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Project Title:

Which Fits Best? Evaluating Chlorophyll-a vs. Phytoplankton Composition as Cyanotoxin Predictors in U.S. Lakes.

Introduction

Cyanotoxins such as Microcystins and Cylindrospermopsins are harmful compounds produced by cyanobacteria in freshwater ecosystems (Millie et al., 2009). Monitoring these toxins is critical for assessing public health risks and maintaining water quality. Chlorophyll-a (chl-a) is widely used as a proxy for algal biomass and bloom intensity due to its availability and ease of measurement (Canfield et., 2019). However, the composition of phytoplankton communities such as cyanobacterial biovolume and density may provide more targeted insights into cyanotoxin production (Fig. 1). This study evaluates the predictive power of chl-a compared to more detailed phytoplankton composition metrics in forecasting Microcystins and Cylindrospermopsins concentrations in U.S. lakes. Specifically, I assess whether the same biological indicators are equally predictive of both toxin types and if distinct indicators better capture variability in each. My research questions are: 1). Which of the following biological indicators is the best predictor of cyanotoxins concentrations in U.S. lakes: chlorophyll-a (chl-a) concentration, total phytoplankton biovolume, or cyanobacterial abundance? 2). Are the same biological indicators equally predictive of Microcystin and Cylindrospermopsin concentrations in U.S. lakes?

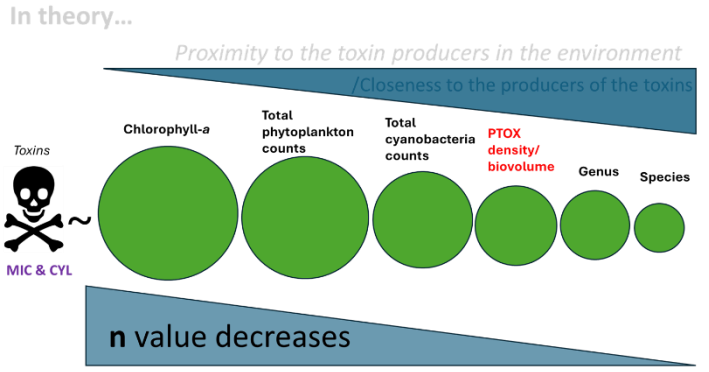

Figure1. Conceptualized diagram depicting the significance of derived potentially toxigenic cyanobacteria group.

Methods

Data for this analysis were obtained from the U.S. EPA's NLA 2022 surveys. The dataset includes cyanotoxin concentrations (Microcystins and Cylindrospermopsins), chl-a levels, and phytoplankton composition counts, including total phytoplankton density, cyanobacterial density, and biovolume fractions. Other derived data include grouping of potentially toxigenic cyanobacteria species into PTOX based on Chapman & Foss (2019). Statistical analyses included multiple linear regression and random forest models to assess the relative predictive power of chl-a versus more detailed phytoplankton indicators. Models were run separately for Microcystins and Cylindrospermopsins to identify potential differences in predictive relationships.

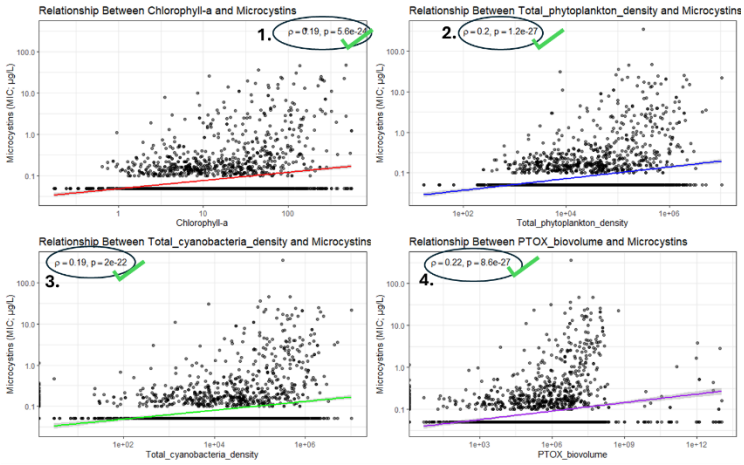

Figure 2. Relationships between Microcystins and common biological indicators.

Results

Spearman ranks correlation analysis:

Spearman ranks correlation analysis showed a significant positive relationship between MIC and 4 biological indicators such as Chl-a, total phytoplankton density, total cyanobacteria density and PTOX biovolume (Fig. 2). Whereas, for CYL only 2 of the 4 biological indicators have significant relationships (Fig. 3). They are total phytoplankton density and total cyanobacteria. Chl-a and PTOX biovolume have a non-significant relationship with CYL.

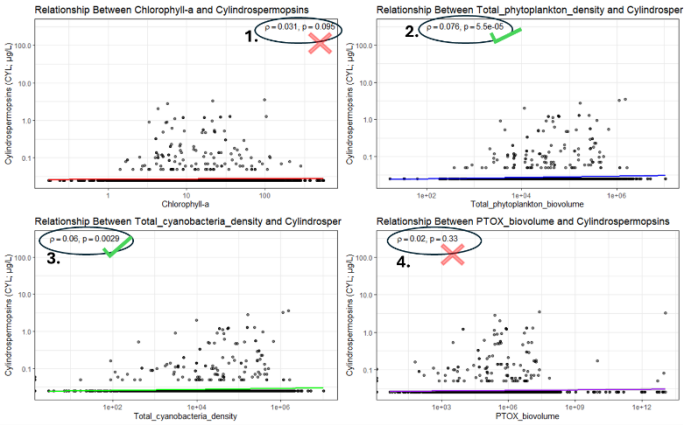

Figure 3. Relationships between Cylindrospermopsins and common biological indicators.

Linear Regression Models:

The linear regression model for Microcystins revealed that chl-a was a significant predictor, with a positive association ($p < 0.001$). However, total cyanobacterial density and percent cyanobacterial biovolume also emerged as significant positive predictors. Conversely, predictors associated with potentially toxin-producing cyanobacteria (PTOX biovolume) were not significant.

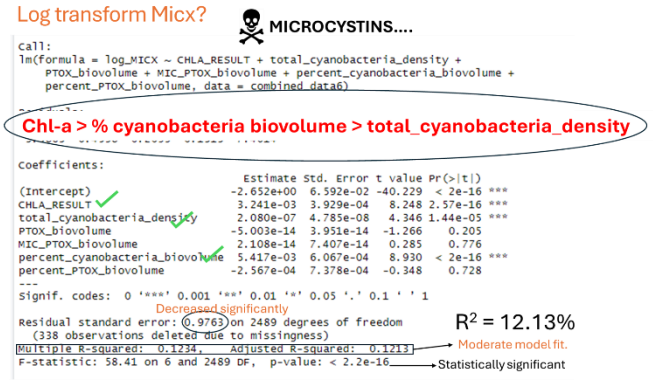

Figure 4. Linear regression models for MIC shows that 3 biological indicators are significant predictors.

For Cylindrospermopsins, chl-a was marginally significant ($p \approx 0.05$), and percent cyanobacterial biovolume remained a significant positive predictor. Interestingly, PTOX biovolume emerged as a significant positive predictor for Cylindrospermopsins, suggesting differences in the factors influencing each toxin type.

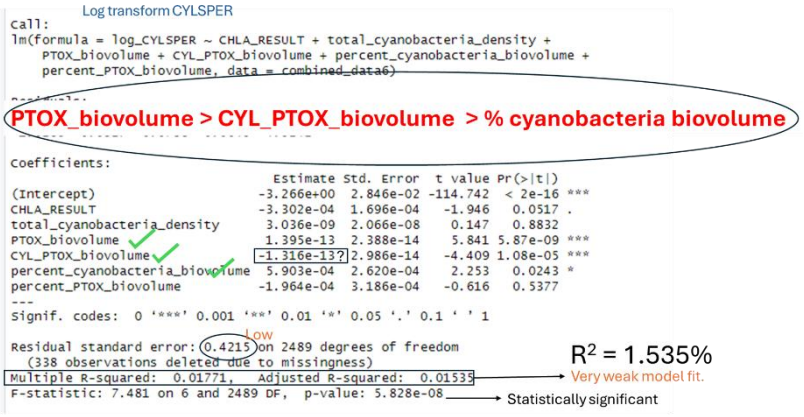

Figure 5. Linear regression models for CYL shows that 3 biological indicators are significant predictors.

Random Forest Analysis:

Random forest models indicated that chl-a, while informative, was not the top predictor for either toxin type (Fig. 6). For Microcystins, percent cyanobacterial biovolume and total cyanobacterial density were more influential predictors, indicating that toxin production may be more closely linked to cyanobacterial composition than overall phytoplankton biomass.

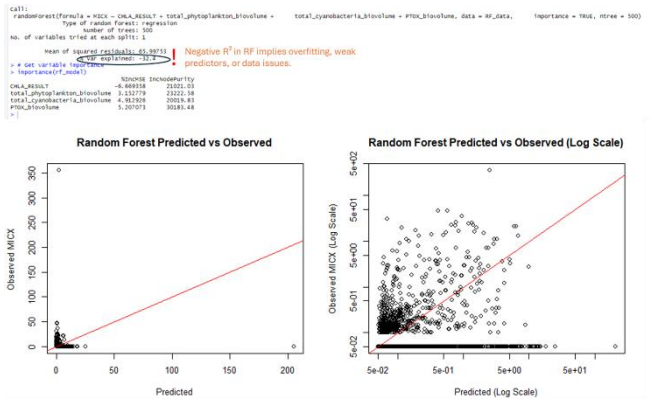

Figure 5. Random Forest Analysis for Microcystis (MIC) showed PTOX biovolume is the most influential predictor, however, the model is week and may be overfitting.

For Cylindrospermopsins, PTOX biovolume was ranked as the top predictor, followed by percent cyanobacterial biovolume, further emphasizing the importance of cyanobacterial composition over general algal biomass for this toxin type.

Discussion

The findings highlight that while chl-*a* is a convenient and widely available indicator, it may not adequately capture variability in cyanotoxin concentrations, particularly for Cylindrospermopsins. Phytoplankton composition, especially metrics related to toxin-producing taxa, demonstrated stronger predictive power in both linear regression and random forest models. These results suggest that monitoring programs relying solely on chl-a may overlook critical cyanotoxin risks, particularly when specific cyanobacterial taxa are present at low abundances relative to overall phytoplankton biomass. Future work should explore the feasibility of incorporating targeted phytoplankton metrics into routine monitoring to improve cyanotoxin prediction accuracy and early warning capabilities.

Conclusion

This study underscores the differential predictive power of chl-a versus phytoplankton composition metrics in forecasting cyanotoxin concentrations in U.S. lakes. While chl-a remains a valuable indicator, incorporating cyanobacterial-specific metrics, particularly biovolume and density of potentially toxin-producing taxa, could enhance prediction accuracy for both Microcystins and Cylindrospermopsins. Integrating these findings into monitoring protocols may provide more reliable early warning tools for managing cyanotoxin risks under changing environmental conditions.

References

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