Using Imagery Collected by an Unmanned Aerial System to Monitor Cyanobacteria in New Hampshire, USA, Lakes

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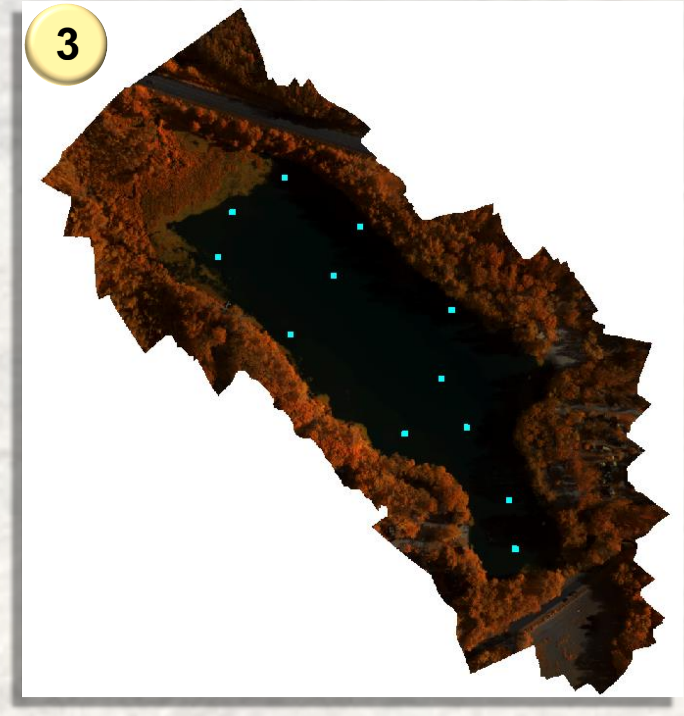
Introduction

Cyanobacteria are naturally occurring in many waters globally and can release various toxins which can cause skin irritations and dog fatalities. Monitoring this biological component is an integral factor when studying freshwater ecosystems. **With the increasing occurrence and growing public health concern that cyanobacteria blooms pose, it is even more crucial that we continue to explore ways to improve our ability to accurately, efficiently, and safely monitor water quality in impacted lakes.** We used a DJI M300 unmanned aerial system (UAS), equipped with a high resolution 10-band multispectral dual imaging sensor (MicaSense), to quantify cyanobacteria in six NH lakes. Five of these six lakes experienced cyanobacteria blooms during the 2022 field season. **Using the UAS collected spectral data coupled with collected in-situ water quality data, we used the random forest algorithm to classify the remotely sensed data, and logarithmic regressions to predict water quality parameter concentration on a per-pixel basis.**

Methods



Coastal Blue	Blue	Green	Green	Red	Red	Red Edge	Red Edge	Red Edge	NIR
444nm	475nm	531nm	560nm	650nm	668nm	705nm	717nm	740nm	842nm

4

- Program UAS Flights → (1) Collect UAS Imagery → (3) Image Processing → (4) Calculate Spectral Indices (NDVI, BNDVI, NDRE, NGBDI, NGRDI +)
- Determine Water Sample Collection Locations → (2) Collect Water Samples → Water Sample Processing (Speciation, Cell concentration, Chlorophyll-a, Phycocyanin, Phycoerythrin) → (5) Water Quality Parameter Relationships
- Perform the Random Forest Classification → Calculate the Accuracy → (6) Highest Level of Accuracy Achieved → (8) Apply the Classification Model to the Entire Waterbody
- Perform the Random Forest Classification → Most important features → Perform the Regressions → (7) Calculate the R^2 values for prediction

NOTE: The yellow numbers in the flowchart refer to the corresponding numbers in the figures and tables.

Results

Table 1. Significant simple linear regression R^2 outputs between water quality parameters ($p < 0.01$). Cells = cell concentration (mg/L), PC = phycocyanin concentration (μg/L), PE = phycoerythrin (μg/L), Chl-a = chlorophyll-a concentration (μg/L).

5	#	Cells/ PC	Cells/ PE	Cells/ Chl-a	PC/ PE	PC/ Chl-a	PE/ Chl-a
All Lakes	184	0.76		0.94		0.69	
French Pond	18	0.98					
Greenwood Pond	25					0.72	
Keyser Pond	61	0.76		0.78		0.93	
Showell Pond	25						
Silver Lake	43	0.97	0.72	0.60	0.79	0.61	
Tucker Pond	12	-0.72					

Table 2. Average classification results from random forest algorithm for each water quality parameter.

6	Classes		Average Accuracy
Cell Concentration (cells/mL)	Low <70k	High >70k	93%
Chl-a Concentration (ug/L)	Low <10	High >10	87%
Phycocyanin Concentration (ug/L)	Low <54.8	High >54.8	92%

Table 3. Significant simple logarithmic regression results for the top 10% of the UAS parameters for each water quality parameter ($p < 0.001$)

7	Band or Index	Log R^2
Log Cell Concentration (cells/mL)	NGBDI_4	0.31
	NGRDI_4	0.28
	Blue_475	0.26
	Green_Stdev_531	0.19
	Green_531	0.18
	Green_Stdev_560	0.16
	Red_Stdev_650	0.12
Log Chlorophyll-a Concentration (μg/L)	Blue_475	0.24
	NGRDI_4	0.23
	Green_531	0.22
	NGRDI_3	0.14
Log Phycocyanin Concentration (μg/L)	NGBDI_4	0.27
	Blue_475	0.27
	NGRDI_4	0.24

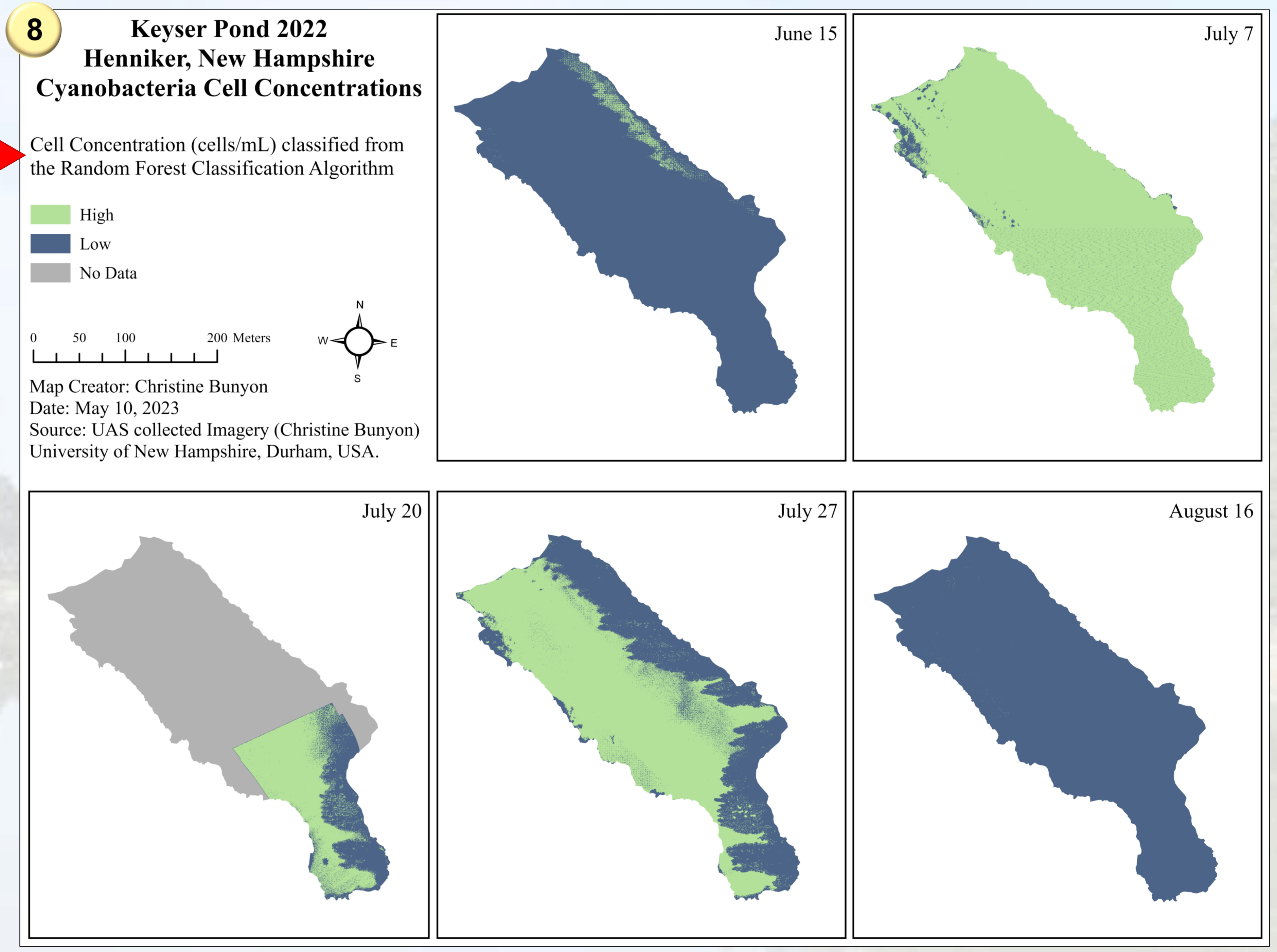


Figure 1. Cell concentrations (cells/mL) per 0.3m area classified from the random forest classification algorithm as High or Low to represent areas of Keyser Pond exceeding the NHDES threshold for cyanobacteria (70,000 cells/mL) before (June 15), during (July 7, July 20, and July 27), and after (August 16) the 2022 NHDES cyanobacteria bloom advisory.

The analysis yielded very high overall accuracies for cyanobacteria cell concentration (93%), chlorophyll-a concentration (87%), and phycocyanin concentration (92%) when classified into either High or Low, above or below thresholds set by the New Hampshire Department of Environmental Services, World Health Organization, and/or this study.

Discussion and Conclusions

- This method assesses the entire waterbody, including coves, littoral areas, and open water areas
- Promotes sampler safety through decreased time spent at each waterbody and the elimination of the need to contact the water for sampling.
- The UAS approach took significantly less time to complete than the traditional water quality sampling and analysis approach, therefore opening the possibility for these results to be applied in larger area, state, or region-wide studies.
- Identified significant correlations between cyanobacteria cell concentration to chlorophyll-a concentration, and cyanobacteria cell concentration to phycocyanin concentrations.
- Successfully classified cyanobacteria cell, chlorophyll-a, and phycocyanin concentrations in the sampled NH lakes using a 10-band multispectral sensor equipped to a UAS.
- The NGBDI_4, NGRDI_4, 475nm, 560nm, and 668nm were found to be the most important indices and bands for identifying the presence and concentration of cyanobacteria, chlorophyll-a, and phycocyanin through the UAS classification and regression approach.

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