Using Lake Attributes to Predict Chloride Concentrations in Minnesota Lakes

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Introduction

- Globally, Sodium Chloride (road salt) is used to improve winter road conditions
- Chloride runoff can cause chemical stratification in lakes and toxicity to zooplankton populations.
- 125 water bodies in Minnesota already pass or are near the maximum chloride limit of 250 mg/L[1].
- Not all Minnesota lakes are subject to Chloride monitoring
- There is more Specific Conductance (SC) data available than Chloride (CHL)
- Lakes are an integral part of Minnesotan culture (fishing, outdoor recreation)

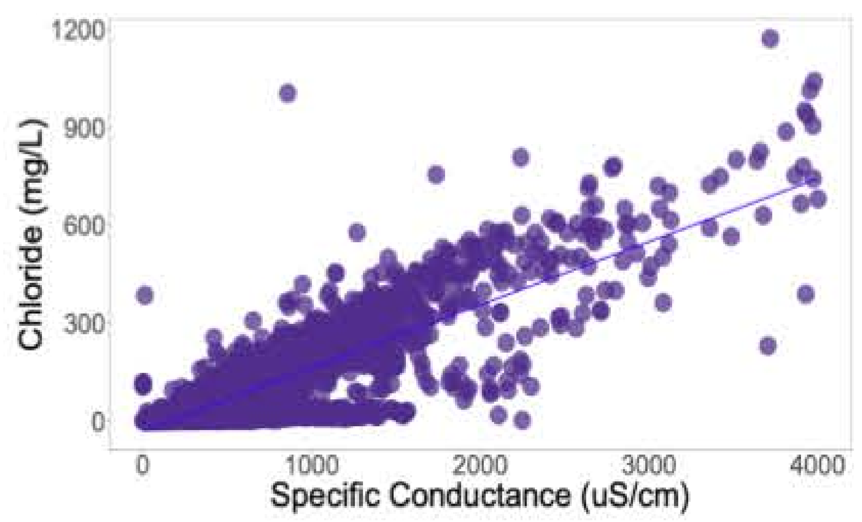
Purpose

- Evaluate the relationships between CHL and widely monitored lake characteristics in order to identify potential chloride hotspots and trends in unmonitored lakes
- Create a model to produce accurate CHL estimates using SC and important covariates
- Estimate CHL values for lakes with no CHL data and identify which lakes need specific attention from management

Methods

- Historical CHL & SC data was gathered from state, county, and local organizations in collaboration with the Minneapolis-St. Paul Metropolitan Area (MSP) Urban Long Term Ecological Research (LTER) program.
- Paired observations from 1,835 lakes in Minnesota from 1991-2019 and quantified the relationship and predictive power of specific conductance and chloride.
- Selected 4 GAM models to find best fit
- Chose model with lowest MSE based on k-folds cross validation
- Used model to predict chloride in unsampled lakes

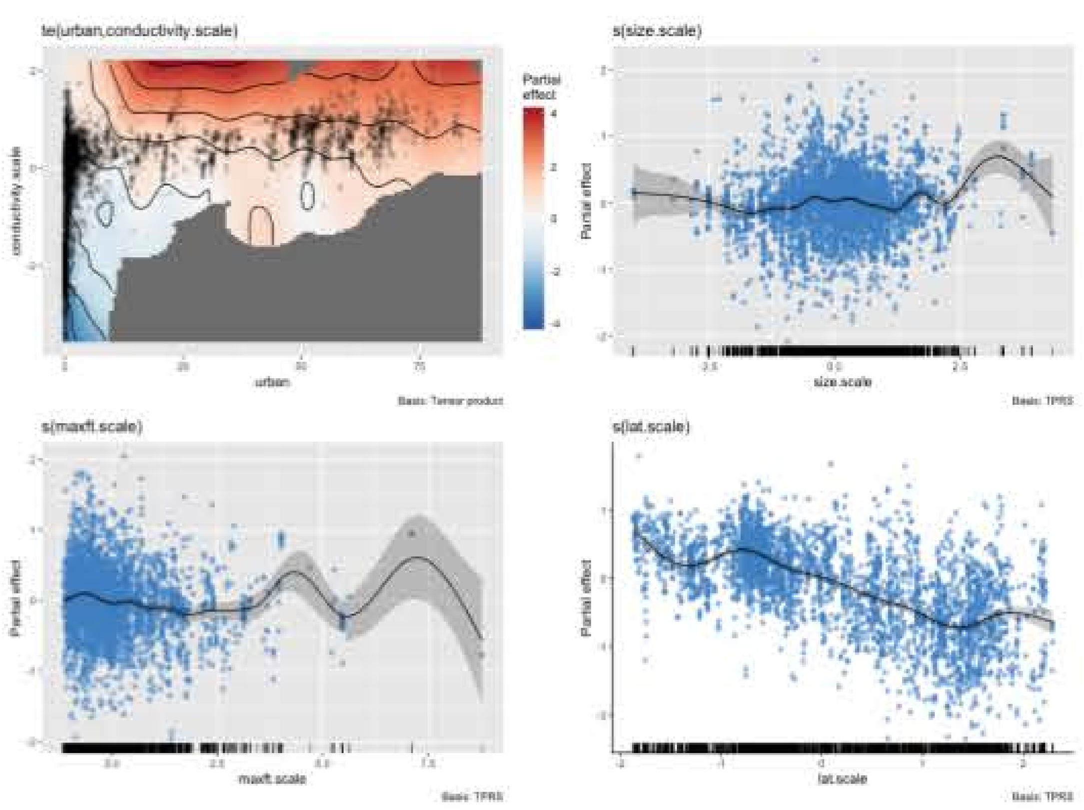
Results



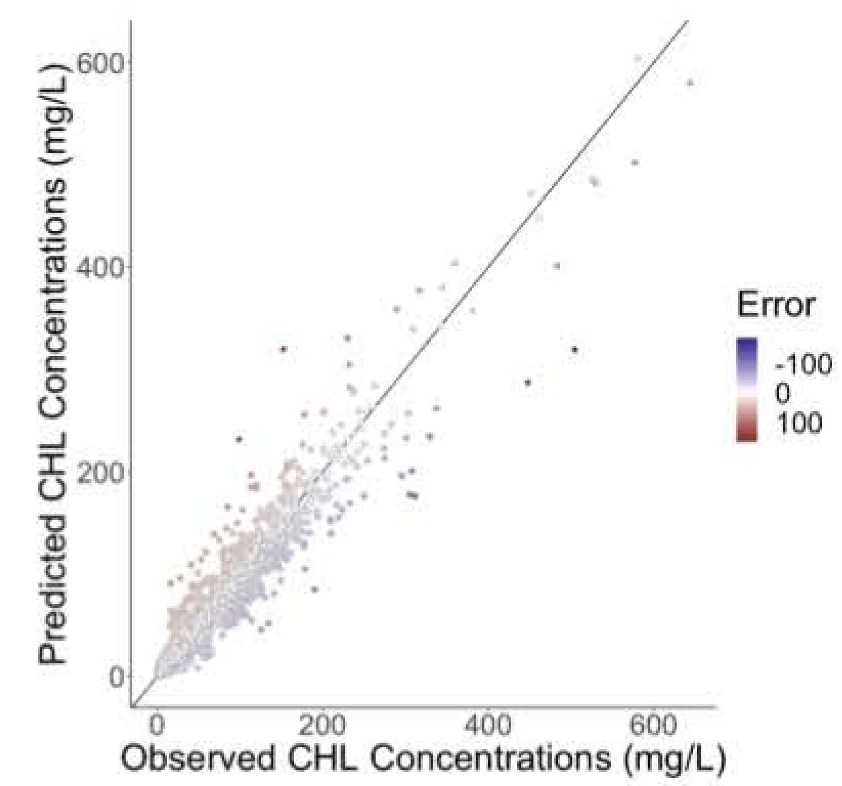
Plot 1. CHL and SC concentrations from 1,835 lakes located in Minnesota (1991 - 2019)

Model	Covariates Used	Interactions	MSE
A	• Specific Conductance • Lake size • Urban • Latitude • Longitude • Max depth	None - all variables are individual terms	0.5178
B		Interaction between SC and Urban - everything else the same as Model A	0.5051
C		Interaction between lake size and SC - everything else same as Model A	0.5097
D		Interaction between lake size and Urban - everything else same as Model A	0.5059

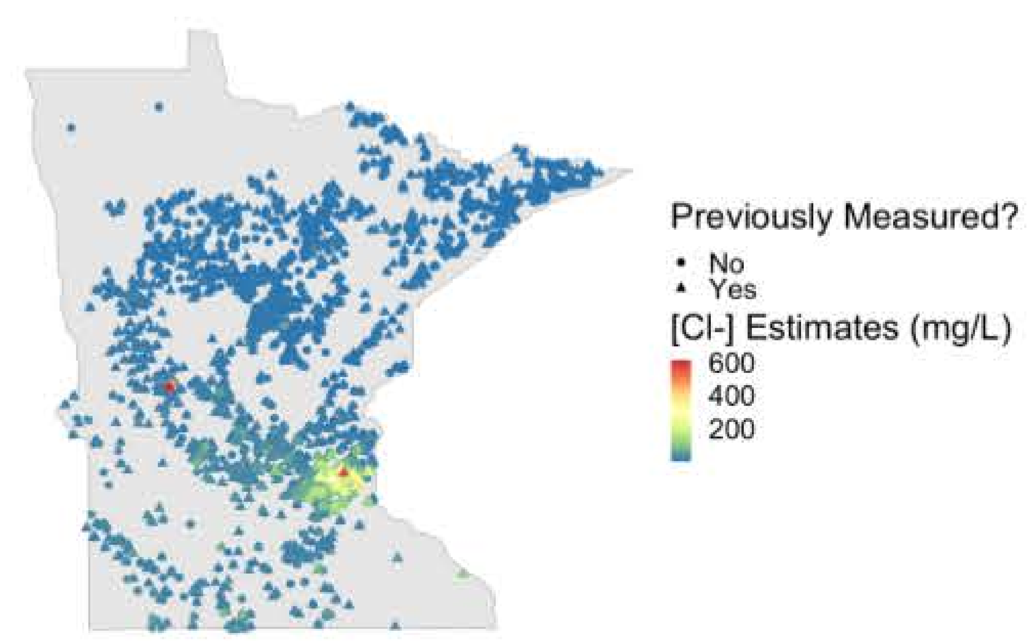
Table 1. Four GAM models that were used for Model Validation, including the covariates added in the models. Model B (highlighted) is the one we chose since it had a lower mean square error (MSE).



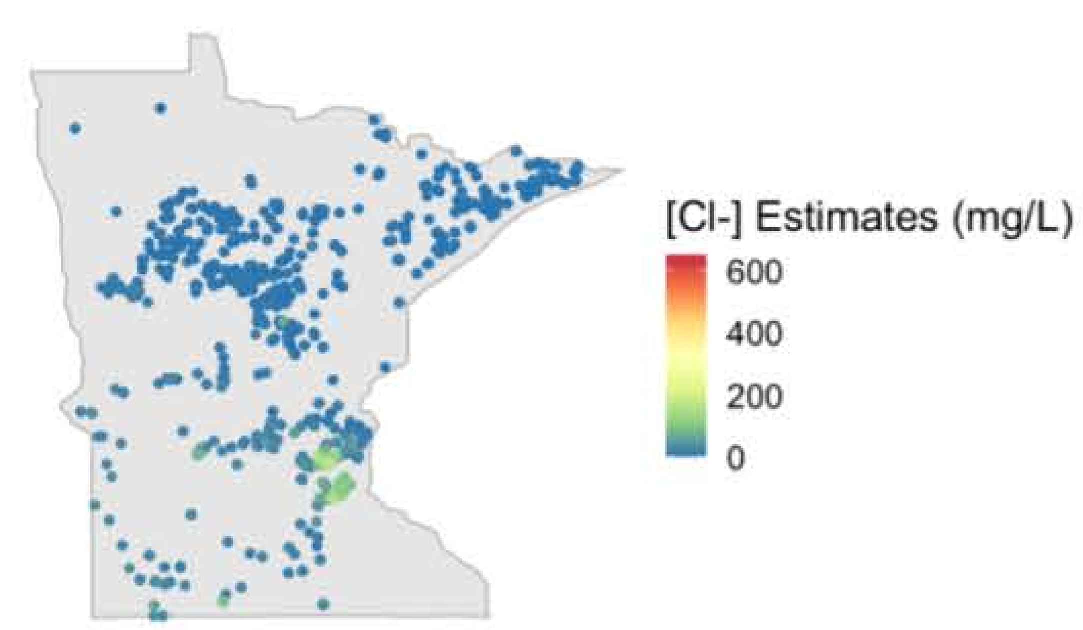
Plot 2. Scaled covariate relationships with log CHL for Model B
Top-left: log CHL relationship with Urban-SC interaction
Top-right: log CHL relationship with scaled size
Bottom-left: log CHL relationship with scaled max feet
Bottom-right: log CHL relationship with scaled latitude



Plot 3. Observed CHL concentrations by predicted CHL observations. Predictive errors are higher with low and extremely high CHL concentrations.



Map 1. Estimates of CHL for lakes in Minnesota using Model B. There are higher CHL estimates near the Twin Cities



Map 2. Estimates of CHL for lakes in Minnesota that have no previously observed CHL values using Model B. CHL near the Twin Cities metropolitan area have lakes with CHL above 150mg/L

Discussion

Our model made near accurate chloride predictions for lakes with specific conductance and the covariates, especially as SC values were increasing. However, the model produced more errors with lower SC concentrations. Additionally, there was a higher error with extremely high SC values, with the model underestimating CHL concentrations.

Urban land use interacted with SC to predict CHL. Specifically, at low levels of urban land use, CHL was low even at high levels of SC. However, moderate to high levels of urban development were associated with high chloride concentrations and high conductance. These results suggest that in non urban systems, SC is a function of other ions not included in this study.[3]

When CHL concentrations are low, the relationship between CHL and SC are weak. When calcium is added as a covariate, the relationship between CHL and SC becomes significant. This is likely because when chloride has low concentrations, other ions, such as calcium are more significant[2]. However, Calcium was not included in the model as it is less accessible than chloride.

At 120 mg/L, there are heavy consequences for zooplankton populations, as they can decrease in abundance, biomass, and richness[4]. Out of the 560 lakes that had no previous observed CHL data, we had 5 lakes with CHL estimates above 120mg/L. The reduction of Daphnia can lead to the increase in phytoplankton and algal blooms which can increase the rates of eutrophication and limit dissolved oxygen concentrations which are crucial for the survival of aquatic species.

Our chosen model included an interaction between urban and SC, but management organizations might prefer Model A, the simpler model given the small loss of accuracy. Our analysis is relevant for programs working to reduce chloride inputs to improve water quality in Minnesota and beyond. Using data that is readily available to predict CHL will save time for managers and is cost effective.

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References

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