

Advantages of Hyperspectral Remote Sensing for Harmful Algal Bloom Detection

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Abstract

Harmful algal blooms (HABs) pose a growing threat to aquatic ecosystems, human health, and economies worldwide. Climate change and nutrient enrichment have driven an increase in both the size and frequency of blooms, making accurate observation more urgent than ever. Remote sensing has become a critical tool for monitoring HABs, yet commonly used multispectral instruments such as MODIS, Landsat, and Sentinel face major limitations. Their coarse spatial resolution prevents reliable observation in smaller inland waters, long revisit times restrict timely monitoring, and limited spectral bands reduce the ability to discriminate key pigments like chlorophyll a and phycocyanin. In contrast, hyperspectral sensors capture hundreds of narrow, contiguous bands at higher spatial, temporal, and radiometric resolutions, enabling the detection of subtle phytoplankton characteristics and bloom dynamics across diverse environments. Hyperspectral imagers mounted on unmanned aerial systems further provide near-daily data collection, making them especially effective for tracking bloom evolution. While forecasting remains an emerging application, hyperspectral observation offers the clearest path forward for improving HAB detection and monitoring. This paper reviews the advantages of hyperspectral remote sensing over multispectral approaches and argues for its adoption as an essential technology in safeguarding aquatic health and mitigating the rising global risk of HABs.

Keywords

Harmful Algal Blooms, Remote Sensing, Hyperspectral, Oceanography, UAVs

1. Introduction

A dangerous trend has emerged in water bodies across the globe. Climate change,

nutrient enrichment, and ocean acidification have made harmful algal blooms (HABs) increasingly common, leading to mass wildlife deaths, human health crises, and severe economic losses (Imai et al., 2021; Zhan et al., 2021). These events damage aquatic ecosystems by creating hypoxic “dead zones” where most organisms cannot survive (Jewell & McCarty, 1971; Dybas, 2005), and they release cyanotoxins, such as microcystins, that are harmful to both people and wildlife (Loftin et al., 2016). The economic consequences are equally serious: Florida alone lost an estimated 2.7 billion dollars in tourist revenue due to red tide HABs (Alvarez et al., 2024).

Harmful algal blooms impose multi-sector costs at global scale, spanning capture fisheries, aquaculture, drinking-water treatment, public health, and coastal tourism. Regional assessments from North America, Europe, and Asia routinely report year-to-year losses that reach into the multi-million to billion range when closures, mitigation, and healthcare are accounted for (Imai et al., 2021). These impacts are amplified by warming waters, extreme rainfall, and nutrient enrichment, underscoring the need for monitoring approaches that are both species-sensitive and operationally scalable across diverse optical water types (Dai et al., 2023).

To address these threats, scientists increasingly rely on remote sensing to observe HABs at large scales. Remote sensing allows for the detection of algal pigments, surface temperature, and water quality indicators across oceans, lakes, and rivers (Uz et al., 2020). Multispectral instruments such as MODIS, Landsat, and Sentinel have been widely used in monitoring programs (Moutier et al., 2019; Liu et al., 2021). While valuable for long-term observation, these sensors face major limitations: coarse spatial resolution that prevents effective monitoring of small inland waters, revisit times too long to track rapidly changing blooms, and restricted spectral bands that cannot reliably identify diagnostic pigments such as phycocyanin (Xu et al., 2021; Isenstein et al., 2014; Torbick & Corbiere, 2015).

Hyperspectral remote sensing offers a solution. By capturing hundreds of narrow, contiguous spectral bands, hyperspectral instruments provide superior discrimination of algal pigments, higher spatial and temporal resolution, and greater resilience to atmospheric interference (Hunter et al., 2010; Becker et al., 2019; Meng et al., 2021). Mounted on unmanned aerial systems, hyperspectral sensors can even provide near-daily coverage of dynamic bloom events (Mitchell et al., 2012). These advantages allow researchers to identify HABs earlier and with greater accuracy than multispectral methods.

This paper reviews existing studies comparing multispectral and hyperspectral approaches for monitoring HABs and argues that hyperspectral sensing is the superior method for harmful algal bloom observation. While forecasting remains an emerging application, this paper focuses primarily on the clear advantages of hyperspectral sensors for detecting, tracking, and understanding HABs in diverse aquatic environments.

2. Understanding Harmful Algal Blooms

2.1. Causes and Formation

Harmful algal blooms (HABs) are events in which a body of water undergoes eutrophication, leading to rapid algae growth over a short period. This growth has detrimental effects on aquatic life, human health, and local economies (Imai et al., 2021). Eutrophication occurs when excess nutrients accumulate in a water body, typically from fertilizers, sewage, or industrial waste, fueling uncontrolled algal growth (Paerl et al., 2001). While HABs can form naturally, the vast majority today are driven by human activity, combined with stressors such as changing atmospheric conditions, warming waters, and pollution (Zhan et al., 2021).

Several environmental drivers often interact to accelerate bloom formation. Warmer surface waters reduce vertical mixing and stratify lakes and coastal zones, locking nutrients in the upper layers where algae thrive. Heavy rainfall events flush more nitrogen and phosphorus into rivers and estuaries, while drought conditions reduce water flow, creating stagnant conditions that favor algal dominance. Once nutrient thresholds are crossed, these combined pressures promote rapid algal growth.

The effects of climate change are particularly concerning. Rising global temperatures and changing precipitation patterns create warmer, nutrient-rich conditions that favor algal growth. Harmful algal blooms have significantly increased in both size and frequency (Dai et al., 2023).

2.2. Ecological, Health, and Economic Impacts

As blooms grow and eventually decompose, they strip oxygen from the water, creating hypoxic or “dead zone” conditions where most aquatic organisms cannot survive (Dybas, 2005). Dead zones can span huge regions, impacting bodies of water such as the Chesapeake Bay, the Gulf of Mexico, and the Great Lakes. The ecological disruption reduces biodiversity and damages habitats essential to fisheries and coastal communities.

Cyanobacteria, the most common bloom-forming organisms, release microcystins and other cyanotoxins that are harmful to wildlife and people (Loftin et al., 2016; Sinha et al., 2021). While microcystins are not a major threat in healthy systems, their concentrations spike during HABs and can contaminate drinking water or cause illness when humans or animals come into contact with contaminated water. The most frequently observed cyanobacterial genera include *Microcystis*, *Anabaena*, *Aphanizomenon*, and *Planktothrix*, all of which have been associated with toxin outbreaks in lakes and reservoirs worldwide (Pelaez et al., 2009).

In marine environments, other algal groups dominate. Dinoflagellates such as *Karenia brevis* are responsible for the red tides common in the Gulf of Mexico, which cause mass fish kills, respiratory irritation in humans, and large economic losses to coastal communities. Similarly, blooms of *Noctiluca scintillans* produce red-orange discoloration in coastal waters and can disrupt food webs by over-

whelming planktonic ecosystems (Zhou et al., 2020). While the species involved differ between freshwater and marine environments, the risks they pose are similar: degraded ecosystems, toxin exposure, and heavy economic consequences.

3. Remote Sensing Approaches to HAB Monitoring

The increasing frequency and intensity of HABs highlight the urgent need for early detection and effective monitoring. Once a bloom reaches full strength, management options are costly and often ineffective. Preventive monitoring provides the best chance to protect ecosystems, safeguard public health, and limit economic losses.

Traditional in-situ monitoring, while valuable, is often too limited in scale and frequency to capture how blooms develop and spread. As HABs continue to escalate globally, it has become essential to explore advanced tools such as remote sensing, which allow researchers to observe large areas, identify bloom characteristics, and track changes over time (Uz et al., 2020). This growing need for scalable observation provides the foundation for comparing multispectral and hyperspectral sensing approaches in HAB research.

3.1. Fundamentals of Remote Sensing

Remote sensing is the science of collecting information about objects or areas from a distance, typically through satellites or airborne platforms (Aggarwal, 2004). In the context of harmful algal bloom (HAB) observation, remote sensing involves the detection of spectral signatures from aquatic environments, which can then be analyzed to infer water quality indicators such as chlorophyll-a, phycocyanin, sea surface temperature, and dissolved organic matter (Uz et al., 2020). These signatures are captured across discrete portions of the electromagnetic spectrum, known as spectral bands, ranging from visible light to the infrared and microwave regions (Chandra et al., 2022). Different types of algae possess unique optical properties that can be distinguished from surrounding water, making remote sensing particularly valuable for monitoring bloom extent and composition.

The effectiveness of a remote sensing system depends on four key forms of resolution: spatial, spectral, temporal, and radiometric. Spatial resolution determines the size of the area represented by a single pixel in an image, influencing the ability to detect blooms in smaller water bodies. MODIS, for example, provides spatial resolutions of 250 m, 500 m, and 1 km depending on the band, which is suitable for open-ocean monitoring but insufficient for smaller lakes and rivers. Spectral resolution refers to the number and width of spectral bands captured by the instrument. Sensors with higher spectral resolution can detect subtle differences between algal pigments, while those with lower spectral resolution may only capture broad wavelength ranges that cannot distinguish between bloom and non-bloom waters. Temporal resolution describes how frequently an instrument revisits the same location. This factor is especially important for HAB monitoring, as blooms can form and decline within days. Landsat-8, for instance, has a revisit cycle of 16

days, making it inadequate for capturing short-term bloom dynamics. Radiometric resolution, or quantization, represents the sensor's sensitivity to brightness differences. An 8-bit sensor can detect 256 levels of brightness, while a 16-bit sensor can detect over 65,000 levels, providing much greater detail in reflectance measurements.

These resolutions rarely operate in isolation, as trade-offs between them shape sensor design. A wider swath can increase geographic coverage but often reduces spatial resolution, while shorter revisit times can limit the number of spectral bands collected. For HAB monitoring, these trade-offs are particularly significant because accurate detection depends on both fine spatial detail in small waterbodies and sufficient spectral coverage to identify diagnostic pigments. As blooms become more frequent and variable, the limitations of existing multispectral systems highlight the need for improved approaches.

3.2. Multispectral Monitoring

Multispectral instruments capture a limited number of broad spectral bands, generally ranging between four and thirty-six, and have long been the standard in aquatic remote sensing. Their accessibility, lower cost, and extensive historical archives have made them the foundation of most harmful algal bloom (HAB) monitoring programs (Connah et al., 2004). These instruments have been employed to estimate chlorophyll-a concentrations, map bloom extent, and track long-term changes in water quality across a range of aquatic environments.

Several multispectral platforms have been central to HAB observation efforts. The Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Aqua satellite provides daily global coverage with spatial resolutions ranging from 250 m to 1 km, making it valuable for monitoring large-scale coastal blooms (Moutier et al., 2019). Landsat's Operational Land Imager (OLI), with a 30 m spatial resolution, has been widely applied to inland lakes and reservoirs, though its 16-day revisit time limits its use for short-term monitoring (Liu et al., 2021). The Ocean and Land Colour Instrument (OLCI) on Sentinel-3 offers improved coverage of ocean color with 21 bands across the visible and near-infrared spectrum, while the Visible Infrared Imaging Radiometer Suite (VIIRS) provides near-daily global coverage at moderate spatial resolution (Schueler et al., 2002). Together, these instruments have provided insight into bloom frequency and distribution, as demonstrated by studies showing significant increases in global bloom occurrence over the past two decades (Dai et al., 2023).

Despite their limitations, multispectral systems remain valuable for their long-term archives, consistent global coverage, and free data availability. They allow for the detection of broad-scale bloom patterns and have been instrumental in identifying HAB hotspots, seasonal trends, and interannual variability. These contributions underscore the role of multispectral remote sensing as a cornerstone of HAB research, while also highlighting the need for higher-resolution approaches capable of addressing finer-scale and more dynamic bloom events.

3.3. Limitations of Multispectral Sensors

While multispectral systems have advanced the study of HABs, their inherent technical constraints limit their effectiveness for detailed observation. Spatial resolution is a primary limitation: sensors such as MODIS, with pixels spanning hundreds of meters, cannot resolve blooms in small lakes, reservoirs, or rivers where HABs frequently develop. Even Landsat-8, with a 30 m resolution, often struggles to capture the fine spatial heterogeneity of blooms in smaller waterbodies (Xu et al., 2021). Temporal resolution poses another challenge. Landsat's 16-day revisit cycle is inadequate for observing blooms that can appear and dissipate within days, and while MODIS and VIIRS offer daily coverage, their coarse resolution sacrifices local detail (Isenstein et al., 2014).

Atmospheric interference further constrains multispectral monitoring. Clouds, haze, and sunglint regularly obscure water signals, forcing researchers to discard large portions of imagery and reducing the temporal continuity of bloom records (Torbick & Corbiere, 2015). These effects are particularly problematic during peak bloom seasons when rapid changes demand continuous coverage. Finally, the restricted spectral resolution of multispectral sensors limits their ability to detect diagnostic pigments such as phycocyanin and to quantify fluorescence, both of which are critical for distinguishing cyanobacterial blooms from other forms of phytoplankton (Isenstein et al., 2014; Xu et al., 2021).

These limitations have significant implications for bloom management. As HABs increase in frequency and severity, coarse-resolution instruments cannot provide the detailed, species-specific information needed for early detection or mitigation planning. Multispectral data remain valuable for global and regional assessments, but for fine-scale, high-frequency monitoring, they are insufficient. These challenges underscore the importance of advancing toward hyperspectral sensing, which is designed to overcome many of the shortcomings inherent to multispectral approaches.

4. Hyperspectral Remote Sensing for HAB Observation

4.1. Spectral Resolution and Pigment Discrimination

Hyperspectral sensors capture hundreds of narrow, contiguous spectral bands, providing far greater detail than the limited broad bands used in multispectral systems. This higher spectral resolution allows researchers to identify specific pigments such as chlorophyll-a, phycocyanin, and phycoerythrin, which are vital for detecting and distinguishing harmful algal species (Hunter et al., 2010; Becker et al., 2019). Each pigment absorbs and reflects light differently, and these unique spectral signatures can be captured and analyzed to determine both bloom presence and composition. This is particularly significant for cyanobacteria, which exhibit distinct phycocyanin absorption near 625 nm (Pelaez et al., 2009). Because common multispectral sensors use wide spectral bands, this narrow absorption feature is often averaged or entirely missed, reducing sensitivity to cyanobacteria. Hyperspectral sensors, with continuous narrow bands, maintain the full shape of

this feature and therefore provide a more reliable signal for bloom detection (Pyo et al., 2021).

Hyperspectral imaging enables scientists to measure subtle differences in pigment ratios, fluorescence, and scattering that reveal not only bloom occurrence but also biological characteristics such as species composition and toxicity. For example, the AISA Eagle, Compact Airborne Spectrographic Imager (CASI-2), and NASA's Hyperspectral Imager for the Coastal Ocean (HICO) have been used to estimate chlorophyll-a and accessory pigments, successfully differentiating between toxic and non-toxic cyanobacteria and even discriminating HAB species in mixed populations (Kudela et al., 2015; Pyo et al., 2021). Because hyperspectral data provide continuous information across the visible and near-infrared spectrum, they are more reliable for classifying bloom type and intensity, even under complex or turbid conditions where multispectral sensors often fail.

The ability to isolate diagnostic pigments early in bloom formation allows for more effective monitoring and earlier management responses. Traditional multispectral satellites such as MODIS and Sentinel-3 OLCI detect blooms only once pigment concentrations surpass a threshold. In contrast, hyperspectral instruments can identify changes in pigment composition that signal the beginning stages of a bloom, offering a critical advantage for water quality forecasting and public health protection.

4.2. Spatial and Temporal Resolution Improvements

Beyond their spectral precision, hyperspectral systems also achieve superior spatial and temporal resolution. Many airborne and UAV-mounted hyperspectral instruments capture images with pixel sizes of just a few meters, compared to the tens or hundreds of meters typical of multispectral satellites. This level of detail is crucial for monitoring small inland lakes, rivers, and estuaries where HABs often originate but remain invisible at coarser resolutions (Mitchell et al., 2012; Orych, 2015). High spatial detail enables researchers to map bloom boundaries accurately, observe fine-scale distribution patterns, and detect early formation zones that might otherwise be overlooked.

Temporal resolution—how frequently a sensor revisits the same area—is equally important. HABs can appear and expand rapidly, often within a few days, and long revisit intervals limit the ability to track their development. UAV-based hyperspectral systems can be deployed as frequently as needed, offering daily or even sub-daily monitoring. This flexibility makes them invaluable for capturing short-term dynamics in bloom intensity, spread, and dissipation (Becker et al., 2019).

Recent developments in spaceborne hyperspectral systems have also improved temporal coverage. NASA's Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) satellite, launched in 2024, carries the Ocean Color Instrument (OCI), which collects data across more than 200 spectral bands spanning the visible to near-infrared range. Compared to its multispectral predecessors, PACE's OCI offers both higher spectral resolution and improved spatial detail, allowing for the discrimi-

nation of species-specific pigments across coastal and oceanic environments. The mission marks a major advancement in global-scale bloom monitoring and demonstrates how new satellite designs can combine the detail of airborne sensors with the coverage of spaceborne platforms (NASA, 2024).

4.3. UAS-Based Hyperspectral Sensing

Unmanned aerial systems (UAS) equipped with hyperspectral sensors have transformed the ability to observe harmful algal blooms with high precision and frequency. These systems combine the flexibility of low-altitude flight with the analytical power of hyperspectral imaging. Sensors mounted on unmanned aerial vehicles (UAVs) such as the Ocean Optics STS hyperspectral spectroradiometer have produced results that align closely with ground-based and in-situ measurements, achieving correlations above 0.95 for key indicators including chlorophyll and cyanobacteria indices (Becker et al., 2019).

The advantages of UAV-based hyperspectral sensing extend beyond spatial resolution. Low-altitude imaging minimizes atmospheric interference, including the scattering and absorption that often complicate satellite measurements. UAVs can also be deployed during cloudy or variable weather conditions that would otherwise compromise data quality. This flexibility allows for targeted observation of bloom hotspots, validation of satellite imagery, and near-real-time monitoring of water quality changes (Mitchell et al., 2012). UAVs can operate at different times of day to account for lighting variation, further refining radiometric accuracy.

Moreover, UAV hyperspectral systems provide a bridge between localized field sampling and broader satellite observations. By integrating UAV-derived data with satellite imagery, researchers can produce multi-scale assessments that capture both the fine detail of local bloom conditions and the broader regional context. This integrated approach enhances both the accuracy and applicability of HAB monitoring frameworks, making UAVs an essential component of future early warning and management systems.

Operationally, UAS deployments are constrained by limited flight time and payload, susceptibility to wind, precipitation, and cloud ceilings, and compliance requirements (e.g., airspace authorization, visual-line-of-sight rules), which can limit coverage relative to satellites and should be planned for in mission design. These operational barriers can be mitigated through coordinated flight scheduling, modular sensor payloads, and hybrid monitoring frameworks that integrate UAS with satellite and in-situ observations. Such combined approaches maximize spatial detail and temporal frequency while reducing the dependence on any single sensing platform, making UAS a practical complement rather than a replacement in large-scale HAB observation (Torbick & Corbiere, 2015; Orych, 2015).

4.4. Challenges, Limitations, and Outlook

While hyperspectral sensing offers substantial advantages, several limitations have historically constrained its operational use. High instrument and mission costs,

limited swath widths, data volume, and computational demands all present obstacles (Kudela et al., 2015; Orych, 2015). Hyperspectral systems collect large amounts of data due to their numerous spectral bands, generating storage and processing challenges. However, advances in data compression, cloud computing, and artificial intelligence are rapidly reducing these burdens. Machine learning algorithms such as convolutional neural networks (CNNs) and random forest classifiers have already been used to automate pigment detection and noise reduction, improving both accuracy and efficiency (Pyo et al., 2019; Yang et al., 2023). These models process each pixel's full spectral signature and, in some cases, small spatial-spectral neighborhoods, learning characteristic patterns that correspond to different algal groups or pigment concentrations. By automatically extracting hierarchical features, CNNs can differentiate subtle spectral variations that conventional thresholding or empirical band-ratio methods often overlook. When trained on labeled datasets from multiple optical water types, CNNs can classify bloom extent or estimate pigments such as chlorophyll-a and phycocyanin with improved accuracy and generalization (Mitchell et al., 2012; Uz et al., 2020).

Atmospheric interference remains another technical challenge. Cloud cover, haze, and sunglint can obscure optical signals, but hyperspectral data allow for more effective correction through spectral unmixing and radiative transfer modeling (Kudela et al., 2015). UAV-based sensors further minimize atmospheric effects by operating below cloud layers, collecting data even under poor visibility conditions (Becker et al., 2019).

The narrow swath width of many hyperspectral imagers once limited their large-scale applicability, but new mission architectures are beginning to close that gap. NASA's PACE mission and Europe's upcoming CHIME mission will deliver near-global coverage with high spectral fidelity. When coupled with drone-based and airborne campaigns, these satellites can form a hybrid observation network that combines regional coverage with local precision.

Cost and accessibility, which were once the biggest barriers of hyperspectral sensing, are also being addressed. The miniaturization of sensors and the emergence of commercial imaging spectrometers have made hyperspectral technology more accessible to research institutions and environmental agencies. Open-source analysis tools and shared data repositories now allow researchers to process and interpret hyperspectral imagery without proprietary software.

As these advances continue, the long-standing challenges of hyperspectral monitoring are steadily being overcome. The integration of satellite, UAV, and in-situ datasets now provides an unprecedented opportunity for multi-scale observation of harmful algal blooms. Hyperspectral remote sensing is no longer limited to experimental applications, becoming both practical and essential technology for the accurate detection, monitoring, and mitigation of HABs.

5. Conclusion

Harmful algal blooms (HABs) have become an increasingly urgent global issue,

driven by nutrient pollution, climate change, and the cumulative effects of human activity. Their ecological, health, and economic impacts continue to grow, threatening the stability of aquatic ecosystems and the communities that depend on them. As these events become more frequent and severe, effective monitoring is no longer optional. Traditional field-based observation and multispectral satellite systems have laid the foundation for HAB research, but their limitations in resolution, frequency, and spectral detail leave critical gaps in detection and response.

This review demonstrates that hyperspectral remote sensing represents the next major advancement in HAB observation. The ability to capture hundreds of narrow, contiguous bands, allows for the detection of subtle pigment signatures and species-level discrimination that multispectral sensors cannot achieve. High spatial and temporal resolution makes it possible to monitor small inland lakes and fast-developing coastal blooms with unprecedented precision, while UAV-based systems add flexibility and reduce atmospheric interference. These combined strengths make hyperspectral imaging the most accurate and efficient method for identifying, tracking, and analyzing harmful algal blooms across diverse aquatic environments.

While hyperspectral sensing has faced challenges in cost, swath coverage, and data management, these barriers are steadily diminishing. The miniaturization of instruments, the deployment of next-generation satellites such as NASA's PACE mission, and the growing use of artificial intelligence for data processing have made the technology more accessible and operationally feasible than ever before. Integrating hyperspectral observation with existing multispectral and *in-situ* networks will enable a more complete, multi-scale understanding of bloom dynamics and their environmental drivers.

In operational practice, this integration functions as a tiered workflow that links broad-scale and high-resolution observations. Multispectral satellite imagery first provides continuous, wide-area coverage to identify potential bloom hotspots using established bio-optical indices or anomaly detection. These flagged regions can then be targeted by hyperspectral sensors—whether spaceborne, airborne, or UAS-based—to resolve species-level spectral features and quantify pigment concentrations with higher precision. Concurrent *in-situ* sampling supplies calibration and validation data, enabling cross-sensor harmonization and refinement of retrieval algorithms. Together, these coordinated datasets strengthen early-warning systems, reduce false detections, and support adaptive management decisions for HAB mitigation (Batina & Krtalic, 2024; Schueler et al., 2002).

Ultimately, the transition from multispectral to hyperspectral monitoring is a necessary shift in how scientists and policymakers observe and protect aquatic systems. By enabling earlier detection, more accurate classification, and faster response to bloom events, hyperspectral remote sensing offers a path toward sustainable management of water resources in the face of a rapidly changing environment.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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