Hydrodynamic and water quality modeling in Missisquoi Bay

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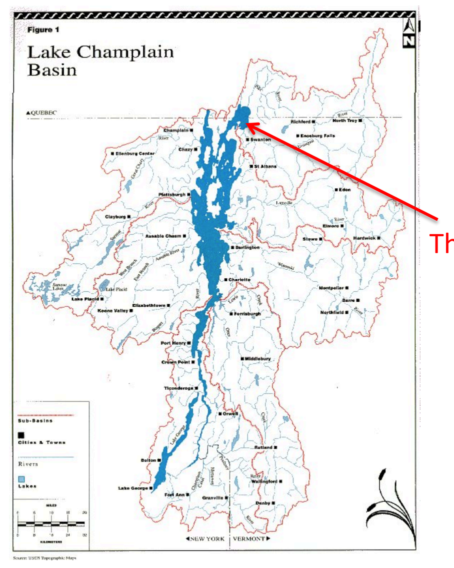
Introduction

- Modeling allows for predictions of water quality based on weather and inflow parameters
- General Lake Model (GLM) and Aquatic Ecodynamics (AED), both of which can be accessed in R, produce 1D models of bodies of water
- GLM generates hydrodynamic model plots with vertically resolved temperature profiles and water mass balances of lakes over time
- Modeled temperature profiles were calibrated against hourly observations from a monitoring buoy in Missisquoi Bay
- The calibrated model was used to predict changes in lake temperature from 1979-2040 using downscaled climate projections from UVM researchers
- AED generates plots involving other water quality parameters including nutrients and phytoplankton

Missisquoi Bay

- Located in Lake Champlain between Vermont and Quebec
- Three rivers flow into it (Missisquoi, Pike, and Rock)
- Maximum depth of the bay is approximately 4.9m



The Buoy

A buoy located in the bay monitors water quality parameters via a Sonde which measures depth, temperature, oxygen, turbidity, pH, chlorophyll, and phycocyanin among others, as well as an ISCO sampler which collects daily samples of water for measurements of phosphorus and nitrogen in the lab. In addition, weekly water samples were collected to gain information about nutrients and phytoplankton in the bay.

Buoy measurements:

- Depth (from surface)
- Temperature
- Conductivity
- pH
- Oxygen
- Turbidity
- Chlorophyll
- Phycocyanin

Fig. 1: Buoy in Missisquoi Bay

Hydrodynamic Model

Input Parameters:

- Relative humidity
- Air temperature
- River temperature[3]
- Solar radiation
- Cloud cover
- Wind speed
- Flow[5]

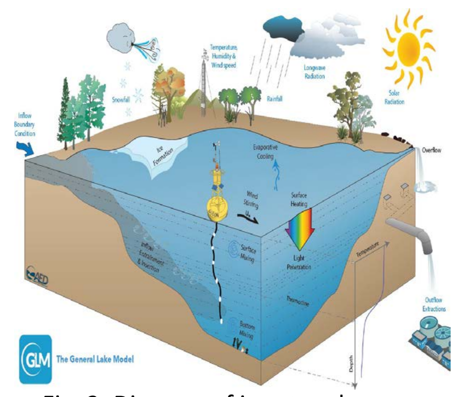


Fig. 2: Diagram of input and output parameters for the GLM[2]

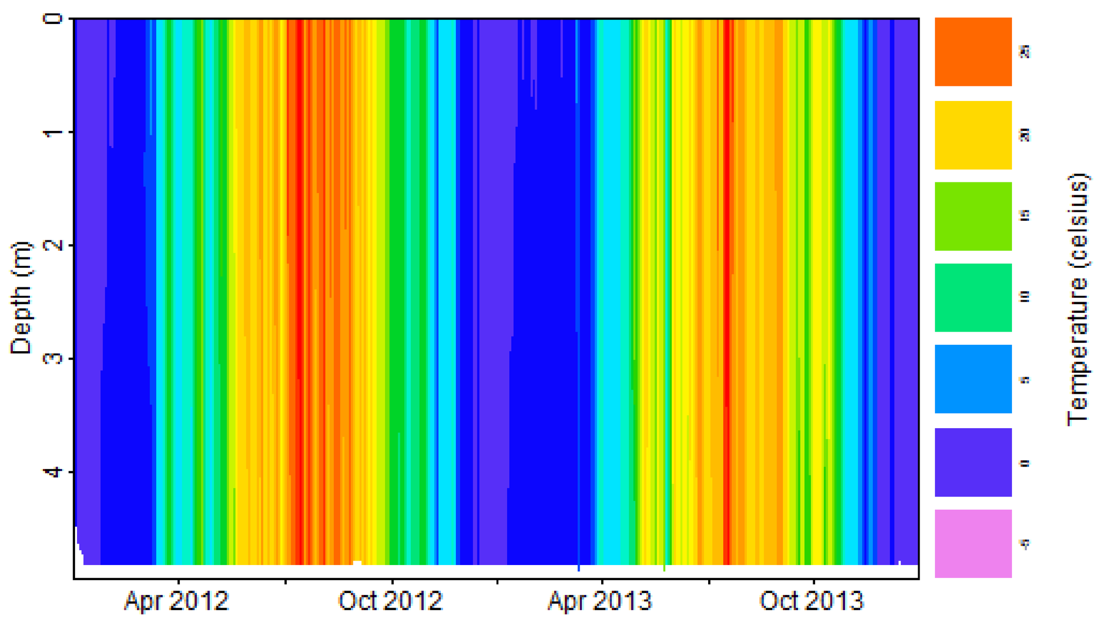


Fig. 3: Hydrodynamic plot for the years 2012-2013

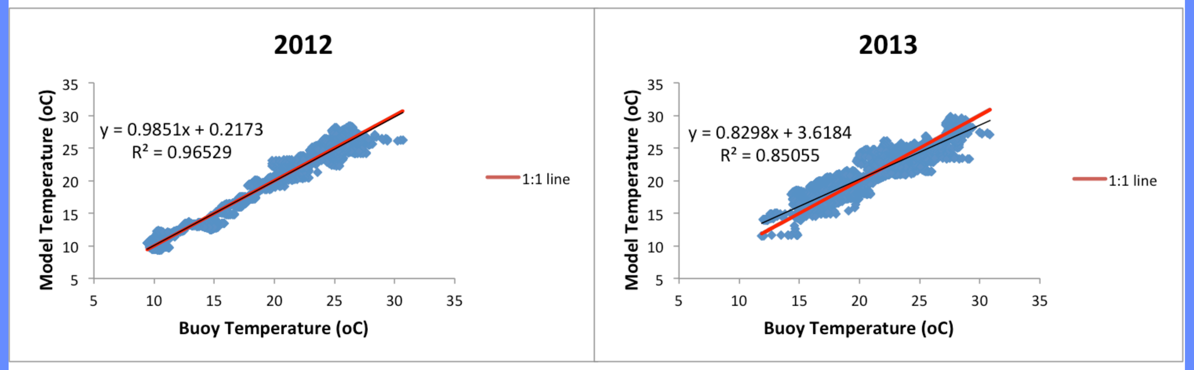


Fig. 4: Calibration plot demonstrating the positive correlation between the actual temperature (buoy) and the model temperature as extracted from the hydrodynamic model above. The red line indicates the line y=x on the plots. The root-mean squared error for 2012 is 1.040685 and for 2013 is 1.428805.

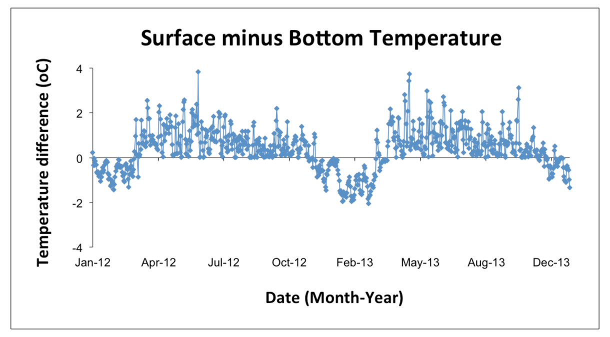


Fig. 5: Thermal stratification in the Missisquoi Bay demonstrating the difference between surface and bottom water temperatures. Short-term changes in stratification are important to internal nutrient cycling and bloom dynamics in Missisquoi Bay.

The Future of the Bay

Using historical (1979-2013) and predicted (2014-2040) climate data for a typical greenhouse gas emission scenario, lake temperatures were predicted using the calibrated hydrodynamic model. The average temperature for each month was calculated, and the points were extrapolated from the line of best fit.

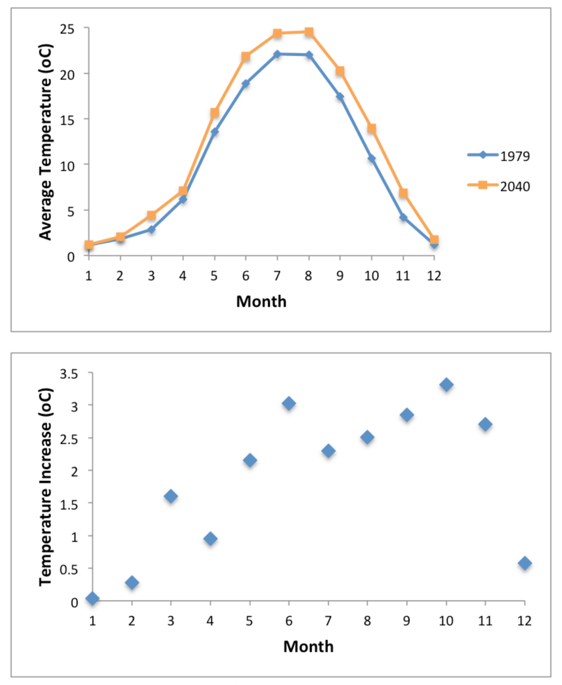


Fig. 6: Projected surface temperatures (top) and projected increase in temperature (bottom) for Missisquoi Bay from 1979 to 2040 based on the hydrodynamic model

What if the Predictions are Wrong?

Global climate model predictions of wind and solar radiation are very uncertain. Wind and shortwave solar radiation were adjusted by factors of 10% while all other factors were held constant in order to get an idea of the subsequent changes to surface water temperature. Overestimating the wind speed or underestimating the shortwave radiation both result in lower temperatures than the model shows. In the same way, too little wind or too much shortwave result in higher surface temperatures.

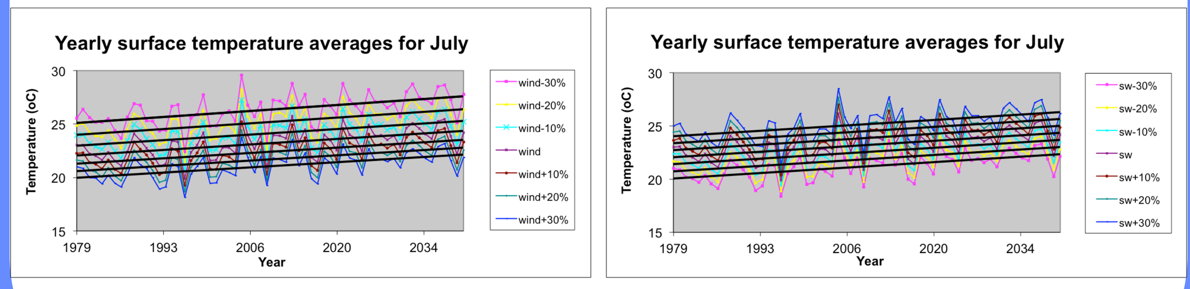


Fig. 7: Wind (left) and shortwave (right) sensitivity analyses

Water Quality Model

Input Parameters:

- Phosphorus
- Nitrogen
- Oxygen
- Carbon
- Phytoplankton

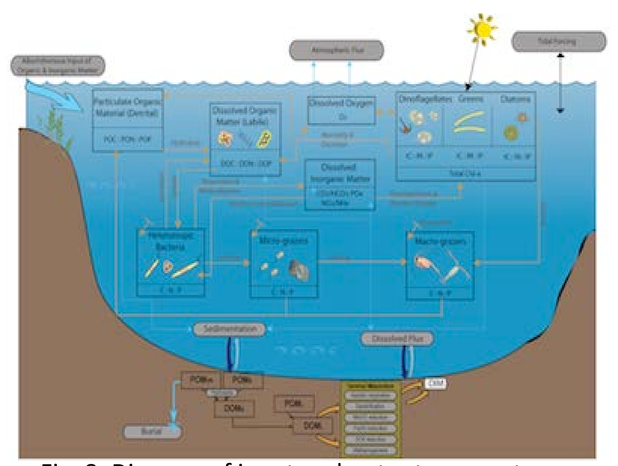


Fig. 8: Diagram of input and output parameters for the AED model[1]

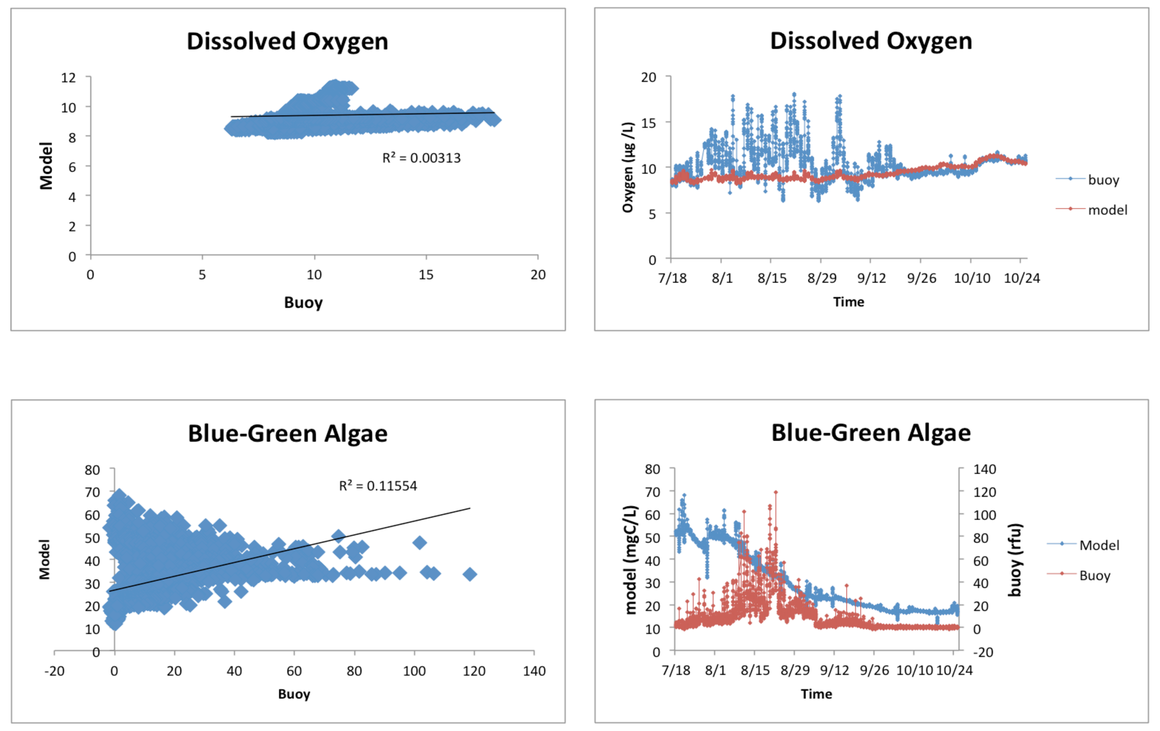


Fig. 9: Plots demonstrating the fit of the water quality model to dissolved oxygen (top) and blue-green algae (bottom). The left graphs demonstrate the level of fit between the buoy and model data to show how the values correspond. The right graphs show the overall trends in order to see how well the patterns are captured.

It is evident that the collected data do not fit the water quality model as well as they fit the hydrodynamic model. The general trend is more accurate for oxygen than blue-green algae, indicating that the model may capture nutrient processes better than phytoplankton. Changing the accuracy of the input parameters could help improve this, as it is harder to collect predictive data for nutrients and phytoplankton than for the data used in the hydrodynamic model.

Conclusions

- The 1D hydrodynamic model accurately plots trends in water temperature through time and depth
- The calibrated model run with predicted datasets captured the same trends for the years 2012-2013, thus justifying its use for future years
- Missisquoi Bay is projected to see increases in surface temperature, with larger increases in the summer and fall months
- The model, as run, does not capture oxygen and nutrient data accurately, but can be modified and further improved to get a better idea of those trends.

References

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