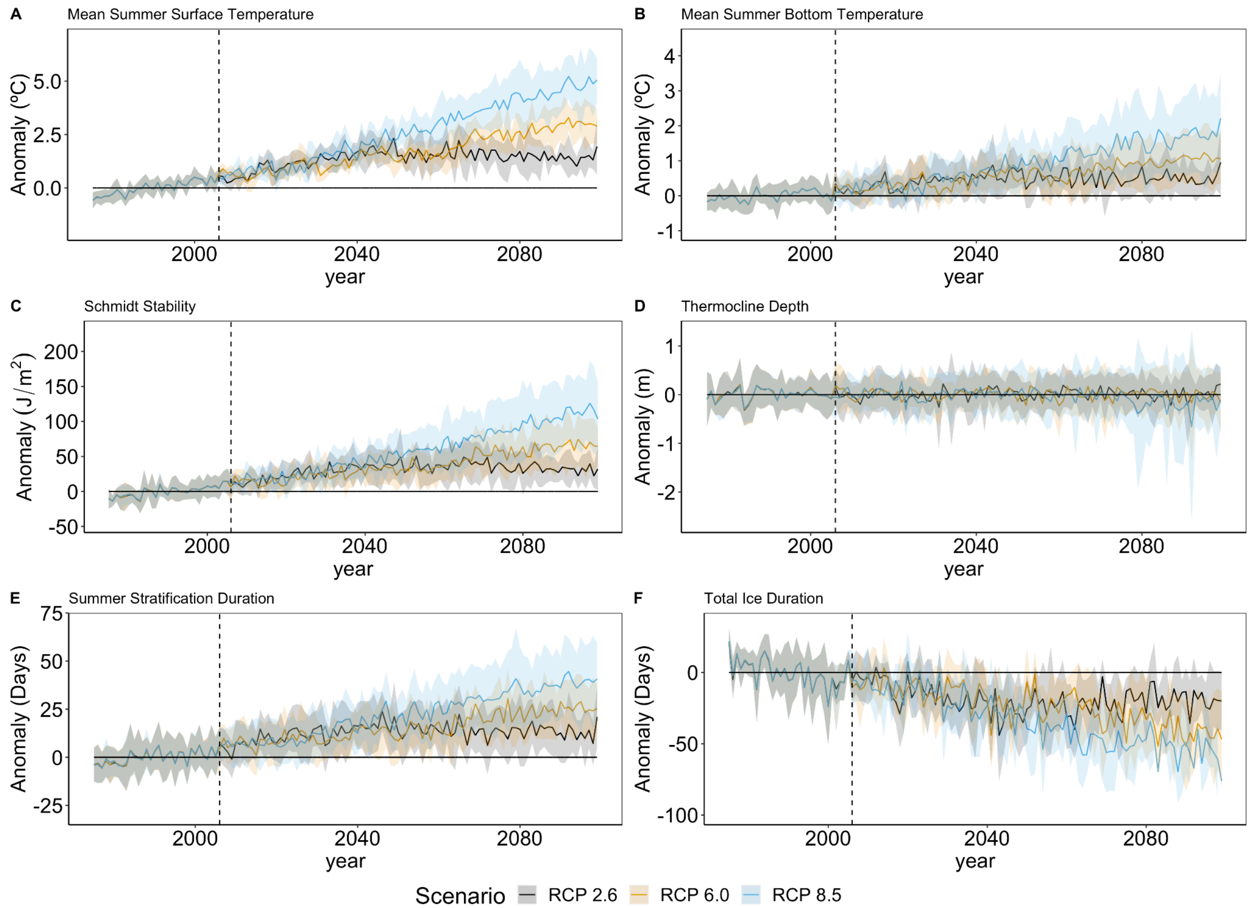

Figure 2. Projected anomalies for A) mean summer surface temperature, B) mean summer bottom temperature, C) Schmidt stability, D) thermocline depth, E) summer stratification duration, and F) Total Ice Duration from 2006-2099. The vertical dashed line represents the beginning of the projection time period, with the left of the dashed line representing the historical mean calculation period on which anomalies were based (1975-2005). Each solid line represents the ensemble mean under RCP 2.6, 6.0 or 8.5 and each shaded area around the solid lines represents total projection uncertainty under RCP 2.6, 6.0 or 8.5.

Q2. How does uncertainty across lake model and climate model vary with thermal metric?

The relative proportion of uncertainty due to General Circulation Models (GCMs) and lake models varied among thermal metrics and over time (Fig. 3). Uncertainty in mean summer surface temperature was consistently dominated by GCM uncertainty (>80%) throughout the entire projection period (Fig. 3A). In contrast, mean summer bottom temperature was dominated by GCM uncertainty up until mid-century, after which ~75% of uncertainty was due to lake model uncertainty (Fig. 3B). Uncertainty in Schmidt stability was dominated by GCM uncertainty until mid-century (~75%), after which lake model and GCM uncertainty contributed equally (Fig. 3C). Uncertainty in thermocline depth was evenly contributed by lake model and GCM uncertainty from the beginning of the projection period, which increased over time with an overall proportion of >75% by the end of the century (Fig. 3D). Total stratification duration was initially dominated by GCM uncertainty until mid-century (~75%), when lake model uncertainty became the primary source (~75%). Lastly, uncertainty in total ice duration was dominated by GCM uncertainty over the course of the entire projection period (60-75%; Fig. 3E).

In all metrics but mean summer surface temperature, the proportional contribution of lake model uncertainty increased over time (Fig. 3). Additionally, there were no metrics with a shift from lake model dominance to GCM dominance over time. For mean summer bottom temperature and total stratification duration, the dominant source of uncertainty switched from GCM to lake model mid-century (Fig. 3B, 3E). For mean summer surface temperature and total ice duration, GCM remained the dominant source of uncertainty throughout the projection time period (Fig. 3A, 3F). Interestingly, lake model uncertainty in mean summer surface temperature, Schmidt stability, thermocline depth, and total stratification duration did not increase at a constant rate and increased more quickly in the beginning of the projection period (2006-2099) leading up to mid-century (Fig. 3).

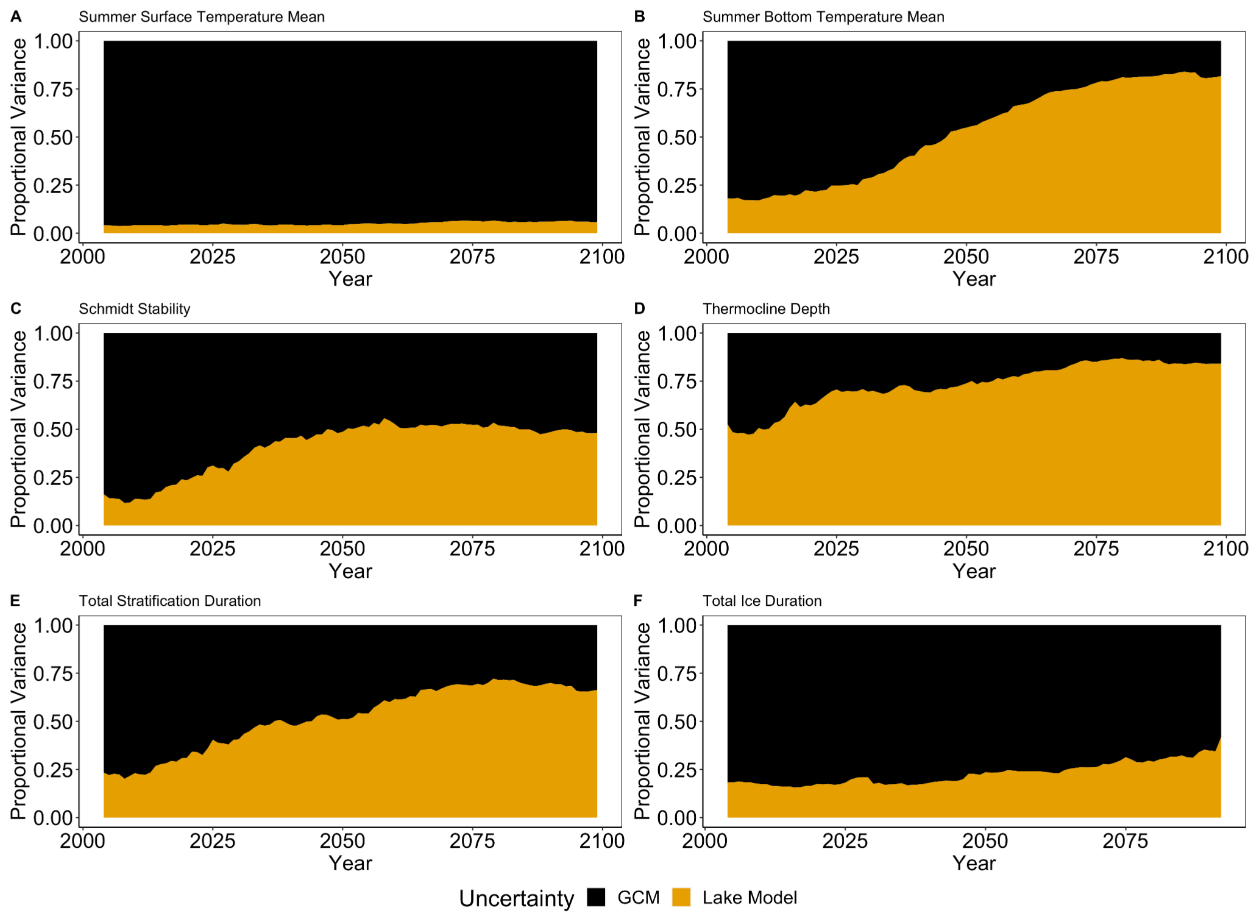

Figure 3. Proportional variance plot of A) surface temperature mean (T_sMean), B) bottom temperature mean (T_bMean), C) Schmidt stability, D) thermocline depth, E) total stratification duration, and F) total ice duration from 2006-2099. Proportional variance was calculated for general circulation model (GCM) uncertainty and lake model uncertainty under RCP 8.5

Q3. How does doubling of inflow nutrient concentrations (nitrogen and phosphorus) and inflow discharge rates in 11 different sub-catchments affect within-lake nutrients?

GLM-AED generally reproduced observed trends in whole water column temperature and surface TP. Over the calibration period, goodness of fit metrics as measured by RMSE were 2.31 °C for whole water column temperature and 1.57 µg/L for surface TP, indicating a reasonable fit with observed data.

When doubling inflow nutrients (the Nutrients x2 scenario) in each of the 11 subwatersheds, some sub-watersheds had a greater impact on within-lake nutrients than others (Fig. 4). In particular, sub-watershed 505 (Georges Mills) had the greatest contribution on whole-lake nutrients, with doubling its nutrients resulting in an increase in the whole-lake TP concentration by 0.02 mmol/m^3 or 22.65% above the reference simulation (Fig. 4A). Doubling of nutrients in 665 (Chandler Brook) and 800 (Pike Brook) had the next largest contributions, resulting in increases in whole-lake TP by 0.01 $mmol/m^3$ or 12.18% and 0.006 $mmol/m^3$ or 6.87%, respectively, over the reference simulation (Fig. 4A). Similarly, TN was most sensitive to doubling in sub-watershed 505 (Georges Mills) with an increase of 5.35 $mmol/m^3$ or 30.93% over the reference simulation. The other sub-watersheds' TN contributions were relatively similar (Fig. 4B).

When doubling discharge rates (the Discharge x2 scenario) in each of the 11 sub-watersheds, we found that some watersheds had a greater impact on within-lake nutrient concentrations (especially 505, 665, and 800) but that the relative importance of each sub-watershed was different than for the Nutrients x2 scenario (Fig. 4). Additionally, the degree of change on within-lake nutrients due to doubling discharge (Discharge x2) was less than that when doubling nutrients (Nutrients x2). For example, doubling discharge rates in sub-watershed 665 (Chandler Brook) had the greatest increase in within-lake TP, with a change of 0.004 $mmol/m^3$ or 4.62% increase from the reference simulation (Fig. 4C), followed closely by 800 (Pike Brook) with 0.004 $mmol/m^3$ or 4.10% increase, and minimal change from the reference simulation across several other sub-watersheds. For TN, doubling discharge rates in sub-watershed 505 (Georges Mills) had the greatest change over the reference simulation, with little change in within-lake TN concentrations due to discharge doubling in other watersheds (Fig. 4B). Interestingly, for some Discharge x2 scenarios, we found a decrease in within-lake nutrient concentrations from the reference simulation (e.g., 805, Fig. 4C, D), which may be a result of biological processing or physical mixing of incoming nutrients. Across both Nutrients x2 and Discharge x2 scenarios, we found more year-to-year variability across our simulations relative to the reference simulation (Fig. 4).

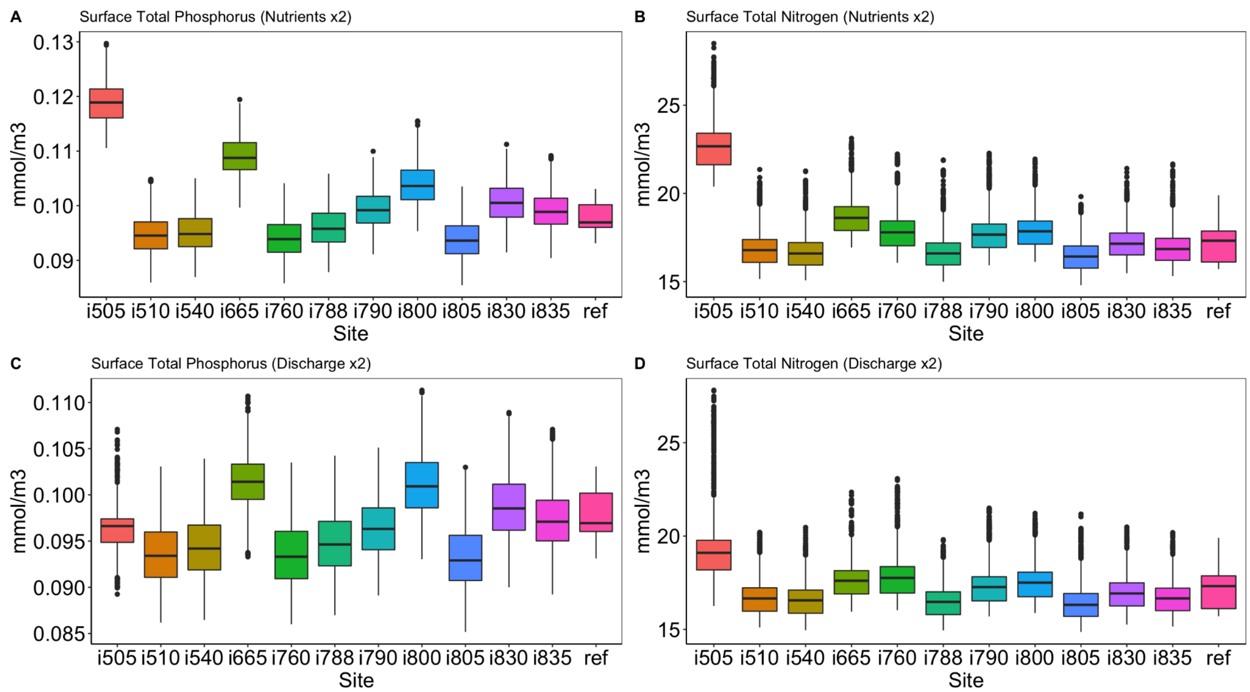

Figure 4. Simulation results for all land-use scenarios showing within-lake concentrations of A) Total Phosphorus (TP), and B) Total Nitrogen (TN) for Nutrients x2, and C) TP and D) TN for Discharge x2 scenarios. Nutrient concentrations were aggregated across the simulation period after spin-up (2010 - 2020). The sub-watershed listed on the x-axis indicates the manipulated sub-watershed, where nutrients or discharge were doubled from observed concentrations in isolation from the other sub-watersheds (see Fig. 1 map for sub-watershed names). "ref" stands for "reference" in all panels.

5. Conclusions and Next Steps

Overall, our study demonstrates the potential impacts of climate change on lake thermal dynamics, showing an increase in surface and bottom water temperatures, longer and stronger stratification, and a decrease in ice coverage. Additionally, our calibration and validation process demonstrates the value of using an ensemble mean, which outperforms individual models, and quantifying relative model performance. Our study also demonstrates that the dominant source of uncertainty was both dependent on the variable modeled and the RCP scenario being run. However, across all thermal metrics, process uncertainty was the dominant source for most variables. Altogether, our results emphasize the importance of using an ensemble modeling approach to inform uncertainty in climate projections of ecological variables. Specifically, our results demonstrate that for different thermal metrics, different modeling approaches may be appropriate. That is, if modeling surface temperatures or ice dynamics, the use of multiple GCMs may be critical to appropriately quantifying uncertainty in these thermal metrics. In contrast, predictions of bottom temperatures and stratification metrics should be made with an ensemble of lake models to properly capture the processes which determine changes in these metrics.

Following our watershed modeling results, we found that changes in both nutrient concentrations and discharge rates among sub-watersheds increased within-lake concentrations of both total nitrogen and total phosphorus. Importantly, this pattern was dependent on the identity of the individual sub-watersheds, with sub-watersheds 505, 665, and 800 (Georges Mills, Chandler Brook, and Pike Brook) having the greatest effect on within-lake nutrient concentrations, regardless of whether nutrient concentrations or discharge rates were doubled. As a result, these particular sub-watersheds may be areas of prioritization for watershed management.

These modeling studies provide an important first step for future work. For the land-use modeling study, additional model calibration of dissolved oxygen and chlorophyll-a is needed, as well as more realistic (and complex) model scenarios that take into account hydrology, seasonality, and specific changes in land-use type. Ultimately, with future work this modeling may be helpful for informing Lake Sunapee's watershed management plans.

Both our long-term projections and nutrient scenario modeling at Lake Sunapee will continue to provide insight into predicting lake water quality. Building off of this work, we plan to produce near-term forecasts of Lake Sunapee water quality variables, including water temperature and dissolved oxygen, providing valuable information on future changes in water quality, led by Whitney Woelmer as part of her Ph.D. dissertation.

6. Acknowledgements

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Table 1. Root mean square error (RMSE) of mean summer surface temperature (T_sMean), summer, mean summer bottom temperature (T_bMean), Schmidt stability, total stratification duration (TotStratDur), and ice off (IceOff). Throughout all model simulations, goodness of fit calculations for FLake were made using the mean water column depth only. Summer is defined as June-August. Cal = Calibration; Val = Validation

Model	*T_{wwc}Mean* (°C)		*T_sMean* (°C)		*T_bMean* (°C)		*Schmidt_stability (J/m^2)*		*ThermoDepth (m)*		*TotStratDur (days)*		*IceOff (days)*	
	Cal	*Val*	*Cal*	*Val*	*Cal*	*Val*	*Cal*	*Val*	*Cal*	*Val*	*Cal*	*Val*	*Cal*	*Val*
FLake	2.23	2.43	1.51	1.72	NA	NA	240.70	305.73	2.98	2.36	86.03	19.56	4.46	6.18
GOTM	1.91	2.60	1.13	1.57	4.79	5.67	69.78	95.70	3.96	4.27	84.51	48.39	59.90	70.46
Simstrat	1.48	2.27	1.03	1.01	3.50	7.29	75.22	91.08	2.78	2.70	93.60	23.74	4.33	28.58
MyLake	1.52	1.94	1.13	1.82	3.45	4.87	55.37	125.75	5.39	8.55	87.41	83.75	4.89	8.56
GLM	1.67	1.69	1.47	1.34	3.51	1.72	113.50	113.14	6.89	6.06	83.53	71.79	NA	NA
Ensemble Mean	1.29	1.65	0.85	0.76	2.94	4.74	56.82	95.85	2.14	2.11	86.71	43.61	14.78	26.37

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