

Can low-cost autonomous drones detect early algal blooms as accurately as satellites?

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Abstract

Harmful algal blooms can make drinking water and recreational water unsafe for people and wildlife. Satellites can monitor large areas, but their images may miss small blooms near shore. This project asks whether a low-cost autonomous Crazyflie drone equipped with an AI Deck can detect early algal blooms as accurately as satellites. The drone was built as a proof of concept for autonomous, close-range image collection and processing. To create a satellite benchmark, California bloom records and satellite products were combined with field measurements from the Water Quality Portal. The field data included 5,160 chlorophyll-a and 2,864 phycocyanin measurements which indicate algae growth, and 1,630 microcystin results, which is a dangerous toxin produced by some blooms from California lakes and reservoirs. After carefully matching measurements taken from the same lake on the same date, the satellite data showed a moderate correlations with field chlorophyll ($\rho = 0.53$) and phycocyanin ($\rho = 0.65$), but a weaker correlation with microcystin ($\rho = 0.22$). These findings indicate that satellite and drone images may help detect where algae are growing but cannot determine whether the water contains dangerous toxin levels. Most matched observations came from Clear Lake, so more testing is needed in other California lakes. The results support using drones for detailed local imaging, and laboratory samples for toxin confirmation. Code availability: <https://github.com/s1010101111101/algae-drone>.

Introduction

Harmful algal blooms occur when algae or cyanobacteria grow rapidly in a body of water. In freshwater lakes and reservoirs, these blooms can reduce water quality, harm aquatic ecosystems, and make recreational or drinking water unsafe [5]. Some cyanobacteria can also produce toxins such as microcystins, which can be harmful to humans and animals. Detecting blooms early is therefore important because it can help water managers identify affected areas before the bloom becomes more severe.

One important method for monitoring algal blooms is satellite remote sensing. Satellites can repeatedly observe lakes over large geographic areas and detect changes in the light reflected from the water. These measurements can be used to estimate indicators of algal growth, such as chlorophyll-a and cyanobacteria-related pigments [3, 4]. This makes satellites useful for monitoring many water bodies at once. However, satellite observations also have limitations. Clouds can block the view of the water, and the spatial resolution of satellite images can make it difficult to observe small blooms or detailed changes close to the shoreline [4].

Drones can provide a complementary way to monitor these areas. A drone can fly much closer to the water surface and collect images at a much finer spatial scale than a satellite. Here we investigate whether a low-cost autonomous drone could be used as a local monitoring tool for early algal blooms. The system is based on the Bitcraze Crazyflie 2.1+ equipped with an AI Deck, which provides a camera and an onboard processor that can support image collection and artificial-intelligence applications [1]. The drone is developed as a proof of concept for autonomous, close-range observation. Satellite measurements are compared with field measurements

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of chlorophyll-a, phycocyanin, and microcystin from California lakes and reservoirs to establish how accurately remote sensing reflects actual water conditions. This comparison provides a benchmark for evaluating where a small autonomous drone could complement satellite monitoring, particularly for localized or near-shore blooms that may require more detailed observation.

Methods

Hovering the drone

To hover at a set height, the Bitcraze Crazyflie 2.1+[2] uses a Proportional-Derivative (PD) controller loop that was implemented into the firmware of the drone. The loop starts with raw data from the sensors, namely the Optical Flow sensor, which measures horizontal velocity (v_x, v_y) , and the Time-of-Flight (ToF) sensor, which shoots a laser at the ground to measure the height of the drone (z_s) . These two sensors are housed in the Flow Deck v2, an expansion board for the Crazyflie 2.1+ drone.

The raw data was then refined through a Kalman filter to produce two numbers; estimated height $(\hat{z})$ and estimated velocity $(\hat{v})$ using information from an onboard Inertial Measurement Unit (IMU), which measures acceleration and angular velocity. The filter estimates the height by using the formula below:

$$\hat{z} = z_p + k(z_s - z_p) \quad (1)$$

where z_p is the height according to the IMU, z_s is the height according to the ToF sensor, and k is the Kalman gain, formulated as:

$$k = \frac{\sigma_p}{\sigma_p + \sigma_s} \quad (2)$$

where σ_p is the uncertainty of the IMU, and σ_s is the uncertainty of the ToF sensor.

Using the IMU and the ToF sensor, velocity can be estimated using kinematic equations. The first step in the prediction phase is written as:

$$v_p = v_i + at \quad (3)$$

where v_p is the velocity according to the IMU, v_i is the previous velocity according to the IMU, a is the acceleration, and t is the time interval. The second step in the prediction phase is started by using the formula below:

$$z_p = z_i + v_i t + \frac{1}{2}at^2 \quad (4)$$

where z_p is the height according to the IMU, z_i is the previous height according to the IMU, v_i is the previous velocity according to the IMU, a is the acceleration, and t is the time interval.

Finally, to estimate the velocity and correct the prediction, the following formula is used:

$$\hat{v} = v_p + k_v(z_s - z_p) \quad (5)$$

where $\hat{v}$ is the estimated velocity, v_p is the velocity according to the IMU, k_v is the velocity Kalman gain, z_s is the height according to the ToF sensor, and z_p is the height according to the IMU.

With having found $\hat{z}$ and $\hat{v}$, the drone implements them into the PD Controller:

$$T = mg - k_p(\hat{z} - z_0) - k_v(\hat{v}) \quad (6)$$

where T is thrust, m is mass, g is acceleration due to gravity, $\hat{z}$ is the estimated height, $\hat{v}$ is the estimated velocity, and k_p and k_v are the proportional and derivative gains.

The resulting thrust command is then converted into a signal for the motors of the drone to follow, changing their RPM and causing the drone to move accordingly. Now that the drone is in a different position, this process repeats in a loop until the target height is reached.

To function efficiently, the drone must be in a specific environment, detailed by a textured surface so that the optical flow sensor has physical contrast, and a non-reflective surface so as to not interfere with the laser from the ToF sensor.

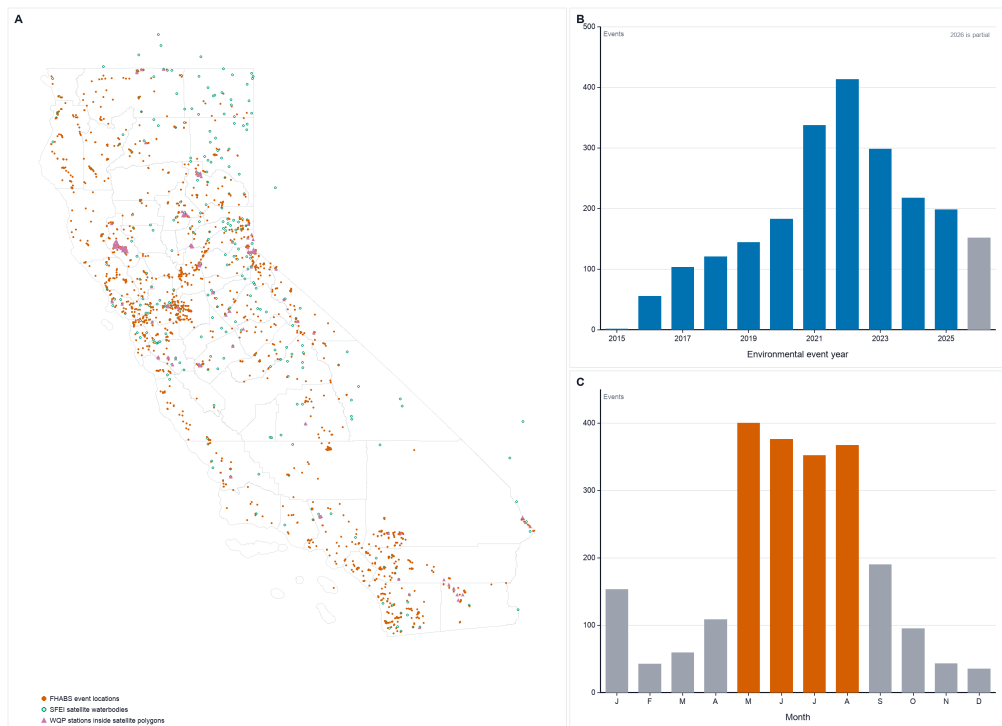


Figure 1: (A) Locations of reported bloom events, satellite-monitored waterbodies, and field-monitoring stations. (B) Number of reported events by year; 2026 is incomplete. (C) Reports were most common from May through August.

Results

Figure 1 shows the locations and timing of reported harmful algal blooms in California. Bloom events, satellite-monitored waterbodies, and field-monitoring stations were spread across the state, although monitoring was more concentrated in some regions than others (Figure 1A). The number of reported bloom events increased over the study period and reached its highest level in 2022 (Figure 1B). The lower count in 2026 should not be interpreted as a decrease because data collection for that year was incomplete. Bloom reports also followed a clear seasonal pattern. Most events were reported from May through August, while fewer were reported during the winter months (Figure 1C).

I next compared field measurements with satellite observations from the same waterbody and date. As shown in Figure 2A–C, higher field concentrations of chlorophyll-a and phycocyanin were generally associated with higher satellite values. However, there was considerable variation among individual measurements. The agreement was strongest for phycocyanin, with a Spearman correlation of $\rho = 0.65$ ($n = 178$). Chlorophyll-a showed a moderate correlation of $\rho = 0.53$ ($n = 293$). Microcystin showed a much weaker correlation of $\rho = 0.22$ ($n = 114$). The confidence intervals in Figure 2D support the same overall result: satellite observations agreed more closely with indicators of algal growth than with the measured toxin concentration.

Figure 3 examines whether satellite observations could identify unusually high field measurements before the sampling date. Field measurements were separated into the highest 25% and the remaining 75%. Seven days before field sampling, satellite data distinguished these two groups best for phycocyanin, with an area under the curve (AUC) of 0.82 (Figure 3A). The corresponding AUC values were 0.66 for microcystin and 0.57 for chlorophyll-a. An AUC of 0.5 represents chance-level performance. Satellite values around high-phycocyanin dates were consistently higher than those around the remaining dates (Figure 3C). The separation was smaller for chlorophyll-a

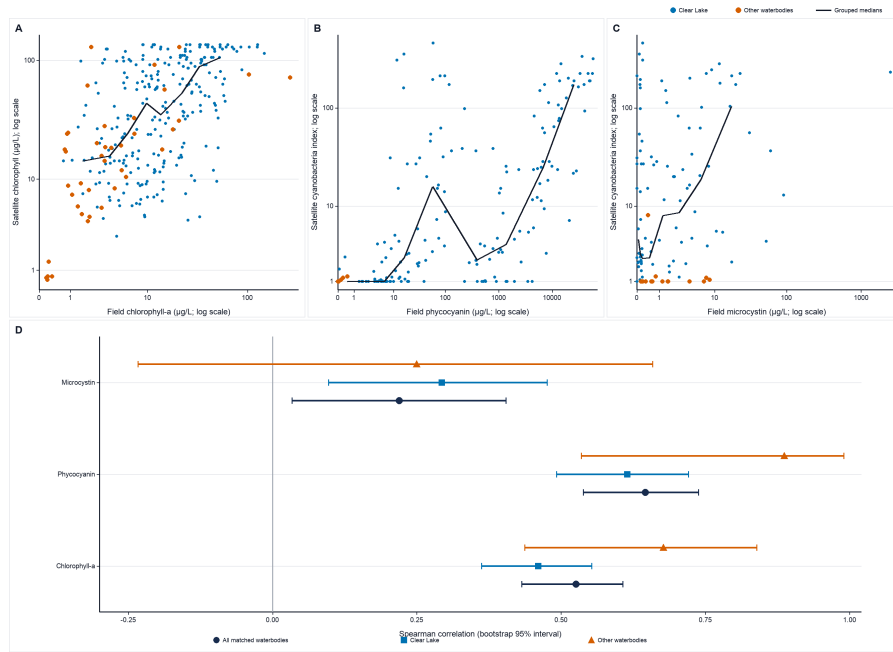


Figure 2: (A–C) Chlorophyll-a, phycocyanin, and microcystin measurements are compared with the satellite value for the same waterbody and sampling date. The satellite value comes from the rolling 7-day maximum ending on that date. The black curve summarizes the overall pattern: field measurements are divided into eight roughly equal-sized groups from low to high concentration, and the curve connects the median field and satellite values in each group. (D) The satellite data agreed more closely with chlorophyll-a and phycocyanin than with microcystin. Points and intervals show Spearman correlations and 95% bootstrap intervals.

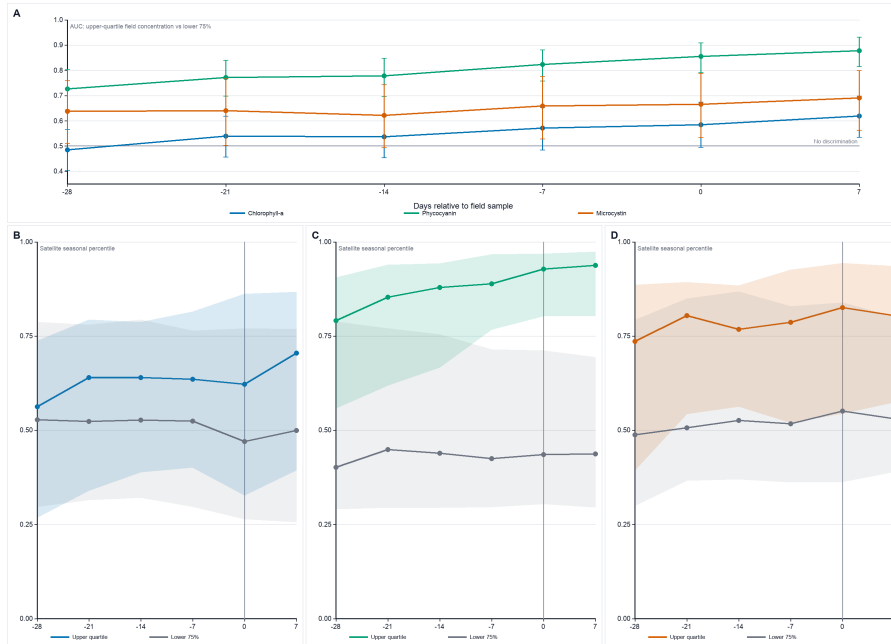


Figure 3: For each water-quality measure, field measurements were divided into the highest 25% and the remaining 75%. (A) A value of 0.5 means that the satellite could not distinguish the two groups better than chance. Seven days before field sampling, the satellite distinguished the groups best for phycocyanin (0.82), followed by microcystin (0.66) and chlorophyll-a (0.57). (B–D) Colored lines show satellite values around dates in the highest 25%; gray lines show values around the remaining dates. Negative days occur before field sampling, and the shaded areas show the middle half of the observations.

and microcystin (Figure 3B,D).

Clear Lake provided most of the matched field and satellite observations and was therefore examined in more detail. Figure 4A shows the locations of reported bloom events and field-monitoring stations within the satellite boundary. During 2021, periods with high satellite cyanobacteria values often occurred near periods with high field phycocyanin values (Figure 4B). The agreement with field microcystin measurements was less consistent (Figure 4C). This example supports the larger statewide comparison: remote sensing can help identify increased cyanobacterial growth, but it is less reliable for estimating toxin levels.

Conclusion

This project examined whether remote sensing can support the early detection of harmful algal blooms and provide a benchmark for a low-cost autonomous drone system. Satellite measurements showed moderate agreement with field chlorophyll-a and phycocyanin measurements, which are indicators of algal growth. The strongest relationship was found for phycocyanin. Satellite observations could also identify unusually high phycocyanin levels several days before field sampling.

However, satellite measurements showed only a weak relationship with microcystin. This means that remote images may help locate areas where cyanobacteria are growing, but they cannot reliably determine whether the water contains dangerous toxin levels. Laboratory testing is therefore still necessary to confirm whether a bloom is toxic.

The Crazyflie drone was developed as a proof of concept for autonomous, close-range monitoring. Its small size and camera could make it useful for examining near-shore areas and small blooms that satellites may miss. Future work should collect drone images over several lakes, train

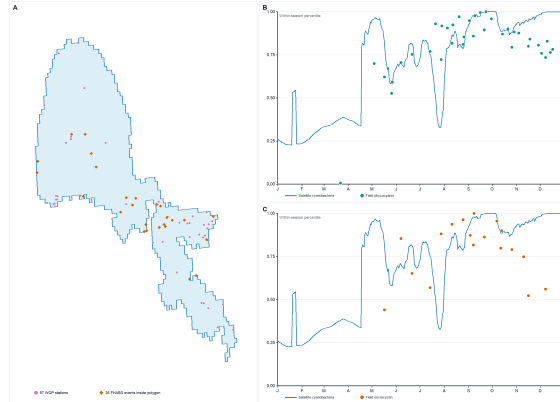


Figure 4: (A) Locations of field-monitoring stations and reported bloom events within the Clear Lake satellite boundary. (B) Satellite cyanobacteria and field phycocyanin measurements during 2021. (C) Satellite cyanobacteria and field microcystin measurements during 2021. Values are shown on a scale from 0 to 1. A value near 1 means that the measurement was high compared with other measurements of the same type and season.

an image model to recognize bloom conditions, and compare its predictions with satellite observations and laboratory samples. A combined system using satellites for broad monitoring, drones for detailed local imaging, and laboratory tests for toxin confirmation may provide a practical approach to early bloom detection.

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