# Constraining uncertainties in lake thermal responses to global climate change using an ensemble of models

## Abstract

Oligotrophic lakes provide valuable ecosystem services, yet their clear-water trophic state is increasingly at risk due to human impacts such as global climate change, which are expected to worsen over the next 100 years. However, the uncertainty surrounding how the climate will continue to change and how this will affect lake thermal budgets is not well quantified. As a result, stakeholders such as researchers, ecosystem managers and law-makers are unable to make decisions regarding how these projections pertain to the real-world. Using an ensemble modeling approach, we will quantify multiple sources of uncertainty in thermal dynamics of Lake Sunapee, a northern oligotrophic lake, from 1986 to 2099. We will use the representative concentration pathway (RCP) 8.5 scenario coupled with four general circulation models (GCMs), and five one-dimensional (1D) hydrodynamic lake models. Using these projections, insights regarding projected changes in the thermal budget of Sunapee will be discussed such as stratification depth, water column temperature, and ice on/off. Through our ensemble model projections, we will propagate and quantify important sources of uncertainty, including climate model uncertainty, and lake model uncertainty. The results of this study will be relevant to both stakeholders of Lake Sunapee as well as climate modelers and researchers, as further understanding of lake thermal dynamics will aid in decision making revolving around climate change response in lakes.

## Introduction

Freshwater lakes provide critical ecosystem services such as drinking water and cultural and economic value. However, many lakes are experiencing relatively abrupt and severe water quality problems in response to climate change and local land-use change (Hering et al., 2010, Watson et al., n.d., Field et al., 2014). Further, increased pressure due to human activity is expected to continue threatening lake ecosystems with eutrophication (Bennett et al., 2013). Because of this, new tools to predict future water quality are vital to improving the management of oligotrophic lakes and combat water quality degradation (Thomas et al., 2020). However, there is considerable uncertainty when predicting future lake water quality because of the variation in how humans will continue to impact climate, how climate will change in response to human-induced drivers, as well as how lake ecosystems will respond to climate forcing. New methods which incorporate all these sources of uncertainty are critical to informing our understanding of future lake ecosystems.

Uncertainty is a critical aspect of predicting ecological systems. When producing predictions, it is important for scientists to understand the greatest contributors of uncertainty throughout the modeling process. This allows researchers to focus resources on constraining the largest sources of uncertainty in a study, thereby improving their models and their predictions (Raiho et al., 2020, M. Dietze, 2017). For example, Raiho et al., 2020 found that process uncertainty was a large factor of uncertainty within the majority of their models, pointing to a need for models that more accurately predict the latent state of an ecological system (Raiho et al., 2020). Other studies point to uncertainty in climate model projections, indicating that a better understanding of how climate will change is important for making predictions of how ecological variables will change as well (Mishra & Singh, 2009). Gaining insight into the predictability of ecology makes ecology more relevant to policy, management and decision making as information about the future ecological states allows for greater consensus around scientific problems and their solutions (Lemos & Rood, 2010). It also informs what data are collected, how models are structured, and the statistical tools linking models to data (M. C. Dietze, 2017). The following study will require propagating the contributions of model parameters, lake hydrodynamic model processes, and climate model projections (Thomas et al., 2018). By propagating these different sources of uncertainty, we will improve our understanding about lake thermal response to climate change and the inherent difficulties in quantifying a robust and accurate projection.

Thermal stratification in lakes is important to many physical, chemical and biological processes in lakes and reservoirs, including complete water turnovers, (Yankova et al., 2017) deep-water oxygen levels, (Jankowski et al., 2006, Piccolroaz & Toffolon., 2018) atmospheric gas exchange, (Tranvik et al., 2009, Read et al., 2012) primary production (Leach et al., 2018), and quality of fisheries habitats (Hansen et al., 2017, Stetler et al., 2020). As climate change alters the thermal budget of lakes through increased water surface temperatures (Woolway et al., 2019), one response is a shift in mixing regimes. Particularly in temperate lakes, there is a documented shift from multiple mixing events annually (polymictic and dimictic) to a single mixing event (monomictic and meromictic) (Kirillin, 2010). Changes in mixing regimes can have important implications for the ecosystem and community services which oligotrophic lakes provide, including drinking water. This could have major implications for lakes processes such as primary production, fish habitat and atmospheric gas exchange and lake turnover. In addition, ice cover is expected decrease an average of 29 ± 8 days under possible future climate change (Woolway & Merchant, 2019). The implications of this finding are especially important as lake ice coverage is increasingly understood to be relevant for both summer and winter lake ecology, affecting lake hydrodynamics and leading to changes in the distributions of microorganisms and fish (Salonen et al., 2009, Hampton et al., 2017).

However, there is considerable uncertainty in how global climate will continue to change in the future. First, there is uncertainty in how societies will respond to global climate change and curb carbon emissions which drive changes in climate (Schneider & Kuntz-Duriseti, n.d.). As a result, there are several representative concentration pathway (RCP) scenarios which combines assumptions about multiple ecological and sociological factors, including high population, slow income growth, and modest technological change and energy intensity improvements (Riahi et al., 2011). This study will use the RCP 8.5 scenario, which assumes that greenhouse gas emissions continually increase over time, leading to a radiative forcing (the additional amount of energy in Earth’s climate system) of 8.5 W/m2 at the end of the century. The RCP 8.5 scenario is the most aggressive and adopts a “business as usual” attitude from the current emission outputs, which is the best match out to midcentury and likely further under current and stated policies. Under RCP 8.5, end of century warming outcomes range from 3.3° C to 5.4° C globally (Schwalm et al., 2020). In order to represent the effects of various climate scenarios, global general circulation models (GCMs) are needed, which model Earth’s oceans and atmosphere using the radiative and thermodynamic properties of the atmosphere as well as the frictional dissipation and dynamics of kinetic energy on multiple scales (Phillips, 1956). However, among GCMs there can be disagreement in how various global climate variables will respond (Pirtle et al., n.d.), resulting in uncertainty about the directionality of future climate change.

Uncertainty surrounding how lake ecosystems will respond to changes in climate is also a major barrier to understanding how climate change will affect lake thermal budgets. One way to estimate uncertainty in lake thermal processes is to use a suite of different lake models. The LakeEnsemblR (LER) R package is one tool which can be used to predict lake thermal budgets using a suite of lake models. Using multiple lake models to predict the same scenario allows us to conduct comparative analyses between outputs, resulting in novel insights regarding a lack of consensus between models which aim to represent the same processes (e.g., lake thermal dynamics). LER includes five different lake models, all of which use different methods of estimating lake thermal properties. These lakes include Freshwater Lake model (FLake) which simulates lake systems using a two-layer parametric representation focusing on heat budget, General Lake Model (GLM) which applies a Lagrangian structure to replicate mixing dynamics, the General Ocean Turbulence Model (GOTM) which is a vertical 1D hydrodynamic water column model, Multi-year Lake simulation model (MyLake) which simulates daily vertical profiles of water temperature, seasonal ice and snow cover as well as others, and Simstrat, which is a vertical 1D hydrodynamic model combining a buoyancy-extended k-epsilon model with seiche parameterization (*LakeEnsemblR: An R Package That Facilitates Ensemble Modelling of Lakes*, n.d.). By predicting lake thermal properties using the above suite of lake models, we can better estimate the range of uncertainty in future lake responses to climate change. Studies of this nature that partition uncertainty are few and far between, and virtually nonexistent concerning individual lakes and their future projected outcomes.

As discussed above, we will take a novel approach to quantifying the numerous uncertainties involved in lake thermal projections by coupling a global climate scenario with four general circulation models. Further, we will estimate lake thermal properties’ response to climate change by coupling our global climate model output with five lake models in LakeEnsemblR to make projections of lake thermal dynamics nearly a century into the future, up to 2099. The goals we aim to complete in this study are a) quantifying the contribution of climate model uncertainty against lake model uncertainty, and b) gaining further insight into lake thermal properties and their response to climate change up to the year 2099.

## Materials and Methods

In order to better quantify the uncertainty surrounding how lake thermal dynamics will respond to climate change, we will use one future climate change scenario representative concentration pathway (RCP 8.5) to drive four general circulation models (GCM), coupled with five vertical 1D hydrodynamic lake models within LakeEnsemblR. Each model within LakeEnsemblR will be calibrated to within a minimum RMSE for each thermal metric with 5 years of historical water temperature (2005-2010) and using the climate forcing data which was used to bias correct the GCM’s (EWEMBI). Two scenarios and their anomalies will be calculated for each GCM: a historical scenario using observed CO2 and a RCP 8.5 scenario. Anomalies between GCM’s will then be compared between 2020-2050 and 2069-2099. We will assess changes to lake thermal properties such as thermocline depth, length of stratification, thermocline strength, and ice coverage. The variation in these properties between GCM’s and lake models will be quantified in order to assess the uncertainty due to both climate model and lake model.

*Study Site*

Lake Sunapee is an oligotrophic, clear-water lake located between Merrimack and Sullivan Counties in New Hampshire, USA (Figure 1) (Ward et al., 2020). The lake is dimictic, with ice cover ranging from December or January-March or April (Bruesewitz et al., 2015). The mean thermocline maximum depth is 6-8 m (Carey et al., 2014). Furthermore, the Lake Sunapee region has experienced a rapid increase in observed air temperature, at a rate of 0.42 C per decade from 1979 to present (Ward et al., 2020).

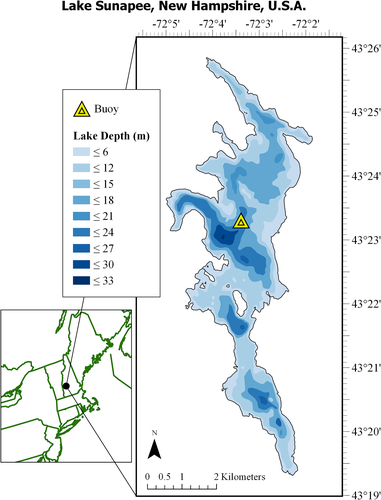


Figure 1: Location and Bathymetry of Lake Sunapee, New Hampshire, USA. Taken from Ward et al.

*Data*

Historical observations for Lake Sunapee will be used, including inflow and outflow data collected from 1981-2021, hypsography data, and water temperature data collected from 1986-2020 . The EartH2Observe, WFDEI and ERA-Interim data Merged and Bias-corrected for ISIMIP (EWEMBI) (*EartH2Observe, WFDEI and ERA-Interim Data Merged and Bias-Corrected for ISIMIP (EWEMBI)*, n.d.) meteorological forcing data (1979-2016) will be used in place of locally collected meteorological data in order maintain consistency when using the GCMs in a post-calibrated LER setup.

*General Circulation Models*

Four EWEMBI-driven general circulation models (GCMs) MIROC5, IPSL-CM5A-LR, GFDL-ESM2M, and HADGEM2-ES (Table 1) will be used under RCP 8.5 conditions out to 2099 for the purposes of future projections of lake thermal dynamics in Lake Sunapee. These GCMs are bias-corrected climate model projections from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), which uses community-defined scenarios with standardized climate variables and socioeconomic projections as inputs (Ruane et al., 2017).

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| --- | --- | --- | --- |
| Name | Abbreviation | Components | Reference |
| Geophysical Fluid Dynamics Laboratory Earth System Model (GFDL) with Modular Ocean Model version 4 (MOM4) component (ESM2M) | GFDL-ESM2M | Coupled carbon-climate earth system model with Modular ocean model using vertical pressure layers | (Dunne et al., 2012) |
| Met Office Hadley Centre Earth System Model | HADGEM2-ES | Terrestrial and oceanic ecosystems; Tropospheric chemistry | (Collins et al., 2011) |
| Institut Pierre-Simon Laplace Climate Model 51 – Low Resolution | IPSL-CM5A-LR | Interactive carbon cycle, tropospheric and stratospheric chemistry, comprehensive representation of aerosols | (Dufresne et al., 2013) |
| Model for Interdisciplinary Research on Climate | MIROC5 | Atmosphere, ocean, sea ice, terrestrial | (Watanabe et al., 2010, p. 5) |

Table 1. Summary of General Circulation Models used for ISIMIP

*Calibration and Evaluation*

LakeEnsemblR will be calibrated from 1 January 2005 to 31 December 2009 as these years cover a wide range in annual temperature and precipitation (LSPA et al., 2021b, LSPA et al., 2021a) and contain a continuous year of ice cover data in 2007-2008 (Bruesewitz et al., 2015). Calibration shall be carried out using a Latin Hypercube simulation (LHC) to first establish the priors of the parameters, and subsequently a Monte Carlo Markov Chain (MCMC) in order to return the most accurate parameter values for each model. Models will be evaluated using Root Mean Square Error (RMSE) and will be calibrated to within 2 degrees Celsius RMSE for each of the five lake models for temperature for the whole water column. We will also calibrate all LER models to within 1 meter of observed thermocline depth, and dates of ice-on and ice-off within 7 days of observed ice-on and ice-off. In addition to this, evaluation will include visually comparing observed and modeled stratification using a heatmap (e.g., Figure 2)

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Figure 2: Thermal Profiles visualizing water column stratification in Lake Sunapee within each LER model

*Model Analysis*

The lake models will be simulated from 1979-2016 using the historical scenario for each GCM with calibrated parameter values. Following this, GCMs under RCP 8.5 conditions will be forced through the lake models from 2020 up to 2099. Using the results of each projection, anomalies will be calculated by taking the difference between the historical scenario and the RCP 8.5 projection within each GCM, a step that must be taken in order to compare results across GCMs. We will compare anomalies of thermal properties, including water column temperature, thermocline depth, and ice on/off for each of the different lake model-GCM combinations, resulting in a total of 20 lake model combinations for each of these thermal properties (Figure 3). These variables will be analyzed using 30-year intervals as this reduces climatic noise when projecting a climate scenario over individual years.

Variables will be subset into two 30-year intervals, for subsequent comparison, 2020-2050 and 2069-2099. These intervals will be representative of current day to midcentury and midcentury to end century. Once these metrics of interest have been calculated for each model over the two 30-year intervals, a comparative analysis between all lake model/GCM model combinations will be carried out including comparing the anomalies of thermocline depth, water column temperature and ice on/off.



Figure 3. Scaffold structure visualizing the output of the RCP/GCM/LER combination

***Uncertainty partitioning***

*Climate Model Uncertainty*

Climate model uncertainty will be estimated by generating projections of lake thermal properties using four different GCMs under RCP 8.5 conditions. In order to isolate climate model uncertainty from other types of uncertainties, calibrated parameter values will be held constant and process uncertainty will not be propagated. The mean estimate of all five lake models will be used to avoid uncertainty between lake models. Each climate model will be assumed to be equally likely, with the metric of uncertainty being defined as the width of the 95% quantile interval of percent change in total temperature between 2010 and 2099 (Thomas et al., 2018).

*Lake Model Uncertainty*

Lakemodel uncertainty will be estimated by generating projections across all 5 LER models from all 4 GCM models under RCP 8.5 conditions. In order to isolate ecosystem uncertainty from other types of uncertainties, calibrated parameter values will be held constant and process uncertainty will not be propagated. The mean of the four GCM’s will be used across lake models in order to avoid uncertainty between climate models. Each ecosystem model will be assumed to be equally likely, with the metric of uncertainty being defined as the width of the 95% quantile interval of percent change in total temperature between 2010 and 2099.

*Total Forecast Uncertainty*

Total forecast uncertainty is calculated by simultaneously propagating uncertainty from the climate model uncertainty, lake model uncertainty, parameter uncertainty and lake model process uncertainty. Assuming that each model is equally likely, simulations from each model will be combined into a single distribution. The metric of uncertainty will be defined as the width of the 95% quantile interval from the projected output (Thomas et al., 2018).

## Implications

This project will be multifaceted in its outcomes: first, the outputs of the LakeEnsemblR models will give insight into the future of a culturally and economically important oligotrophic lake, Lake Sunapee, given a future climate scenario. This will provide desired insights to managers and homeowners residing at Lake Sunapee, who are greatly interested in mitigating the impacts of climate change on their lake in order to maintain its community-wide and personal values. Second, this project will lead to novel insights revolving around the modelling itself. Because all models have inherent uncertainty, whether that be revolving around future temperature projections, global circulation methods, or water column properties, it is important for researchers to understand how much uncertainty is present and where that model uncertainty is coming from (e.g., driver data, model representation of processes). Because this project contains multiple models for both climate projections and lake temperature, the ability to compare an ensemble of predictions is possible and extremely useful. These insights will be relevant to researchers and modelers carrying out similar climate change impact studies to mitigate future negative impacts on lake water quality.

## Timeline

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|  | **Summer 2021** | **Fall 2021** | **Spring 2022** |
| All 5 LER models running |  |  |  |
| Calibrate LER with historical data |  |  |  |
| Validate model |  |  |  |
| Finish analysis of GCM outputs |  |  |  |
| Uncertainty analyses |  |  |  |
| Prospectus submitted to VT BIO |  |  |  |
| Thesis started |  |  |  |
|  |  |  |  |
| Draft of thesis finished |  |  |  |
| VLWA conference |  |  |  |
| Dennis Dean Conference |  |  |  |
| Submit Thesis |  |  |  |

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