Universities Council on Water Resources
Journal of Contemporary Water Research & Education
Issue 177, Pages 83-93, April 2023

Case Study Article

Monitoring Algal Blooms in Small Lakes Using Drones: A Case Study in Southern Illinois

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Abstract: Harmful Algal Blooms (HABs) persist in many water bodies around the world and pose adverse health and economic impacts to the affected communities. Small Unmanned Aerial Vehicles (UAVs) have recently been applied as a cost-effective tool for HABs monitoring. In this study, HABs in two small lakes in Southern Illinois (Carbondale Reservoir and the Campus Lake of Southern Illinois University) were monitored using UAVs and biomass concentrations in lake waters. By analyzing vegetation indices derived from multispectral UAV images and chlorophyll-*a* concentrations in the two lakes, statistical regression models were established for each waterbody. The model relates spectral characteristics of the lake water to its algae biomass. It was found that normalized difference vegetation index (NDVI) and blue-to-green band ratio are the best-fit indices to the variation in chlorophyll-*a* in Carbondale Reservoir and the Campus Lake, respectively. The findings in this study can be used for monitoring HABs using UAVs in these lakes in the future.

Keywords: *HABs, drone, UAV, NDVI, spectral analysis*

As a severe water quality problem, Harmful Algal Blooms (HABs) pose serious threats to human health, aquatic ecosystem health, and recreational activities (Brooks et al. 2016; Le Moal et al. 2019). They are commonly linked to eutrophication, a process resulting from increasing accumulation of Nitrogen (N) and Phosphorus (P) from anthropogenic activities (Beusen et al. 2016). These nutrients sometimes trigger excessive growth of cyanobacteria or cyanophyceae that produce cyanotoxins such as cylindrospermopsin and microcystin (Paerl 2009). Consumption of HAB-contaminated fish or direct contacts can cause harmful health implications to community residents, especially children (Heil and Muni-Morgan 2021).

Because of health and environmental concerns, monitoring HABs outbreaks and their dynamics are imperative for managing water quality. However, the current HABs monitoring programs largely rely on regular funding from governmental agencies and/or volunteering efforts from the communities for collecting water samples and conducting biochemical testing. Such programs are often constrained by limited spatial coverage, sample size, and sampling frequency due to formidable financial and labor costs (Lomax et al. 2005; Palmer et al. 2015). Therefore, monitoring the conditions of HABs using cost-effective tools

Research Implications

- A UAV-based workflow was developed to monitor harmful algae blooms in two small lakes in Southern Illinois.
- Spectral indices such as NDVI and blue-to-green band ratio have proven to be useful indicators for HABs monitoring.
- The relationships between chlorophyll-*a* and spectral indices vary by waterbodies.
- The flexibility and low cost of UAVs allow cost-effective community-based HABs monitoring programs.

is critical to develop coping strategies to mitigate and manage their outbreaks.

Remote sensing has proven to be an effective tool for monitoring toxic algal blooms over large water bodies (Anderson 2009). As chlorophyll-*a* (Chl-*a*) is a typical estimator of phytoplankton biomass (Huot et al. 2007; Kasprzak et al. 2008), remote sensing provides a cost-effective solution to monitor HABs conditions by evaluating spectral signatures of Chl-*a* (Kubiak et al. 2016). Conventionally, the monitoring approach was mainly implemented using satellite remote sensing imagery (Matthews 2014). Wolny et al. (2020) detected HABs in the Chesapeake Bay using multispectral data products from Sentinel-3 satellites and identified HABs species based on *in-situ* phytoplankton data and ecological characteristics including salinity/temperature regimes, nutrient preferences, time of year, and locations within the Chesapeake Bay. Ma et al. (2021) propose a multi-source remote sensing approach for HABs monitoring in Chaohu Lake, China, which integrates MODIS, Landsat 8 OLI, and Sentinel-2A/B. However, the reliability of most satellite-based models is subject to a few limitations, including low spatial resolution (e.g., 30-meter for Landsat and 500-meter for MODIS images), relatively long revisiting flyover periods (e.g., ~15 days for Landsat), uncertainties of image quality associated with clouds, and formidable costs of high-quality images (Lomax et al. 2005).

Unmanned Aerial Vehicles (UAVs), also known as drones, or unmanned aircraft system (UAS), have been increasingly utilized in HABs monitoring in the recent decade (Wu et al. 2019). Compared with satellite platforms, they have demonstrated a few unique advantages for HABs monitoring including high spatial resolution (in the scale of centimeters), flexible scheduling, and customizable combined spectral properties (e.g., coupling different optical and/or thermal sensors) (Kislik et al. 2018; Manfreda et al. 2018). As an emerging alternative to satellite-based monitoring, UAVs, equipped with multispectral sensors, have demonstrated successful cases in monitoring algal blooms. Fráter et al. (2015) found that UAVs allow identification of gradual growth of algae that is hard to observe onshore. Lyu et al. (2017) established a HABs monitoring framework using a UAV, which allows responsive monitoring of algae blooms. Kim et al. (2021) used a UAV to successfully develop three spectral indices for monitoring algae in a stream. However, most of these projects were conducted in a single water body without intercomparing spectral responses from different waters.

In this context, the objective of this project is to develop UAV-based monitoring models that can be used to monitor the HABs in two different lakes in Southern Illinois. We developed vegetation indices based on spectrum bands collected by a UAV and established a remote sensing inversion model that can statistically relate the spectral characteristics of UAV images to algae biomass. By comparing models with different vegetation indices, we determine the best-fit models for monitoring HABs.

Methodology

General Workflow

Figure 1 shows the general workflow of UAV-based HABs monitoring. First, we collected water samples from locations near the shorelines of the proposed water bodies. Those water sampling locations were clearly marked using permanent marks that were recognizable from drone images. Second, a DJI Phantom Matrice-100 with an onboard MicaSense RedEdge-MX multispectral sensor was used to capture the images of water bodies in five bands that can be used to derive spectral indices. Third, linear regression models were used to establish the relationships between the Chl-*a* biomass indicators and spectral indices.

Study Area

Carbondale Reservoir and the Campus Lake, both located near or at Southern Illinois University (SIU), were selected for developing the UAV-based monitoring procedure. Two sampling points from each water body were selected and labeled as Site 1 and 2. Table 1 and Figure 2 show the locations of these water sampling sites for statistical analysis.

Data Collection

Our datasets include (1) 5-band UAV images collected from May to October 2021 (Bands: Red, Green, Blue, Near Infrared, Red Edge), and (2) water samples for testing Chl-*a* (unit µg/L) that

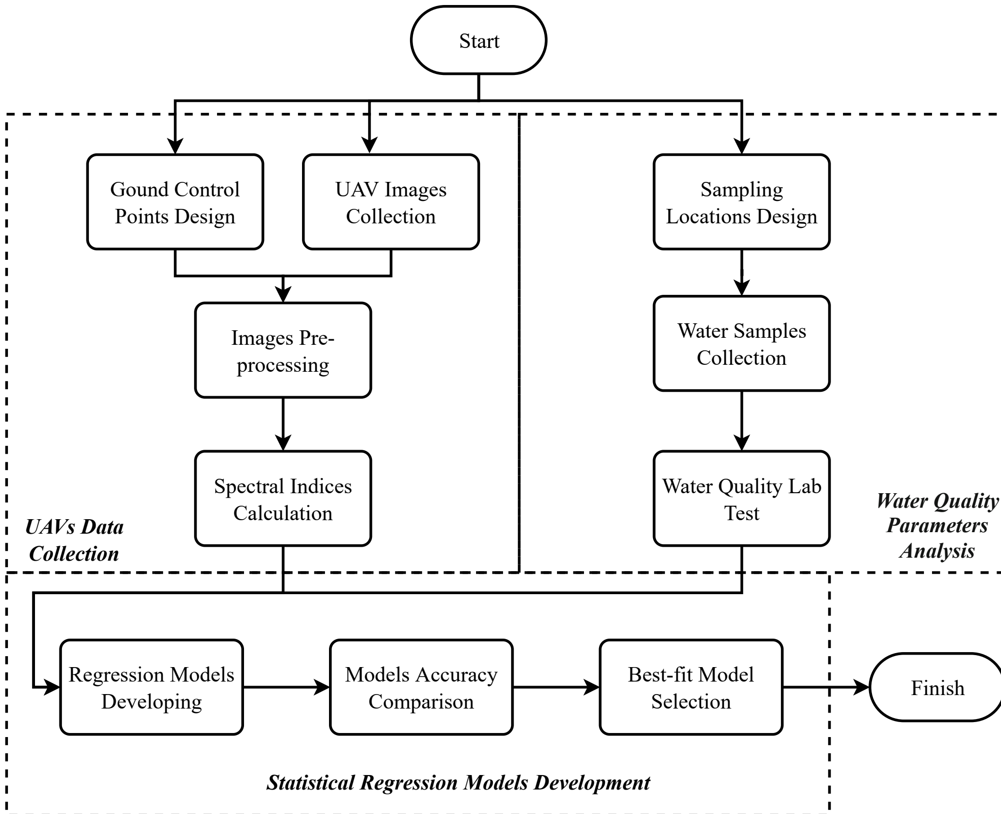


Figure 1. General workflow for developing statistical HABs predictive models.

were collected at the same time with the UAV images collection.

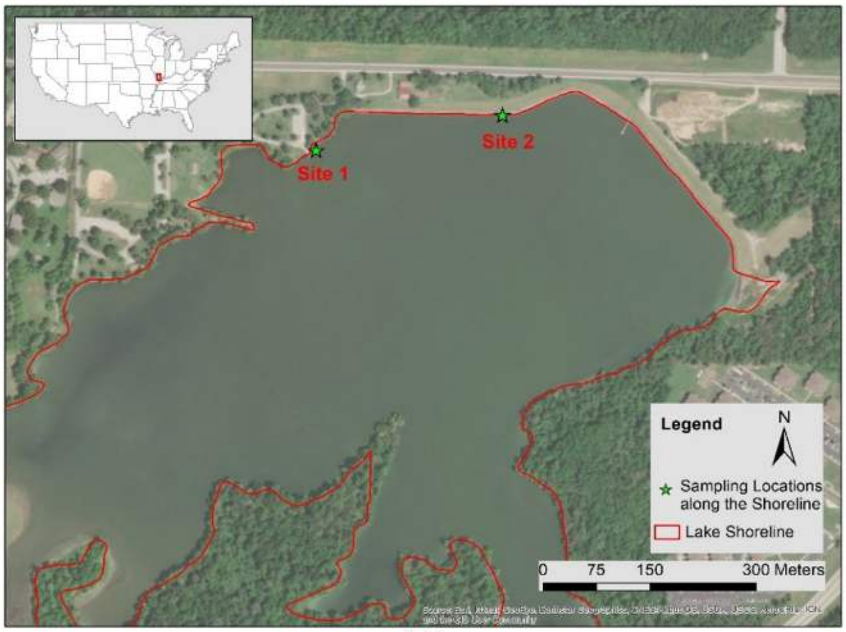
UAV Images Collection. A DJI Phantom UAS equipped with a multispectral sensor, RedEdge-MX, was used to collect aerial images in five spectral bands (Figure 3). As a professional multispectral camera, RedEdge-MX is capable of simultaneously capturing Blue (B, 475 nm ± 20 nm), Green (G, 560 nm ± 20 nm), Red (R, 668 nm ± 10 nm), Near infrared (NIR, 840 nm ± 40 nm), and Red Edge (RE, 717 nm ± 10 nm) bands with 1280 x 960 pixels. Figure 4 shows the spectral reflectance of five image bands at those water sampling sites.

Determination of Chl-a Concentration. Water samples were collected at each labelled location. Water sampler (dipper) and glass bottles autoclaved at 121°C were used to collect samples from the shoreline of the lake at ~ 0.5 m depth. Sampling was conducted once per month from March 2021 to October 2021. After collecting samples, they were stored at 4°C in glass bottles for lab tests. Chl-*a* concentrations of the water samples were measured to determine the biomass of algal species.

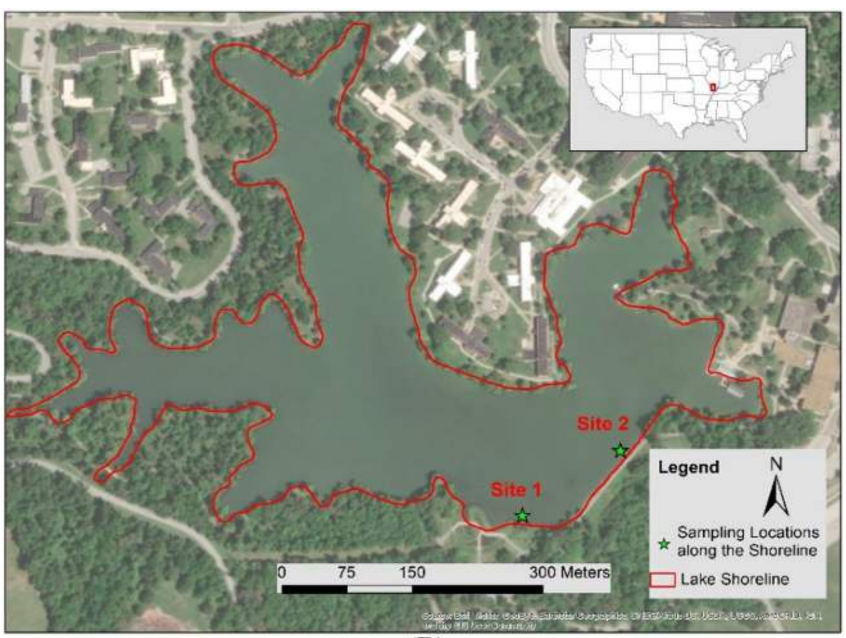
The Chl-*a* concentration was determined by a UV-vis spectrophotometer (Thermo BioMate 3S) based on a method from literature (Sartory 1982). Briefly, water samples of varying volumes (volume ranging from 20 mL to 400 mL) were filtered in 0.45 µm nitrocellulose membrane filters to collect wet algae samples. Filter paper was then rolled and placed into a 15 mL centrifuge tube. Freshly prepared 95% ethanol of 10 mL was added to each tube. The tube was then kept in a water bath at 78°C (boiling point of ethanol) and was boiled for 5 min at that temperature. The tube was then removed from the water bath and kept in the dark for 24 h at room temperature. After 24 h, it was centrifuged at 4000 rpm for 5 min. From the tube, 4 mL of the supernatant was taken into a 1 cm pathlength cuvette and was placed in a UV-vis spectrophotometer. Solvent (95% ethanol) was used as the blank. Peak absorbance reading was taken at 665 nm. Then the sample was acidified in the cuvette by adding 120 µL of 0.1 mol/L HCl solution. The cuvette was

Table 1. Sampling locations for developing statistical models.

Location		Latitude	Longitude
Carbondale Reservoir	Site 1	37° 41' 58.5" N	89° 13' 45.5" W
	Site 2	37°42' 00.5" N	89°13' 32.7" W
Campus Lake	Site 1	37°42' 27.5" N	89°13' 29.1" W
	Site 2	37°42' 29.1" N	89°13' 24.7" W



(A)



(B)

Figure 2. Location maps for Carbondale Reservoir (A) and the Campus Lake (B).

shaken and after 4 min, the absorbance was re-read by scanning for the peak between 664 and 666 nm.

The following equation was used to calculate the concentration of Chl-*a* from the absorbance reading:

$$\textit{Chlorophyll-a concentration}\ (\mathrm{mgL^{-1}}) = (\mathcal{E}_{665,0} - \mathcal{E}_{665,a}) \times \frac{R}{R-1} \times \frac{K}{L} \times \frac{V_{extract}}{V_{sample}}$$

where:

- $\mathcal{E}_{665,0}$ is the absorbance at 665 nm before acidification;
- $\mathcal{E}_{665,a}$ is the absorbance at 665 nm after acidification;
- R is acid ratio;
- K is absorbance coefficient of Chl-*a* in ethanol, which equals to 1000/(*specific absorption coefficient*);
- L is pathlength of cuvette (1 cm);
- $V_{extract}$ is volume of extract used as solvent in liters (10 mL, i.e., 0.01 L); and
- V_{sample} is volume of water sample filtered in liters.

An acid ratio of 1.72 and a specific absorption coefficient of 83.6 $\mathrm{L(g{\cdot}cm)^{-1}}$ have been used for ethanol extraction.

UAV Image Processing and Spectral Indices Calculation

Pix4Dmapper image processing software was used to automatically conduct the image stitching,

Figure 3. The UAV equipment used for data collection.

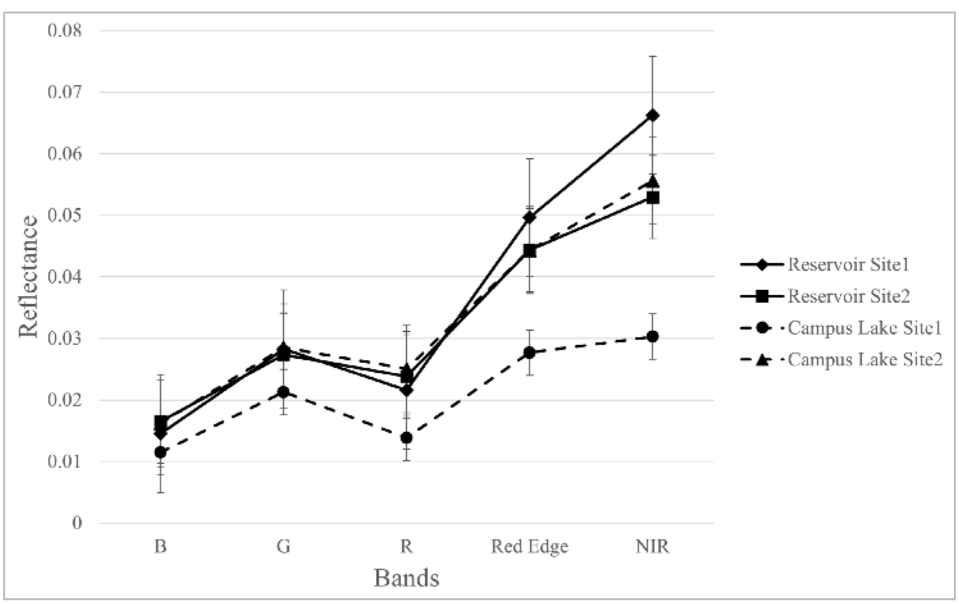


Figure 4. Spectral reflectance from each UAV image band.

radiometric calibration, and orthoimage generation. To fix the potential geometric distortion and topographic displacement, eight Ground Control Points (GCPs) for each lake were set up and applied for polynomial image correction. The original calibration panel accompanying the multispectral sensor was used for radiometric correction. The examples of stitched images from both lakes are shown in Figure 5.

Then ArcGIS georeferencing tool was used to assign the ground truth coordinates to matched pixels on stitched UAV images. The spectral values of image pixels at water sampling sites were extracted using the ArcGIS Spatial Analyst toolset. Seven indices were used to estimate the relationships between Chl-*a* and spectral indices. As shown in Table 2, these UAV-derived spectral indices have been applied in different HABs monitoring projects based on reports in the literature.

Statistical Regression Models Development

Linear regression models describe a continuous response variable as a function of one or more predictor variables, which are commonly applied to analyze environmental data and predict the dynamics of an ecosystem. In this paper, linear regression models were used to establish the relationships between Chl-*a* and the spectral indices. For each index, simple linear regression was applied with its values as independent variables to estimate the correlation with concentrations of Chl-*a*. The performance of each model was evaluated by Coefficient of Determination (R^2). A best-fit model was identified to determine the best-fit spectral indices for HABs monitoring. Based on

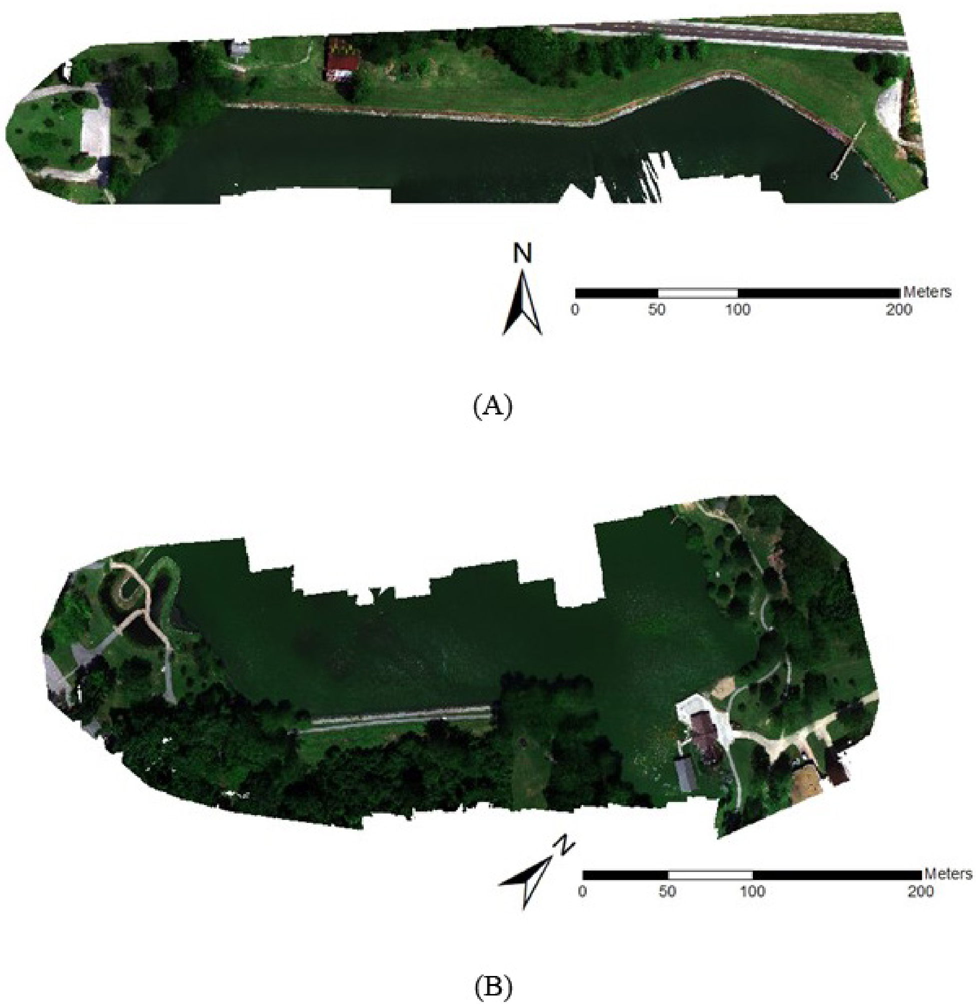


Figure 5. Stitched UAV images from Carbondale Reservoir (A) and the Campus Lake (B).

Table 2. Spectral indices used to estimate Chl-*a* according to relevant literature.

Index	Name	Formula	Reference
NDVI	Normalized Difference Vegetation Index	$\frac{NIR - Red}{NIR + Red}$	Cai et al. 2021
BNDVI	Blue Normalized Difference Vegetation Index	$\frac{NIR - Blue}{NIR + Blue}$	Van der Merwe and Price 2015
GNDVI	Green Normalized Difference Vegetation Index	$\frac{NIR - Green}{NIR + Green}$	Goldberg et al. 2016
NDRE	Normalized Difference Red Edge	$\frac{NIR - Red\ Edge}{NIR + Red\ Edge}$	Song and Park 2020
RVI	Ration Vegetation Index	$\frac{NIR}{Red}$	Han and Rundquist 1997
CVI	Chlorophyll Vegetation Index	$\frac{NIR * Red}{Green^2}$	Balogun et al. 2020
B/G	Band Ratio	$\frac{Blue}{Green}$	Zeng et al. 2016

the best-fit model, the Chl-*a* concentration can be predicted from the UAV-based spectral indices.

Results and Discussion

Table 3 shows a summary of goodness-of-fit for linear regression models with different spectral indices. It was found that NDVI, BNDVI, GNDVI, and RVI exhibit significant positive relationships with the concentrations of Chl-*a* in Carbondale Reservoir. In particular, NDVI was used to establish the best-fit model based on the coefficients of determination (R^2 = 0.4881, Figure 6a). As high chlorophyll concentration reflects more near-infrared light but absorbs more red light, NDVI, measuring the contrast between NIR and red light, would increase when the algae (chlorophyll) density increases. That makes NDVI become a sensitive indicator of lake algae greenness. For the Campus Lake, most spectral indices exhibit no statistically significant relationship except for NDRE (R^2 = 0.4674) and B/G (R^2 = 0.3915), which present significant inverse relationships with Chl-*a* (Figure 6b).

The positive relationship between NDVI and Chl-*a* identified in Carbondale Reservoir is consistent with most literature (Zhang et al. 2011; Goldberg et al. 2016; Salarux and Kaewplang 2020; Ma et al. 2021). The inverse relationship between B/G and Chl-*a* found in the Campus Lake is consistent with Piech et al. (1978), Woźniak and Stramski (2004), and Zeng et al. (2016). Kim et al. (2021) show that the spectral index NDRE had an insignificant statistical relationship for water quality monitoring. Song and Park (2020) did not see the significant change of NDRE when aquatic plants had proliferated. However, Che et al. (2021) proved that the strong and positive correlations existed between *Pyropia yezoensis* (a type of red macroalgae) biomass and NDRE. Therefore, blue-to-green reflectance ratio is deemed as the best-fit model predictor of Chl-*a* for the Campus Lake (Figure 6b).

In addition, Figure 6 indicates that the relationships between spectral indices and Chl-*a* vary at different lakes. Piech et al. (1978) attributed such inter-lake variations to different trophic status. Different phytoplankton community and water constituents like chromophoric dissolved organic matter (CDOM) or mineral particles could also be the potential factors as they could modulate specific

Table 3. Statistical relationships between each spectral index and Chl-*a* (*p-value < 0.05).

Lake	Spectral Index	R Square	p-value (α = 0.05)
Carbondale Reservoir	NDVI	0.4881	0.0115*
	BNDVI	0.4262	0.0214*
	GNDVI	0.3932	0.0291*
	NDRE	0.1809	0.2204
	RVI	0.4137	0.0241*
	CVI	0.1871	0.1602
	B/G	0.0280	0.6033
Campus Lake	NDVI	0.1009	0.3143
	BNDVI	0.0873	0.3511
	GNDVI	0.2190	0.1249
	NDRE	0.4674	0.0142*
	RVI	0.0970	0.3243
	CVI	0.1434	0.2247
	B/G	0.3915	0.0295*

spectral reflectance patterns and refractive indices (Woźniak and Stramski 2004; Zeng et al. 2016).

There are a few limitations to note in this project. First, we only collected water samples from two near-shore locations from each lake due to budget constraints in this concept-proof project. In this case, water sampling sites do not necessarily represent the conditions in the entire water bodies. Rather, the variabilities of tested and modeled Chl-*a* more reflect the temporal patterns of water quality. The small sample size could also limit the accuracy of regression models, since it may not have sufficient statistical power to detect significant relationships between Chl-*a* and spectral indices. To overcome the limitations, future research will be designed to expand to larger sample sizes and more sampling locations.

Conclusions and Policy Implications

UAVs, as an emerging remote sensing technique, have proven to be cost-efficient, flexible, and reliable tools for environmental monitoring in open waterbodies. This study shows the effectiveness and robustness of a UAV and its onboard multispectral sensor for monitoring HABs in two waterbodies from Southern Illinois. Seven vegetation indices were tested for estimating algae biomass in Carbondale Reservoir and the Campus Lake of SIU. Results show that the specific relationships between algae biomass (Chl-*a*) and vegetation indices vary by different waterbodies, which is likely due to the complex compositions of each lake. NDVI was found to be the best-fit spectral index for Carbondale Reservoir, while Blue-Green ratio was the best predictor for the Campus Lake of SIU. In our future work, we plan to substantially expand the number of water sampling locations and increase the sample size in each location. We expect to further examine and verify these statistical relationships that may be directly applied for UVA-based HABs monitoring.

With increasing anthropogenic activities, HABs have become one of the major water quality problems that harass communities around the world. There are critical needs for monitoring the onset and progress of HABs for public safety. However, due to funding limitations, many small water bodies that have been intensively used for drinking and recreation by communities were largely uncovered

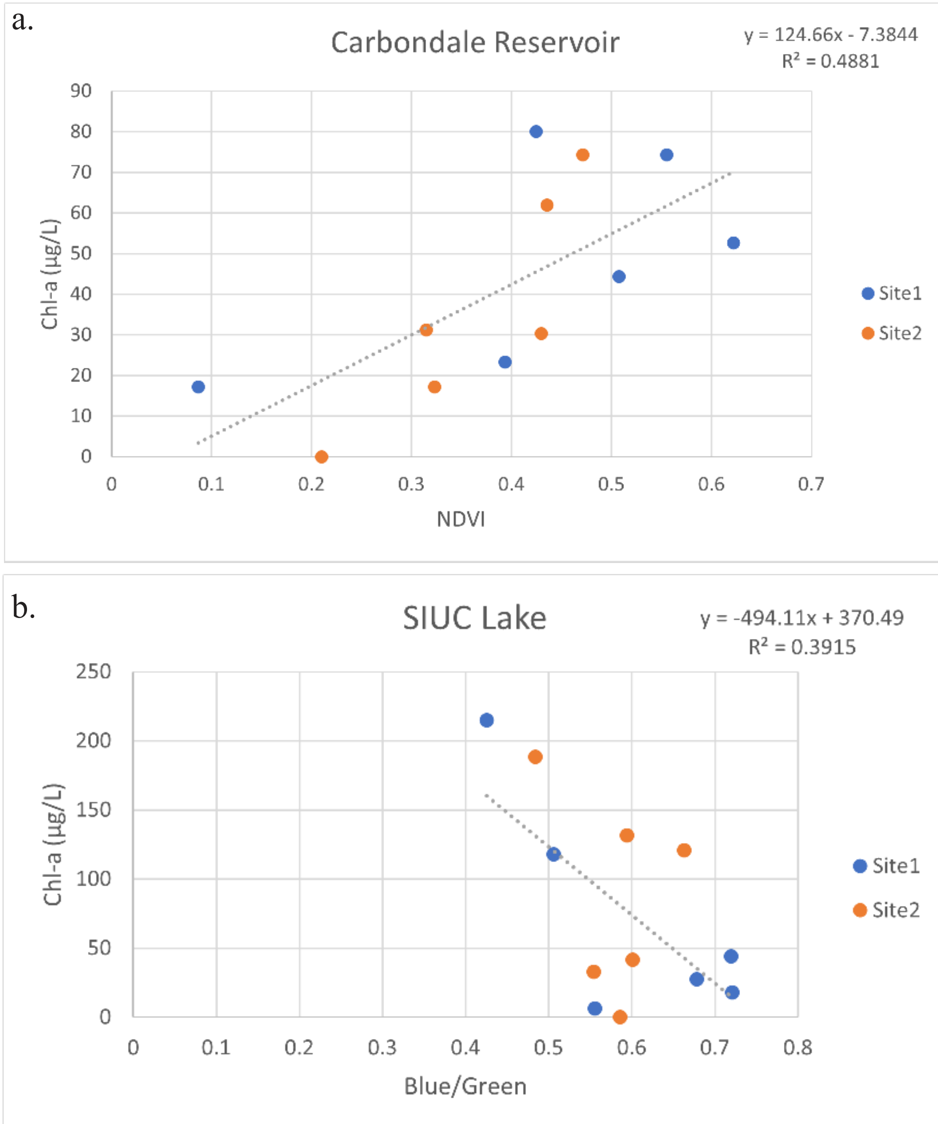


Figure 6. Selected linear regression models that characterize the relationships between spectral indices and Chl-*a* in two lakes.

by government-initiative monitoring programs. Due to its flexibility and lower operational cost, multispectral UAVs have shown tremendous potential for developing community-based HABs monitoring programs that may be operated by local municipalities or even homeowner organizations. It may serve as one of the promising solutions to the 'last mile' problem of broader policies for ensuring public water safety (Cheng 2015; Da Mata et al. 2021). In combination with emerging water technologies such as water treatment using magnetic nanomaterials under solar light (Madany et al. 2021), a UAV-based monitoring program may be used to guide *in-situ*, low-cost treatment of areas with high HABs concentrations. In addition, drone-based HABs monitoring programs can be potentially integrated with existing governmental funding programs as a supplemental monitoring effort. For example, such a program may be integrated with the Harmful Algal Bloom Program and the Volunteer Lake Monitoring Program in Illinois.

Acknowledgements

This research was sponsored by a 104b grant from the DOI USGS Water Resources Research Act program via Illinois Water Resources Center. It was also partially funded by the U.S. Environmental Protection Agency (SU84017401). The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the funding agencies.

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