

Abstract

Harmful algal blooms (HABs) in freshwater systems are being exacerbated due to climate change and pose significant ecological and human health risks, thus necessitating effective monitoring and management strategies. Traditional ground-based monitoring methods are limited by high cost, labor intensiveness, site-specificity and unforeseen disruptions such as the COVID-19 pandemic. In this study, we propose a remote sensing approach to address these challenges, enabling cost-effective and continuous monitoring of HABs in more than 35 lakes around New York State leveraging the existing insitu data from various monitoring programs. We test four different algorithms derived from band relationships to obtain chlorophyll-A (Chl-a) as a proxy for HABs presence on Sentinel-2 Multispectral Instrument (S2-MSI) Surface Reflectance (SR) data. There was a large range in formula accuracy; however, all exhibited ample error, leading us to incorporate different machine learning techniques into an expanded study of several large lakes in NY State, including Lake Champlain. Various S2-SR bands were examined as features and their importance was estimated using the in-situ data. The best-performing algorithm for Lake Champlain, our test region, Gradient Boosting, performed better than others with R^2=0.85. This approach addresses the need for effective regional HABs detection and monitoring in freshwater systems through the incorporation of remote sensing and machine learning techniques.

Background

- Algae, cyanobacteria, and phytoplankton are simple organisms found worldwide, capable of blooming uncontrollably and producing toxins, leading to harmful algal blooms (HABs)
- Factors contributing to HABs include slow-moving water, sunlight, and excessive nutrients/fertilizer from runoff
- Other than producing toxins, HABs can cause eutrophication and hypoxia, negatively impacting many species and aquatic ecosystems
- Climate change and landcover changes exacerbate HAB frequently and severity



- Accurate identification and prediction of HABs in local water sources are essential.
- Current methods involve expensive and time-consuming field studies to collect samples and assess the danger of algal masses.
- Novel approaches, such as satellite sensing and machine learning, are being developed alongside fieldwork to optimize HABs identification and warning systems.

Methods

i. Find in-situ data ii. Research algorithms iii. Evaluate Chl-A algorithms for Cayuga Lake iv. Expand lake dataset to other NY lakes v. Incorporate machine learning; try several methods iv. Compile analytics on ML algorithm &

formula accuracies

Chlorophyll-a Band Algorithms				ľ
NDCI (Normalized Difference Chlorophyll Index)	3BDA	2BDA	SABI (Surface Algal Bloom Index)	
Mainly for use in S2 due to the presence of red- edge band Landsat: $\frac{nir-red}{nir+red}$	Mainly for use in Landsat $\frac{blue-red}{blue+red}-green$	nir red	$\frac{nir-red}{blue+green}$	
Sentinel 2: $\frac{rededge-red}{rededge+red}$				





Detection of Harmful Algal Blooms (HABs) in Lakes at the Regional Scale Using Satellite Remote Sensing and Machine Learning

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fachine Learning Algorithms

Random Forest (RF)		
Gradient Boosting (GB)		
AdaBoost (AB)		
Neural Network (NN)		
K Nearest Neighbors (KNN)		
XGBoost (XGB)		
Support Vector Regression		
(SVR)		





- HAB concentration does not follow a linear relationship alternative for continuous and cost-effective monitoring of HABs
- Mixing in-situ data from different sources is likely to lower final R^2 and accuracy
- Use MPI4Py/parallel computing to speed up reflectance retrieval
- Expand set of lakes to include NJ, PA, VT & other states
- Incorporate near-real-time in-situ data for more accurate and consistent data
- Create opportunities for collaboration between CCRI and CSLAP HAB researchers





Conclusions

0.8

1.0

• Traditional ground-based monitoring methods have limitations, including high cost, labor intensity, sitespecificity, and vulnerability to disruptions like the COVID-19 pandemic. Remote sensing offers a viable

Discussion

While adding more lake in-situ data reduces the R^2, combining data from multiple sources can lead to error as there are different methods of data collection (volunteer sampling vs. consistent station monitoring)

Future Work

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References

combined with in situ data for monitoring small harmful algal blooms in complex