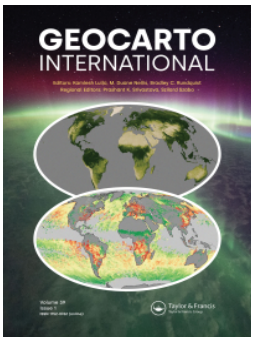

Taylor & Francis
Taylor & Francis Group

Geocarto International

ISSN: 1010-6049 (Print) 1752-0762 (Online) Journal homepage: www.tandfonline.com/journals/tgei20

UAV-based remote sensing of chlorophyll-a concentrations in inland water bodies: a systematic review

Nobubelo Ngwenya, Tsitsi Bangira, Mbulisi Sibanda, Seifu Kebede Gurmessa & Tafadzwanashe Mabhaudhi

To cite this article: Nobubelo Ngwenya, Tsitsi Bangira, Mbulisi Sibanda, Seifu Kebede Gurmessa & Tafadzwanashe Mabhaudhi (2025) UAV-based remote sensing of chlorophyll-a concentrations in inland water bodies: a systematic review, Geocarto International, 40:1, 2452246, DOI: 10.1080/10106049.2025.2452246

To link to this article: https://doi.org/10.1080/10106049.2025.2452246

Published online: 13 Feb 2025.

GEOCARTO INTERNATIONAL
2025, VOL. 40, NO. 1, 2452246
https://doi.org/10.1080/10106049.2025.2452246

REVIEW ARTICLE

OPEN ACCESS

UAV-based remote sensing of chlorophyll-a concentrations in inland water bodies: a systematic review

Nobubelo Ngwenya[a,b], Tsitsi Bangira[b], Mbulisi Sibanda[b,c], Seifu Kebede Gurmessa[a] and Tafadzwanashe Mabhaudhi[a,b,d]

[a]Centre for Water Resources Research, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal (UKZN), Scottsville, Pietermaritzburg, South Africa; [b]Centre for Transformative Agricultural and Food Systems, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal (UKZN), Scottsville, Pietermaritzburg, South Africa; [c]Department of Geography, Environmental Studies & Tourism, Faculty of Arts & Humanities, University of the Western Cape, Bellville, South Africa; [d]Centre on Climate Change and Planetary Health, London School of Hygiene and Tropical Medicine, London, United Kingdom

ABSTRACT

Monitoring chlorophyll-a content is crucial for irrigation water quality, as excessive levels can harm water bodies and reduce their volumetric capacity due to algal growth. While satellite data enhances monitoring, its coarse resolution limits application in small water bodies. Unmanned Aerial Vehicles (UAVs) offer high-resolution, near-real-time data, bridging this gap. This review explores global progress, gaps, and recommendations on UAV-based chlorophyll-a monitoring in small inland water bodies, focusing on sensor characteristics, platforms, validation data and retrieval algorithms, using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) approach. Multispectral sensors onboard DJI UAVs are the most widely used and, machine learning methods like random forest dominate chlorophyll-a inversion models. However, gaps remain in Africa due to high UAV costs, limited expertise and stringent regulations. Additionally, a universal chlorophyll-a retrieval method is also lacking. This review serves as a reference for future studies, highlighting UAVs' potential in water quality monitoring.

ARTICLE HISTORY
Received 29 August 2024
Accepted 28 December 2024

KEYWORDS
Chlorophyll-a; inland waters; remote sensing; systematic review; unmanned aerial vehicle

1. Introduction

Small water bodies between 1 m^2 and 20,000 m^2 with a maximum depth of no more than 8 m (Biggs et al. 2005) support over 70% of the world's population in arid and semi-arid areas, and this proportion is increasing. These small inland water resources store scarce and reliable water for crop irrigation during dry spells (Wisser et al. 2010). They are

CONTACT Nobubelo Ngwenya nobubelongwenya05@gmail.com

among the most vulnerable ecosystems and any changes due to anthropogenic activities can affect specific water uses and endanger aquatic habitats. The major water quality threat in small water bodies is the excessive growth of cyanobacteria. The disposal of phosphorous, nitrogen and nutrients from rivers and streams, as well as prolonged sun-light hours and warm temperatures, accelerates cyanobacteria blooms. Understanding the quantity of cyanobacteria, also known as blue-green algae, in inland water resources is essential for the level of treatment required for agricultural, domestic and industrial use. Therefore, it is more important than ever to consider water quality and strictly monitor the number of harmful bacteria in inland water bodies.

Cyanobacteria is a photosynthetic and toxin-producing bacteria, that significantly impairs water quality (Aranda et al. 2023). These bacteria are characterised by their single chlorophyll type termed Chlorophyll-a (chl-a) and a variety of carotenoids, including the blue pigment phycobilin and the red pigment phycoerythrin. Chl-a is often used as a proxy for phytoplankton biomass (Gregor and Marsálek, 2004; Søndergaard et al. 2011; Stengel et al. 2023). Cyanobacteria are the predominant form of phytoplankton responsible for harmful algal blooms (HABs) in freshwater environments (Cook et al. 2023). This issue has escalated into a global concern, as emphasised by Paerl and Barnard (2020), necessitating increased attention and action to mitigate its impacts. Climate change-induced factors like elevated temperatures and erratic rainfall further exacerbate cyanobacteria blooms (Rankinen et al. 2019). Cyanobacteria blooms can severely degrade water quality, causing increased turbidity, reduced dissolved oxygen levels and decreased water transparency (Liu and Qiu, 2007). Therefore, monitoring chl-a levels, a reliable proxy for estimating cyanobacteria, is essential, as demonstrated by numerous studies (Song et al., 2022; Zhao et al., 2022a; Bunyon et al., 2023). Chl-a is widely employed as a proxy for assessing cyanobacterial harmful algal blooms (cyano-HABs) due to its role as a primary pigment in photosynthetic organisms. However, accurately discriminating cyanobacteria from other phytoplankton often requires complementary approaches, such as phycocyanin and green algae detection (Schalles, 2006; Hunter et al. 2008; Salmi et al. 2021; Cook et al. 2023). Moreover, chl-a may not always accurately represent cyano-HABs, particularly in systems with mixed algal communities or during bloom phases characterised by low pigment concentrations (Becker et al. 2009; Paerl et al. 2011; Adejimi et al. 2023; Li et al. 2023; Pamula et al. 2023; Fournier et al. 2024). Furthermore, challenges inherent to inland waters, including high turbidity, interference from dissolved organic matter (DOM) and overlapping pigment signatures, can complicate chl-a sensing (Kutser, 2009; Matthews, 2011).

Traditional methods for determining chl-a levels involve collecting field samples and conducting laboratory analysis (Ritchie et al. 2003; Batur and Maktav, 2018; Morgan et al. 2020), a time-consuming, labour-intensive, and costly process. Moreover, these *in situ* techniques are limited in their ability to provide comprehensive spatial and temporal coverage, hindering the issuance of timely warnings for intense blooms (Kuhn et al. 2019; Modiegi et al. 2020). Due to their reliance on point sampling, these methods lack spatial representativeness, highlighting the need for robust, spatially explicit and synoptic approaches to detect and monitor chl-a concentrations as a proxy for water quality.

Remote sensing is one approach that is robust and spatially explicit and has been used to estimate chl-a (Su & Chou, 2015; Arango & Nairn, 2019; Xiao et al., 2022). Chl-a exhibits unique optical and spectral properties that enable its detection using remote sensing technologies (Wu et al. 2010; Gao et al. 2015). Remote sensing offers several advantages for measuring chl-a concentration, including extensive coverage, cost-effectiveness, and capturing temporal, spatial and dynamic changes, making it an effective method for comprehensive monitoring (Yang et al. 2022; Tian et al. 2023). Research has shown that chl-a has distinct optical properties, with high absorption rates at 443 nm and 665 nm (Gilerson et al. 2010; Gurlin et al. 2011; Yu et al. 2014; Johan et al. 2018; Warren et al. 2021; Wang et al. 2022) and strong reflectance in the green and red edge spectra 550–555 nm and 685–710 nm, respectively (Gitelson, 1992; Kirk, 1994; Mobley, 1994). High chl-a concentrations are characterised by increased reflectance in the green (G) and red (R) bands and decreased reflectance in the blue (B) band (Pulliainen et al. 2001). The maximum reflectance associated with chl-a occurs at 580 nm (Dekker, 1993) and peak reflection at 700 nm (Gitelson, 1992). Therefore, monitoring changes in reflectance within these specific bands can effectively identify high concentrations of chl-a.

Numerous studies have successfully utilised airborne hyperspectral data to estimate chl-a concentration in inland waters (Moses et al. 2012; Pyo et al. 2018; Kolluru et al. 2023). However, airborne hyperspectral sensors are expensive, limiting their adoption for small water bodies. The freely available multispectral satellite data has been used to estimate chl-a concentration in large water bodies using ocean chlorophyll wavelength-based algorithms (412, 443, 490, 510, 555 nm). These algorithms were originally developed for oceanic monitoring and have since been adapted for use in inland water bodies. The foundation of chl-a algorithms emanated from satellite data and oceans as the primary study area, as reflected in key studies (O'Reilly et al. 1998; O'Reilly et al. 2000; Lins et al. 2017; Markogianni et al. 2018; O'Reilly and Werdell, 2019; Cao et al. 2020; Lai et al. 2021; Kolluru and Tiwari, 2022). On the other hand, freely available multispectral satellite data has limitations such as coarse resolution, limited data control and untimely collection (Yang et al. 2022). Unmanned aerial vehicles (UAVs) offer a promising alternative, enabling remote monitoring of chl-a in small water bodies with higher spatial resolutions, controlled temporal scales and flexible data collection at a relatively low cost (Wu et al. 2019; Xiang et al. 2019; Yao et al. 2019). UAVs address satellite-based limitations, providing enhanced precision and flexibility for effective cyanobacteria monitoring in small water bodies like lakes, rivers, dams, reservoirs, streams and wetlands (Cillero Castro et al., 2020; Silveira Kupssinsku et al., 2020; Xiao et al., 2022; Fu et al., 2023; Lo et al., 2023). Studies have demonstrated UAV-acquired remote sensing data's potential in detecting and monitoring chl-a with high accuracy, including (Cillero Castro et al. (2020), who used empirical approaches and band indices to detect chl-a in a Spanish reservoir and Silveira Kupssinskü et al. (2020), who employed machine-learning models in Brazil. Similarly, Xiao et al. (2022) estimated chl-a downstream of a river using machine learning and traditional regression. Fu et al. (2023) estimated chl-a levels in a Chinese karst wetland using partial least squares and adaptive ensemble algorithms. These studies showcase UAV-acquired remote sensing data's promise in accurately detecting and monitoring chl-a in small water reservoirs.

While there is evidence of using UAVs to monitor chl-a in small water bodies, there is a notable gap in the assessment of of existing literature. Little research has focused on systematically and comprehensively assessing studies that monitored chl-a in small water bodies using UAVs. A comprehensive review is required to assess, evaluate and select the most appropriate method that can be used for chl-a estimation in small inland waters using UAVs. To boost and enhance the knowledge on using UAVs to monitor chl-a levels in small inland waters, this paper took the initiative to track and evaluate the existing literature and document in detail the current progress, challenges and opportunities centred around this subject. The objectives of this paper were to (1) identify and systematically review the literature on UAV remote sensing of chl-a concentrations in small water bodies, (2) evaluate and analyse the methodologies and technologies employed in UAV-based remote sensing for measuring chl-a concentrations, including sensor types, imaging techniques and data processing methods, and (3) assess the progress, challenges, gaps and opportunities in using UAV technology for monitoring chl-a in small inland water bodies. Addressing this gap is important for establishing effective monitoring and management strategies for water resources.

2. Materials and methods

2.1. Literature search Strategy

A literature search was conducted to find global studies on estimating chl-a in small water bodies using UAVs. The first step entailed identifying and compiling keywords and phrases commonly used in the previous UAV remote sensing studies of chl-a. The following key terms were used in the search string "Unmanned aerial vehicle" OR Drone OR "unmanned aerial systems" AND "remote sensing" AND "chlorophyll-a" OR "algae" OR "phytoplankton" OR cyanobacteria blooms" AND "inland waters" OR "lakes" OR "reservoir". A database was then constructed by searching these key terms from research databases: Science Direct, Scopus, Web of Science (WOS), IEEE Xplore and Google Scholar. While the publication end date of papers searched was restricted to December 31, 2023, the publication start date was unrestricted. All articles with a published status were considered, regardless of their geographical location. Due to the variations in the configuration settings in Scopus and Web of Science, the key search strings were slightly different (Table 1).

2.2. Screening and selection strategy

A total of 3295 studies were retrieved: 2262 from WOS, 900 from Google Scholar, 84 from Science Direct, 44 from Scopus and 5 from IEEE Xplore. Retrieved articles were then exported in the Endnote software, where the bibliographic information of articles, including the year, article title, name of the journal, author names, abstract, keywords, Digital Object Identifier (DOI) and Uniform Resource Locator (URL) was compiled. The search was refined by screening titles and abstracts using relevant keywords. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) reporting

Table 1. Number of articles retained using five search engines.

Search engine	Search criterion	Number of articles retained
Web of Science	All fields ("Unmanned aerial vehicle" OR "Drone") AND ("remote sensing") AND ("chlorophyll-a") AND ("algae") AND ("phytoplankton") AND ("cyanobacteria") AND ("inland waters") AND ("lakes") AND ("small water bodies") AND ("multispectral")	2262
Google Scholar	("Unmanned aerial vehicle" OR Drone OR "unmanned aerial systems") AND ("remote sensing") AND ("chlorophyll-a" OR "algae" OR "phytoplankton" OR "cyanobacteria") AND ("inland waters")	900
Science Direct	TITLE-ABS-KEY ("Unmanned aerial vehicle" OR Drone OR "unmanned aerial systems") AND ("remote sensing") AND ("chlorophyll-a" OR "algae" OR "phytoplankton" OR "cyanobacteria") AND ("inland waters")	84
Scopus	TITLE-ABS-KEY ("Unmanned aerial vehicles" OR "drone") AND ("remote sensing") AND ("chlorophyll-a" OR "algae" OR "phytoplankton" OR "cyanobacteria blooms") AND ("inland waters" OR "lakes" OR "reservoir")	44
IEEE Xplore	ALL METADATA ("Unmanned aerial vehicle" OR Drone AND "remote sensing" AND chlorophyll-a OR algae OR phytoplankton OR "cyanobacteria blooms" AND "inland waters" OR lakes OR reservoir)	5

checklist (https://www.prisma-statement.org/, accessed 20 February 2024) was used as a guide to eliminate bias reporting and structure the review. The articles that qualified for the meta-analysis were those that met the following criteria:

1. The scope of the study focused on the estimation of chl-a or assessment of cyanobacteria in a small water body
2. The study utilised data from UAV-based remotely sensed data
3. The results of the study and the accuracy assessment are clearly stated
4. The study is from an accredited journal and is peer-reviewed
5. The study paper is written in English.

The first exclusion step was to remove duplicates. In total, 132 articles were removed as duplicates. The remaining 3163 articles were screened using titles and abstracts to determine their eligibility for this study. Three thousand one hundred twenty-two articles were excluded at this stage for one of the following reasons: beyond the scope of the review, not peer-reviewed, missing full article and imprecise or not clearly stated results. Finally, the remaining 41 studies and 14 studies obtained from backward referencing (Horsley et al. 2011) underwent full-text assessment for eligibility. In total, 55 studies met the final selection criteria and were carried on to the data extraction step. The selection process and screening outcomes are illustrated in a PRISMA flowchart, as shown in Figure 1.

The selected articles were exported from Endnote to Microsoft Excel and downloaded as PDF documents to extract comprehensive data. In addition to the bibliometric data from Endnote, details such as the year and country of study, type of water body, eutrophication water quality parameter monitored, sensor and UAV platform characteristics, vegetation indices, regression models and remote sensing algorithms were retrieved. These categorical attributes were subsequently transformed into measurable variables in preparation for the data analysis phase, and the relevance of the systematic review was evaluated by assessing the quality of the articles. The coefficient of determination (R^2) was

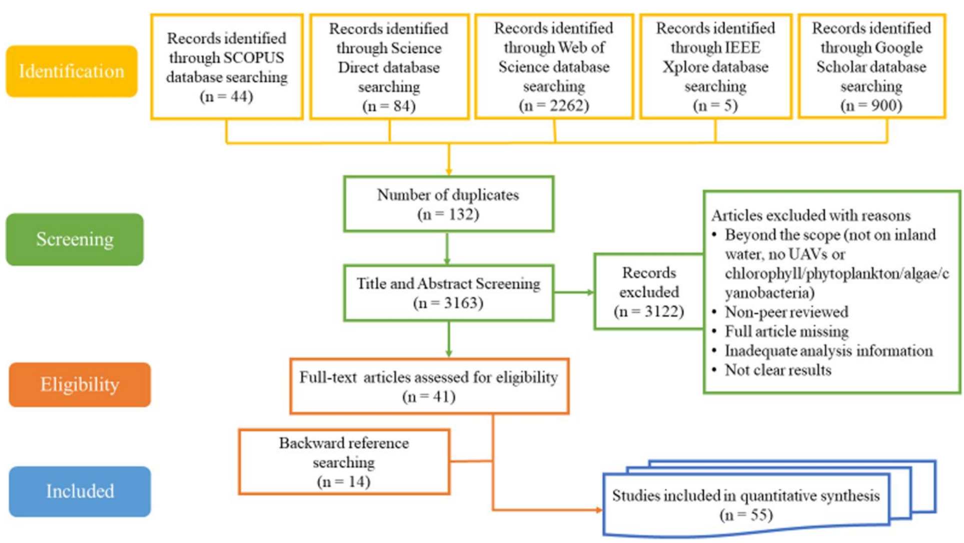

Figure 1. PRISMA flow diagram indicating the article selection process.

extracted from each study for the accuracy assessment, as it measures the goodness fit between predicted and observed values.

2.3. Data analysis

In this review paper, both quantitative and qualitative analyses were conducted on the extracted data. Statistical frequencies and trend analysis were employed to determine the progress of using UAVs to monitor water quality, specifically chl-a in inland water bodies. Microsoft Excel was used to delineate the statistical frequencies (Carlberg and Carlberg, 2014). Additionally, a bibliometric analysis identified trends in the co-occurrence of key terms and interlinkages between keywords related to monitoring chl-a in small water bodies using UAV-derived data. The VOSviewer software (https://www.vosviewer.com/) was used to mine text and quantitatively examine the occurrence and co-occurrence of keywords in the titles and abstracts of the reviewed studies (Van Eck and Waltman, 2007). VOSviewer also illustrated the evolution of concepts and topics related to chl-a from remotely sensed data in small water bodies. Although bias is common in literature analysis, a specific bias assessment was not conducted since the focus was on the occurrence, co-occurrence and frequency distribution of key terms.

To meet the research objectives, this review was structured into two sections. The first section explored the spatial distribution of studies, keyword analysis, types of water bodies and their uses, parameters and quantitative analysis of the algorithms, sensors, platforms and indices employed by the reviewed studies. The second section outlined the challenges, gaps and opportunities identified in the reviewed literature on on estimating chl-a using UAV remotely sensed data in small inland waters.

3. Results

3.1. Evolution and analysis of keywords in UAV-derived chl-a literature

In assessing the evolution and topical concepts of monitoring chl-a in small water bodies using UAV-derived data, the results showed that “unmanned aerial vehicle”, “chlorophyll”, “algae”, “reservoir”, and “multispectral imagery” were the most utilised keywords around 2019 (Figure 2). This indicates the wide use of multispectral cameras during that time to monitor algae in water bodies such as reservoirs. The period between 2020 and 2021 indicates the wide application of remote sensing in water quality to monitor chl-a leveraging on the reflection of water bodies such as rivers. This period also represents the introduction of deep learning algorithms in water quality monitoring. The 2021 to 2022 period was marked by keywords such as “hyperspectral imaging”, “machine learning, “multispectral image”, “uav remote sensing”, “water quality monitoring”, “linear regression”, “cyanobacteria” and “inland waters”. This highlights the growing trend of using UAVs for water quality monitoring, the adoption of advanced methods for model development, such as machine learning and the investment into high-resolution sensors, such as hyperspectral cameras. This significant evolution of key terms can be attributed to the recent technological advancements in analysis techniques and the widespread application of UAVs in monitoring chl-a.

A total of 303 keywords were identified from the reviewed literature. To analyse the trends, the minimum number of occurrences was set to three, which narrowed down the number of keywords to a threshold of 23. These keywords were then grouped into five clusters: red, purple, green, blue and yellow (Figure 3). The red cluster emerged as the

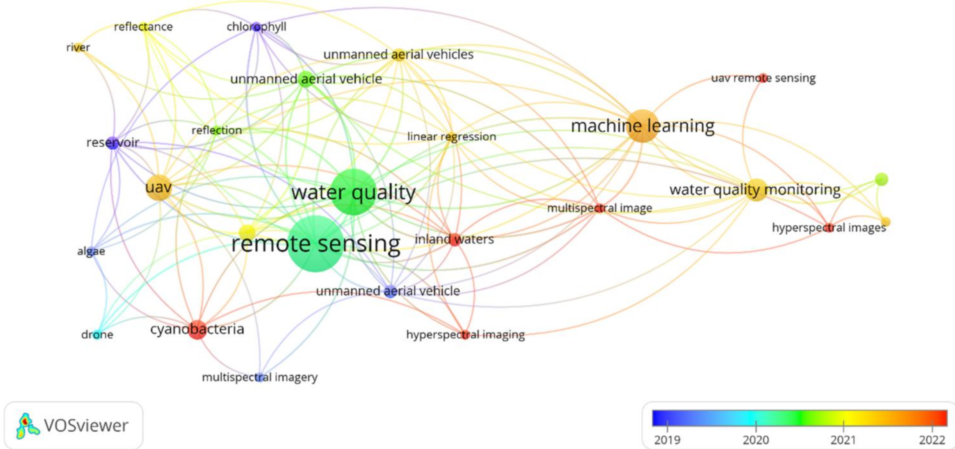

Figure 2. Evolution and direction of topical concepts on chl-a monitoring in small water bodies using UAV remote sensing, derived from abstracts, title and keywords of the selected literature.

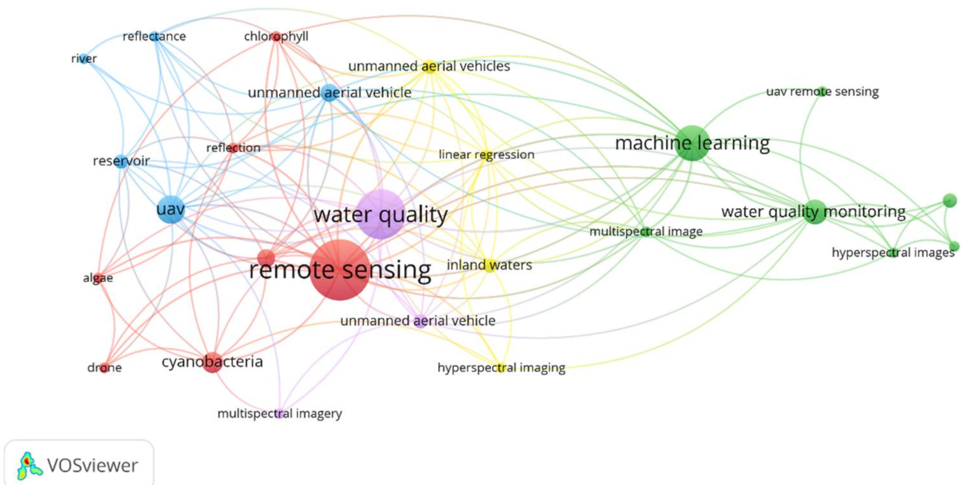

Figure 3. Topical concepts in mapping and monitoring of chl-a in small water bodies.

biggest, representing the keywords most used during the search period. It comprised the keywords such as “remote sensing”, “reflection”, “chlorophyll”, “cyanobacteria” and “drone”. This also shows, the interlinkages between the water quality parameters, water body and imagery. The second cluster (purple) had the following key terms, “water quality”, “multispectral imagery”, and “unmanned aerial vehicle”, indicating a strong association between the use of UAVs equipped with multispectral imaging sensors for monitoring water quality. The third cluster (green) had the keywords “machine learning”, “water quality monitoring”, “uav remote sensing”, “multispectral image”, and “hyperspectral images”. This highlights integrating cutting-edge remote sensing technologies including multispectral and hyperspectral imaging, with machine learning algorithms to monitor water quality. The blue cluster had the following key terms, “uav”, “reservoir”, “river”, and “reflectance”, indicating the use of UAVs to monitor various types of water bodies by leveraging water reflectance. Finally, the yellow cluster is associated with terms like “linear regression”, inland water”, “hyperspectral imaging” and “unmanned aerial vehicles”. This indicates that UAVs equipped with hyperspectral imaging technology commonly estimate chl-a levels in inland water bodies, often utilising linear regression models for analysis.

3.2. Spatial, temporal distribution and trends of publications

To assess trends in articles published on the application of UAV-acquired remotely sensed data for monitoring chl-a, this review revealed that the first study was conducted in 2015 (Su & Chou, 2015). A notable surge in research activity was then observed in 2021 and 2023, accounting for 21% and 25% of the studies, respectively, focusing primarily on rivers, lakes and reservoirs (Ahn et al., 2021; Lu et al., 2021; Hong et al., 2022; Xiao et al., 2022; Cai et al., 2023). A slight decline (22%) in research articles was observed between 2015 and 2019 (Jang et al., 2016; Guimarães et al., 2017; Choo et al., 2018; Arango & Nairn, 2019; Pyo et al., 2022). However, from 2019 to 2023, the adoption of UAVs for chl-a monitoring became increasingly popular, as evidenced by the gradual increase in published studies, as shown in Figure 4.

In terms of the spatial distribution, the retrieved studies were conducted across thirteen different countries, with 66% in Asia, 19% in North America, 9% in Europe and 6% in South America (Figure 5). In Asia, most of the studies were conducted in China (42%) (Zhang et al., 2020a; Chen et al., 2021; El-Alem et al., 2021; Liu et al., 2021; Song et al., 2022; Zhao et al., 2022b; Xiao et al., 2023), followed by South Korea (23%) (Kim et al., 2016; Kwon et al., 2020; Hong et al., 2023). In North America, 12% of the studies were done in the United States of America (USA), while Canada and Brazil (South America) had a limited number of studies, 5% and 7%, respectively (Zeng et al., 2017; Silveira Kupssinskü et al., 2020; El-Alem et al., 2021). Only 2% of studies were conducted per country in the remaining countries of Asia and Europe. The high volume of studies in China can be attributed to several factors. China has extensive and diverse water bodies, including numerous large rivers, lakes and reservoirs, providing ample opportunities for water quality monitoring research using UAV technology. Additionally, China has invested heavily in UAV technology and remote sensing research, leading to more studies. The fewer studies in other regions could be due to various reasons, including less availability of advanced UAV and remote sensing technology and limited research funding. Notably, no studies in the retrieved literature were conducted in Africa.

Regarding temporal distribution, most (75%) of the selected studies focused exclusively on summer-season research (Su & Chou, 2015; Jang et al., 2016; Kwon et al., 2020; El-Alem et al., 2021; Hong et al., 2022; Lo et al., 2023). This preference may stem from constraints such as limited funding, shorter research timelines and the seasonal nature of specific research grants.

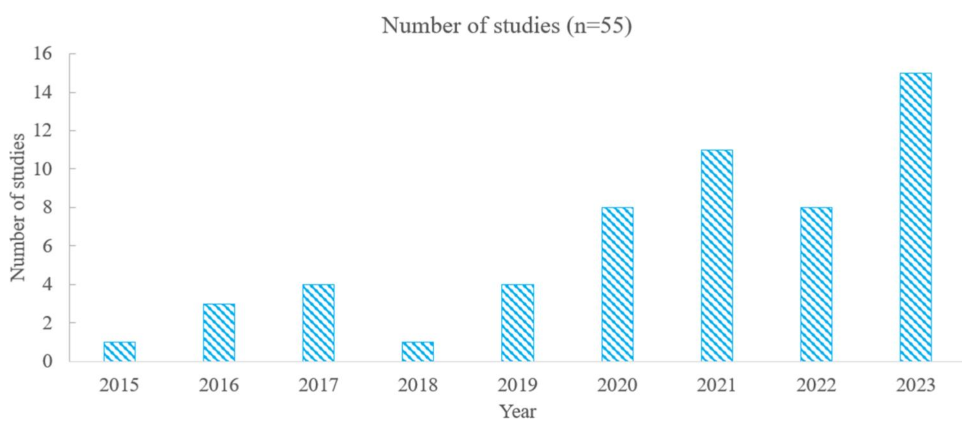

Figure 4. Annual frequency of UAV-based studies that monitored chl-a in inland open water bodies.

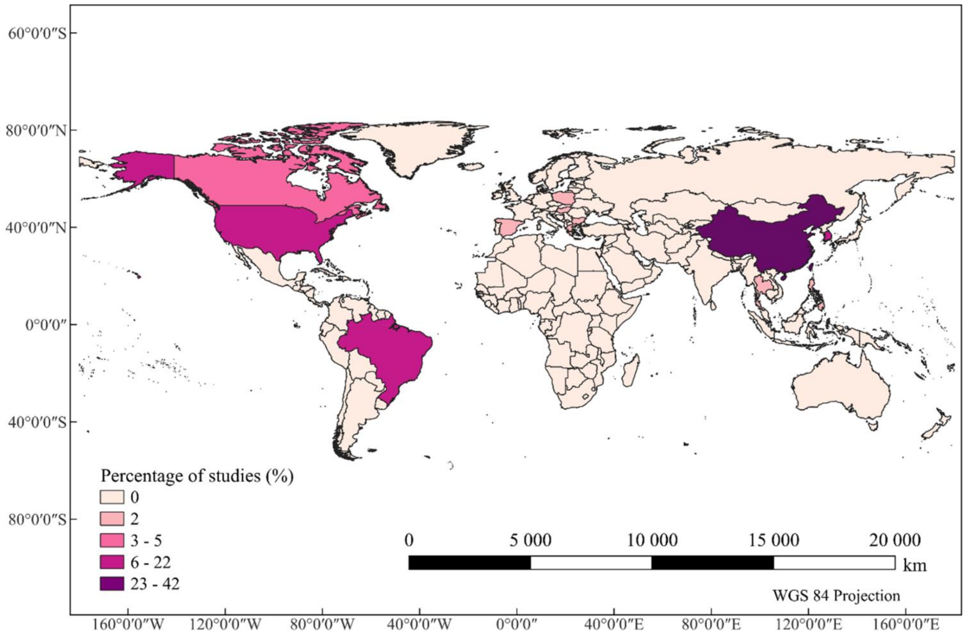

Figure 5. Global spatial distribution of studies that utilised UAVs for chl-a monitoring in inland water bodies.

Despite these limitations, single-season studies can still provide valuable insights, especially during peak periods of algal growth. In contrast, 25% of the studies addressed temporal variations by collecting data across multiple seasons (summer, autumn and winter) (Arango & Nairn, 2019; Chen et al., 2021; Liu et al., 2021; Sharp et al., 2021; Zhao et al., 2022b; Bunyon et al., 2023; Ciężkowski et al., 2023). Such multi-season studies are advantageous as they provide a more comprehensive view of seasonal patterns and trends in water quality.

3.3. Chl-a and associated water quality parameters in various water bodies

The included articles focused on various aspects of algal dynamics, including chl-a, cyanobacteria, harmful algal blooms (HABs) and phytoplankton, often examining these parameters individually or, in some cases combined with other eutrophication parameters. 60% of the articles exclusively focused on the chl-a, underscoring its importance as a key indicator of algal biomass, while 20% examined both chl-a and nutrients such as total nitrogen (TN) and total phosphorus (TP) (Arango & Nairn, 2019; Cillero Castro et al., 2020; Zhang et al., 2020b; Chen et al., 2023). These nutrients are primary drivers of eutrophication, which leads to increased algal growth and potential HABs (Rankinen et al. 2019). Additionally, 9% of the articles explored the relationship between chl-a and dissolved oxygen (DO) (Bunyon et al., 2023; Hong et al., 2023; Yang et al., 2023). This relationship is important because excessive algal growth, indicated by high chl-a levels, can lead to oxygen depletion. Regarding correlations between chl-a and other water quality parameters, 9% of the studies indicated a positive correlation between chl-a and TP (Arango & Nairn, 2019; Zhang et al., 2020a; Zhang et al., 2022), 5% demonstrated a positive correlation between chl-a and TN (Arango & Nairn, 2019; Zhang et al., 2020a; Zhang et al., 2020b) and 2% revealed a positive correlation between chl-a and DO (Morgan et al., 2020).

Regarding the type of water bodies, 39% of the retrieved studies were conducted in rivers (Jang et al., 2016; Choo et al., 2018; Son et al., 2020; Ahn et al., 2021; Liu et al., 2021;

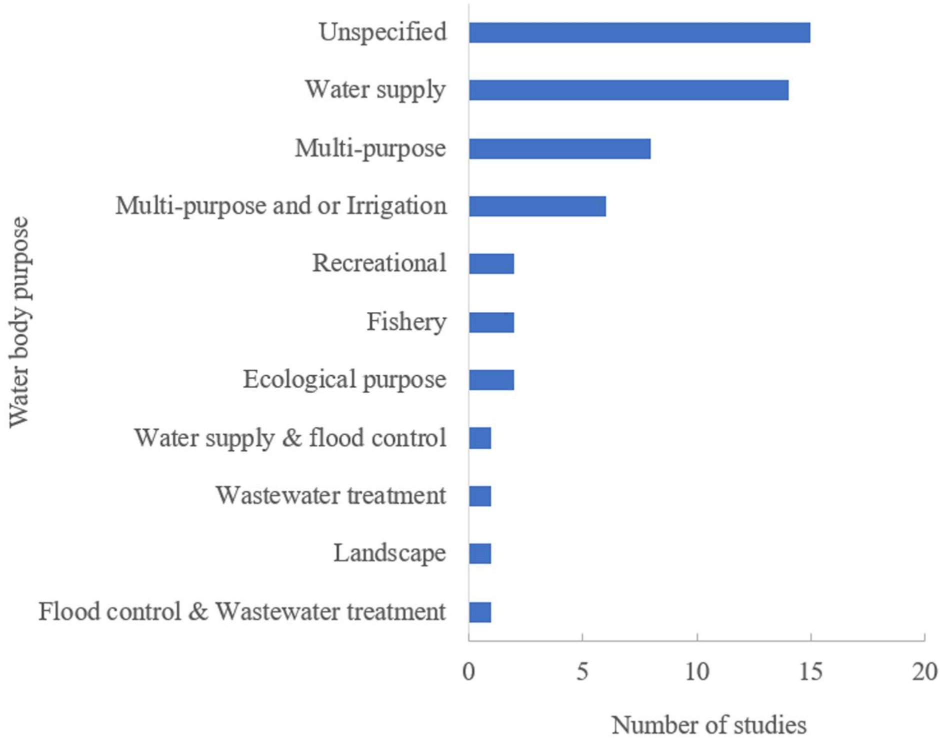

Figure 6. Articles categorised by water body purpose, showing the frequency of studies for each purpose.

Xiao et al., 2022), 25% on lakes (Guimarães et al., 2017; Silveira Kupssinskü et al., 2020; El-Alem et al., 2021) and 14% on reservoirs (Stoyneva-Gärtner et al., 2019; Lu et al., 2021; Pokrzywinski et al., 2022). Interestingly, 2% of the studies focused on a dam, highlighting a significant gap in the literature.

Based on the findings (Figure 6), approximately 26% of the studies focused on water bodies for potable water supply (Su & Chou, 2015; Stoyneva-Gärtner et al., 2019; Son et al., 2020; Zhao et al., 2022b; Xiao et al., 2023), 15% on multi-purpose use (industrial, agricultural, living and drinking purposes) (Kim et al., 2016; Becker et al., 2019; Pokrzywinski et al., 2022) and, 11% directed their focus towards water bodies designated for multipurpose and or irrigation purposes (Morgan et al., 2020; Hong et al., 2022; Ciężkowski et al., 2023). This gives an understanding of the practical applications and relevance of the research findings. It also shows how UAVs are being utilised in different sectors. A considerable portion of studies (28%) did not articulate the intended purpose of the water bodies under investigation, revealing a significant gap in the literature.

3.4. In situ methods of measuring and analysing chl-a data in small water bodies

As shown in Figure 7, the results indicate that 22% of the included articles employed spectrophotometers for chl-a analysis in a laboratory environment (Su & Chou, 2015; Morgan et al., 2020; Tóth et al., 2021). While 22% of the studies utilized both spectroradiometers and spectrophotometers to gather *in situ* data (Kwon et al., 2020; Zhang et al., 2021; Hong et al., 2022). 11% of the articles used spectroradiometers only (Lu et al., 2021; De Keukelaere, 2023) and 9% of the studies used a variety of multiparameter probes,

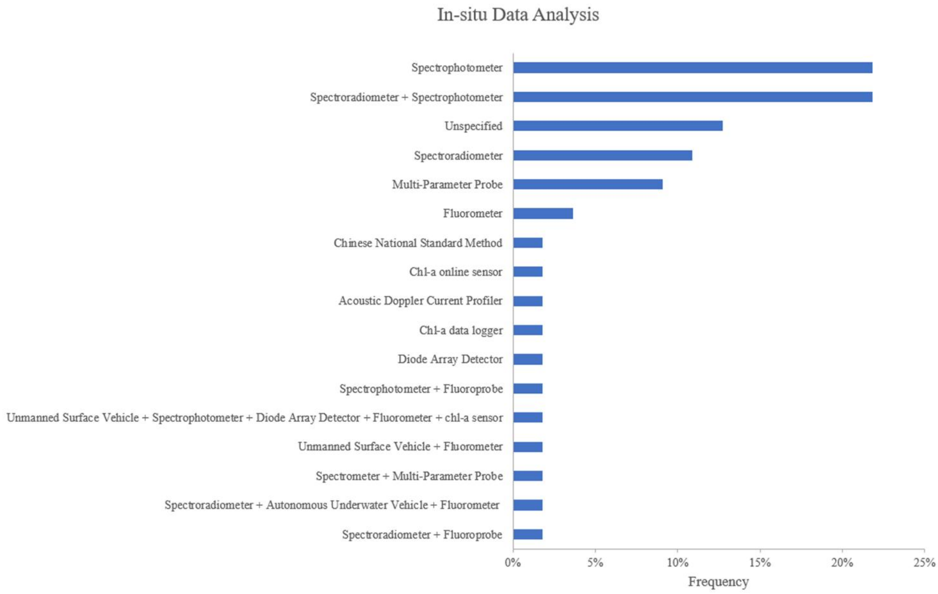

Figure 7. Instruments and methods for measuring *in situ* chl-a data, including field and laboratory techniques, and their frequency of use in the selected studies.

including the YSI EXO-2 and HX-200 meters (Hong et al., 2022; Zhao et al., 2022b; Lo et al., 2023). The rest of the studies used an integration of either a multiprobe or a spectroradiometer to allow for versatile, comprehensive, enhanced accuracy, automated measurements and real-time data collection.

3.5. UAV characteristics and platforms

This review identified two primary UAV platform types used for chl-a monitoring: fixed-wing and multicopters. Multicopters dominated, with 75% of studies employing them, followed by fixed-wing drones (21%) and 4% unspecified. DJI platforms (60%) were the predominant choice among multicopter platforms (Choo et al., 2018; Zhang et al., 2020a; Song et al., 2022; De Keukelaere, 2023), while SenseFly eBee (13%) platforms accounted for a significant share of the fixed-wing vehicles (Jang et al., 2016; Su, 2017; Silveira Kupssinskü et al., 2020). Fixed-wing UAVs offer aerodynamic benefits, enabling longer flight times, larger bloom surveillance and multiple sensor deployment for enhanced chl-a concentration accuracy. They suit mapping wider spatial extents. Multicopters excel in closer proximity analysis due to their vertical take-off and landing (VTOL) capabilities (Zaludin and Harituddin, 2019). This capability makes them easily employed in different environments than fixed-wing platforms, which require substantially flat and dry areas to deploy and launch successfully near water bodies. Other UAV platforms included Aytges (2%) (Cillero Castro et al., 2020), FireFLY BirdsEyeView (2%) (Choo et al., 2018), Begren RC (2%) (Becker et al., 2019), G4 SkyCrane (2%) (Pokrzywinski et al., 2022), ATI AgBot (2%) (Arango & Nairn, 2019), 3DR Solo(2%) (Morgan et al., 2020) and Remo-M (2%) (Kim et al., 2021). Additionally, 23% of the reviewed studies combined UAV and satellite acquired data from sensors which include Sentinel-2 & 3, Landsat 7, 8 & 9, PlanetScope, GF-1 (Gaofen-1), Orbita Hyperspectral Satellite (OHS) and ZY-3 satellite (Jung et al., 2017; Cillero Castro et al., 2020; El-Alem et al., 2021; Fu et al., 2023; Yang et al., 2023). This synergistic approach enhances spatial and temporal coverage, improves data accuracy, and allows for continuous monitoring, event detection and more comprehensive analysis.

3.6. Sensors and spectral bands

In remote sensing, the characteristics of sensors play a pivotal role in estimating water quality parameters. They impact the monitoring system's accuracy, reliability, and effectiveness (Modiegi et al. 2020). Thirteen different sensors and cameras were used in the reviewed studies (Figure 8). These sensors comprised multispectral and hyperspectral types, catering to various spectral bands. Approximately 55% of the studies utilised multispectral sensors, spanning the visible to near-infrared spectrum, including red, green, blue, red edge and near-infrared bands (Su & Chou, 2015; Guimarães et al., 2017; Morgan et al., 2020; Chen et al., 2021; Zhao et al., 2022b; Lo et al., 2023). These sensors predominantly utilised the near-infrared (NIR; 708 nm-842nm) and red (640 nm-668nm) bands as the optimal bands for detecting chl-a. Some studies also incorporated the green band (560 nm) and blue band (475 nm-497nm) and very few used the red edge band (730 nm-740nm) (Xiao et al., 2022; Zhao et al., 2022a). The most commonly used multispectral sensor was the MicaSense Rededge, utilised by 18% of the studies (Figure 8). On the other hand, 36% of the studies employed hyperspectral sensors, which captured data across a wavelength range of 350 nm to 1700 nm (Jang et al., 2016; Kwon et al., 2020; Pokrzywinski et al., 2022; Cai et al., 2023), with the 400 nm-755nm band being the most utilised segment for chl-a detection. A significant number of the studies (16%) used the Nano-Hyperspec hyperspectral sensor (Figure 8), making it highly effective for detecting chl-a in various ecosystem environments. Notably, two studies (Wu et al., 2023; Xiao et al., 2023) employed a synergistic approach by concurrently utilising multispectral and hyperspectral sensors. This approach leveraged the strengths of both types of sensors: the broad spectral coverage and high spatial resolution of the multispectral sensors, detailed spectral information, and high precision offered by hyperspectral sensors. By combining these sensors, the studies enhanced the accuracy and reliability of chl-a monitoring and mapping.

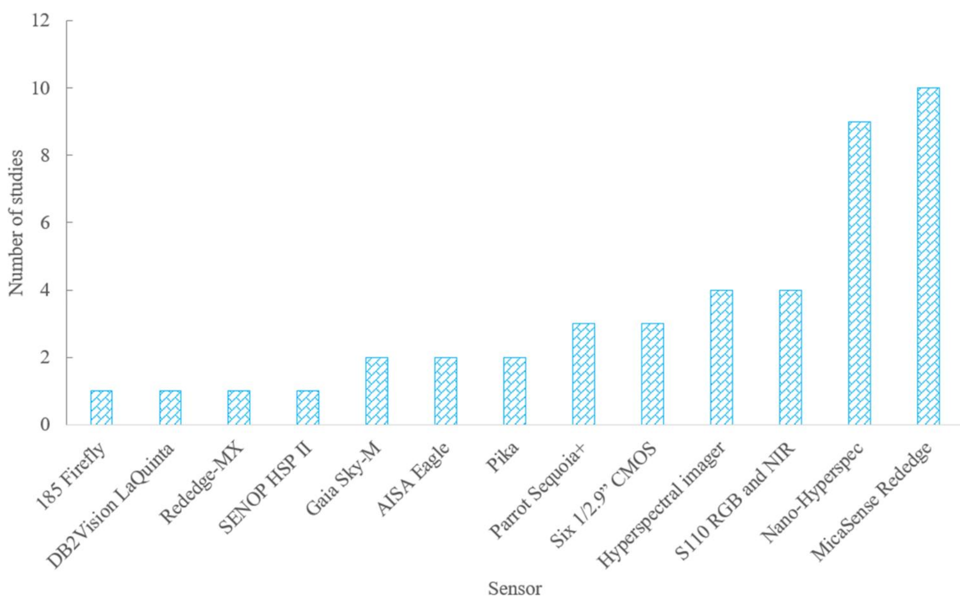

Figure 8. Types of sensors used in chl-a monitoring, showing their frequency in the selected studies.

3.7. Algorithms utilised for detecting chl-a concentrations in small water bodies

3.7.1. Spectral indices and band combinations

This study observed a variety of indices and band combinations for chl-a estimation in inland water bodies (Table 2). The indices comprise the normalised difference vegetation index (NDVI) (Douglas Greene, 2021), normalised difference red edge index (NDRE) (Kim et al., 2021), normalised difference chlorophyll index (NDCI) (Mishra and Mishra, 2012; Pokrzywinski et al., 2022), surface algal bloom index (SABI) (Douglas Greene, 2021). Although each of these indices was tailored to the specific aquatic environment for which it was developed, the fluorescence line height blue (FLH B), three-band algorithms (3BDA), and the NDCI indices were observed to be more effective, each gave a coefficient

Table 2. Accuracy measure for chl-a vegetation indices and band algorithms.

Index name	Abbreviation	Formula	Metric (R^2)	References
Fluorescence line height blue	FLHB	$G-(R+(B-R))$	0.75–0.86, average 0.805	Pokrzywinski (2022); Olivetti (2023)
Three band algorithms	3BDA		0.67–0.86, average 0.765	Pokrzywinski (2022); Cai (2023); Olivetti (2023)
Normalized Difference Chlorophyll Index	NDCI	$\frac{708-665}{708+665}$	0.5–0.82, average 0.707	Pokrzywinski (2022); Olivetti (2023); Xiao (2023)
	INDEX	$\frac{SR_{665}{}^{-1}-SR_{708}{}^{-1}}{SR_{753}{}^{-1}+SR_{708}{}^{-1})}$	0.670	Olivetti (2023)
Two band algorithms	2BDA		0.63–0.96, average 0.646	Hong (2022); Logan (2023); Xiao (2023)
Ratio normalized difference vegetation index	RNDVI	$\left(\frac{NIR-R}{NIR+R}\right)\times\left(\frac{NIR}{R}\right)$	0.611	Zhao (2022b)
	NFH560	$\frac{700}{560\ or\ 675}$	0.610	Xiao (2023)
Red, Rededge and NIR band ratio			0.586	Maravilla (2019)
Excess green minus excess red	EXGR	$EXG-1.4*R-G$	0.580	Zhao (2022b)
Brute-Force Method		$\frac{684}{674}$	0.570	Logan (2023)
Brute-Force Method Normalized difference		$\frac{684-674}{684+674}$	0.570	
Fluorescence line height violet	FLH Violet	$530-(644+[430-644]*SS\ (0.467))$	0.550	Pokrzywinski (2022)
	Ocx	$\frac{443\ or\ 490\ or\ 510}{555}$	0.550	Xiao (2023)
Green Normalized Difference Vegetation Index	GNDVI	$\frac{NIR-G}{NIR+G}$	0.312 – 0.74, average 0.519	Kim (2021); Olivetti (2023); Zhao (2022b)
Ratio vegetation index	RVI	$\frac{NIR}{R}$	0.508	Zhao (2022b)
Normalized difference vegetation index	NDVI	$\frac{(NIR-Red)}{(NIR+Red)}$	0.04–0.72, average 0.497	Choo (2018); Zhao (2022b); Chen (2023)
Green Two Band blue	G2B		0.470	Xiao (2023)
Two-band enhanced vegetation index	EVI2	$\frac{2.5*(N\ IR-R)}{NIR+2.4*R+1}$	0.440	Zhao (2022b)
Modified single ratio	MSR	$MSR=\frac{\left(\frac{NIR}{R}\right)-1}{\left(\frac{NIR}{R}\right)+1}$	0.425	
Normalized difference red edge index	NDRE	$\frac{NIR-RE}{NIR+RE}$	0.04–0.0418, average 0.0409	Kim (2021); Zhao (2022b)

B, blue; G, green; NIR, near-infrared; R, red; RE, red edge, SR – spectral reflectance, SS = Spectral Shape coefficient calculated as $\frac{(\lambda-\lambda^-)}{(\lambda^+-\lambda^-)}$.

of determination, R^2 value of greater than 0.7. Also, the results showed that 34% of the studies utilised two-band algorithms (2BDA) while 15% utilised 3BDA.

The NDVI index was the most employed (25%) spectral index; however, its R^2 values ranged from as low as 0.04 to 0.72. The NDVI was the most utilised index because it uses NIR and red bands which are suitable for estimating chl-a. However, the NDCI index, which combines the red and Rededge bands, demonstrated moderately higher accuracy than the NDVI index. This is because varying depths can affect the reflectance in the red and NIR bands, leading to lower accuracy and lower R^2 values for NDVI. Hence, alternative indices like the NDCI index (Mishra and Mishra, 2012; Olivetti et al., 2023) offer a solution as they are specially designed for chlorophyll estimation in water. The red and red edge bands of the NDCI index exhibit stronger and more reliable correlations, yielding higher R^2 values. The NDCI's targeted sensitivity to chlorophyll reduces the impact of confounding factors such as water turbidity and suspended particles (Chien et al. 2016), hence the higher accuracy.

Additionally, the literature revealed that 3BDA gave a higher precision than 2BDA. 3BDA remarkably exhibited R^2 values, averaging at 0.765, in comparison to 2BDA, which yielded an average of 0.646 for R^2 values. This is because 3BDA leverages extra spectral information from the extra band, enhancing its ability to discern target parameter characteristics. Also, the interaction between different water components can be slightly eliminated by using multiple bands (Gitelson 2003). Therefore, indices like the FLH B and INDEX demonstrate improved performance (Table 2) but only when hyperspectral sensors capture a wide range of the electromagnetic spectrum. Additionally, poor-performing indices (R^2: $0.0001 - 0.16$) were computed from the green, red and blue bands, for example, the visible atmospherically resistant index (VARIGREEN) and green–red ratio index (GRRI) while the moderate-performing indices (R^2: $0.4 - 0.6$) computed from the red and NIR bands, vegetation indices such as NDVI, DVI and green NDVI.

3.7.2. Machine learning

This study revealed that linear regression (LR), followed by random forest (RF), extreme gradient boosting (XGBoost) and support vector machine (SVM), were the most widely used algorithms for the prediction of chl-a from UAV imagery (Figure 9). Linear

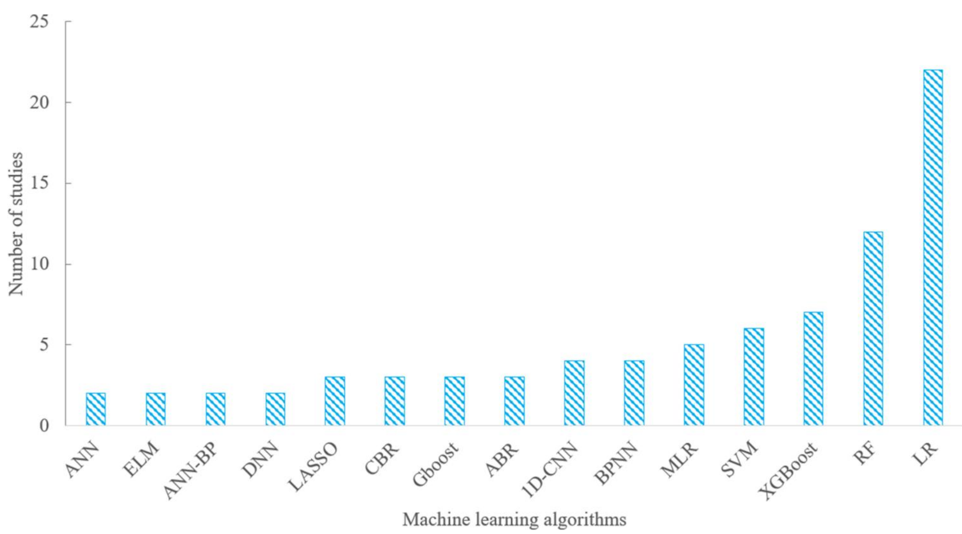

Figure 9. Machine learning algorithms used by the selected studies to estimate chl-a concentration from UAV data.

regression was used in 40% of the studies due to its simplicity in computation. While, 22% of the studies employed RF, which offers several significant advantages. It is quicker than bagging and highly accurate, effective in handling large data dimensionality and multicollinearity, making it suitable for complex datasets. As a non-parametric algorithm, RF does not assume a specific data distribution, adding to its versatility and ability to work with diverse sample types. Its built-in feature selection mechanism reduces overfitting, improving predictive performance. RF is also robust to outliers and noise, enhancing reliability, and can effectively handle imbalanced data. It is also easy to implement, can be parallelised, and significantly speeds up the training process (Breiman, 2001; Pal, 2005; Belgiu and Drăguţ, 2016; Herrera et al. 2019).

Regarding the performance of these algorithms (Table 3), the Catboost, Adaboost regression, Artificial Neural Network (ANN), Deep Neural Network (DNN) and K-Nearest Neighbors (KNN) demonstrated high R^2 values over 0.8 and were used in

Table 3. Accuracy measure for chl-a machine learning and predictive modelling methods.

Algorithm	Abbreviation	Metric (R^2)	References
Self-Adapting Selection of Multiple Neural Networks	SSNN	0.984	Zhang (2020b)
Ensemble-Based System	EBS	0.940	El-Alem (2021)
Hybrid Feedback Deep Factorization Machine	HF-DFM	0.930	Zhang (2021)
Chen Method 2023		0.917	Chen (2023)
Gradient Boost Regression Tree	GBRT	0.900	(Lu 2021)
Catboost Regression	CBR	0.808–0.96, average 0.88	Chen (2021); Lu (2021); Fu (2023)
Extremely Randomized Trees	ERT	0.870	Lu (2021)
Genetic Algorithm_XGBoost	GA _XGBoost	0.855	Chen (2023)
Genetic Algorithm_AdaBoost Regression	GA_ABR	0.826	
AdaBoost Regression	ABR	0.784–0.89, average 0.819	Chen (2021); Lu (2021); Chen (2023)
Artificial Neural Network	ANN	0.73–0.9014, average 0.816	Silveira Kupssinsku et al. (2020); Wu (2023)
Adaptive Ensemble Learning Regression	AELR	0.814	Fu (2023)
Deep Neural Network	DNN	0.805–0.817, average 0.811	Chen (2021); Chen (2023)
K-Nearest Neighbors	KNN	0.703–0.8964, average 0.8	Silveira Kupssinsku et al. (2020); Chen (2021)
Particle Swarm Optimization Algorithm	PSO–LSSVM	0.778	Liu (2021)
Regression trees	RT	0.77	Morgan (2020)
Partial Least Squares Algorithm	PLS	0.764	Liu (2021)
Extreme Learning Machine	ELM	0.7299–0.7609, average 0.745	Zhao (2022b, 2022a)
Extreme Gradient Boosting	XGBoost	0.415–0.92, average 0.737	Chen (2021); Lu (2021); Xiao (2022); Chen (2023)
Genetic Algorithm Partial Least Squares	GA-PLS	0.730	Zhang (2021)
Random Forest	RF	0.317–0.874, average 0.705	Chen (2021); Xiao (2022); Fu (2023); Yang (2023)
Linear regression	LR	0.203–0.980, average 0.7	Su (2017); Silveira Kupssinsku et al. (2020); Yi (2023)
1 Dimensional - Convolutional Neural Network	1D-CNN	0.1932–0.91, average 0.691	Hong (2022); Pyo (2022); Zhao (2022a); Lo (2023)
Transformer		0.650	Yang (2023)
Mixture Density Network	MDN	0.650	
Support Vector Machine	SVM	0.4813–0.759, average 0.623	Silveira Kupssinsku et al. (2020); Zhao (2022a); Lu (2021)
Multi-Layer Perceptron Regression	MLPR	0.620	Lu (2021)
Integrated Data Fusion and Mining	IDFM	0.620	Zhang (2021)
Multiple Linear Regression	MLR	0.101–0.860, average 0.62	Arango (2019); Zhang (2020b); Xiao (2023)
ResNet-182		0.610	Hong (2022)

more than three studies, establishing them as high-performing techniques. LR, RF, XGBoost and Extreme Learning Machine (ELM) had average R^2 values greater than 0.7, positioning them as strong performers. Despite being used by numerous studies, multiple linear regression (MLR) yielded an average R^2 value of 0.62. This performance can be considered moderate compared to other high-performing algorithms and indicates limited performance in chl-a mapping. Conversely, Self-Adapting Selection of Multiple Neural Networks (SSNN), Ensemble-Based System (EBS), Hybrid Feedback Deep Factorisation Machine (HF-DFM), the Chen method (2023) and Gradient Boost Regression Tree (GBRT) achieved R^2 values exceeding 0.9, while Genetic Algorithm_AdaBoost Regression (GA_ABR), Ensemble Learning Regression (ELR), Genetic Algorithm_XGBoost and Extremely Randomised Trees (ERT) surpassed 0.8. However, comparing these models is challenging due to their use in singular studies. Notably, Neural Networks (NN) emerged as a low-performing algorithm, with an accuracy of 0.093, rendering it challenging to assess its efficacy in chl-a estimation.

One of the methods used by the reviewed literature to estimate chl-a from UAV images was the use of stacked models. The Artificial Neural Network_Bayesian probabilistic (ANN-BP) stacked model exhibited the highest performance, achieving an average R^2 value of 0.84 (Zhang et al., 2020a; Zhang et al., 2020b). This was followed by the Random Forest_XGBoost (RF_XGB) model which gave an R^2 value of 0.504 for the testing data and a near-perfect score of 0.999 for its training data (Xiao et al., 2022). Additionally, other estimation models including Environmental Fluid Dynamics Code - Recursive Least Squares (Ahn et al., 2021; Hong et al., 2023), the Bio-optical algorithm approach (Hong et al., 2022), and the matching pixel-by-pixel (MPP) algorithm (Su, 2017) were found in the reviewed literature. These methods demonstrated moderately high accuracies, ranging from 0.7 to 0.85.

4. Discussion

4.1. Progress in the mapping monitoring of chl-a using UAVs

The reviewed studies reveal that between 2015 and 2018, the use of UAV applications in small water bodies was limited. This could be attributed to the high cost of UAVs (Sibanda et al. 2021) during this period, limiting access for research purposes. However, the usage of UAVs has gained traction over the last five years, which can be attributed to several factors such as improved UAV technologies, miniaturing of sensors, cost efficiency, increase in research funding, high-resolution data and real-time monitoring.

The findings showed that most studies were conducted in China, South Korea and the USA (Figure 5). This stems from the fact that UAV technology in these countries/regions evolved as far back as the twentieth century (Sibanda et al. 2021). Also, the world's leading UAV manufacturer, DJI, is based in Shenzhen, China, and this platform emerged as the most used from the reviewed studies. This proximity and ease of access to UAV technology have likely contributed to the region's high concentration of research studies. Additionally, South Korea's strong technology industry and innovative culture have facilitated the adoption and application of UAVs in various fields such as water quality monitoring, leading to more studies in the area. Overall, these countries are well-developed and can fund water quality monitoring programs.

Using a spectrophotometer in *in situ* data collection (Figure 7) indicates a preference for controlled, precise measurements as laboratory settings allow for meticulous calibration and control of experimental conditions, leading to highly reliable data. While spectrophotometers provide high precision, their use is often limited by the need to transport samples to the laboratory, which can introduce delays and potential sample degradation. This justifies why 21% of the studies utilised both spectroradiometers and spectrophotometers to gather *in situ* data. Spectroradiometers are capable of rapid, non-destructive measurements directly in the field and allow for real-time monitoring and immediate data availability (Guimarães et al., 2017). Unlike spectrophotometers, spectroradiometers determine chl-a concentration indirectly using radiances computed in an equation. The combined use of spectroradiometers and spectrophotometers reflects an approach that balances field applicability with data accuracy.

Regarding platforms and sensors, multi-copters were the most prevalent used in mapping chl-a. According to Zaludin and Harituddin (2019), multi-copters are preferred to fixed-wing drones in water quality mapping because of their cost-effectiveness. In this review, multispectral sensors were adopted by most of the studies relative to hyperspectral sensors, because of their cost-effectiveness (Adjovu et al. 2023). The MicaSense sensor was widely used in chl-a monitoring in small water bodies because it can capture images in five distinct bands: red, green, blue, near-infrared and Rededge. These bands are crucial in the estimation of chl-a. On the other hand, according to Shafique et al. (2003), hyperspectral sensors exhibit high spectral resolution which allows them to provide detailed and high-accuracy information on water quality of surface waters. As a result, hyperspectral sensors are considered very useful in water quality as they can detect changes in water quality more appropriately than multispectral sensors. Despite these merits, hyperspectral sensors have drawbacks, including high costs associated with sensor procurement and operational maintenance, limited depth penetration and sensing capabilities due to water absorption and scattering and complex data processing and analytical requirements (Bangira et al. 2024). Some reviewed studies utilised multispectral and hyperspectral sensors to achieve comprehensive datasets leveraging the wide range of the electromagnetic spectrum and cost-effective solutions (Topp et al. 2020; Yang et al. 2022).

4.2. Application of chl-a estimation algorithms

The findings of this review highlight the strengths and limitations of various algorithms used for chl-a estimation in UAV remote sensing applications. While linear regression is widely used due to its simplicity, it has limitations in accuracy evaluation. As Arias-Rodriguez et al. (2021) noted, linear regression assumes a linear relationship between predictor variables and the response variable, which may not always be the case. If the actual relationship is non-linear, linear regression may fail to capture the true pattern, leading to poor accuracy.

In this study, random forest was the most popular machine learning algorithm but it exhibited inconsistent performance. Despite an average R^2 value of 0.7, it showed good results in training data ($R^2 > 0.7$) but poor generalisation in testing data (R^2 as low as 0.3) (Su & Chou, 2015; Xiao et al., 2022; Lo et al., 2023). This inconsistency may be attributed to the weak correlation between chl-a and spectral indices, which limits model performance (Lo et al., 2023). In contrast, algorithms like XGBoost demonstrate high accuracy due to their operational efficiency, flexibility and ability to handle small sample sizes, control model complexity and reduce bias. For instance, Chen et al. (2021), Lu et al. (2021), Chen et al. (2023) and (Fu et al., 2023) achieved R^2 values greater than 0.8 using sample sizes of 44, 33, 59 and 31, respectively, showcasing the superior performance of XGBoost in chl-a estimation. The SVM algorithm was also widely used due to its robustness, ability to handle nonlinear relationships and accuracy in predicting results with small sample sizes (Raghavendra & Deka, 2014; Zhao et al., 2022a). However, its moderate accuracy ($R^2 = 0.62$) highlights the need for alternative approaches.

Probabilistic methods such as BPNN are suitable for large study areas, as they can accurately estimate water quality parameters even with imbalanced datasets and handle non-linear relationships. For example, Zhang et al. (2020a) successfully applied BPNN to a 0.42 km^2 river section with 35 samples. However, BPNN has drawbacks like convergence issues and local minimisation. Liu et al. (2021) observed significant deviations between predicted and true values with the BPNN algorithm, reducing model accuracy and performance. Convolutional Neural Networks (CNN) were the most adopted deep learning method, with reliable feature extraction capabilities from multi-dimensional data (Sothe et al. 2020). However, deep learning algorithms are based on black box models, making it challenging to interpret their outputs (Koh and Liang, 2017; Lee et al. 2021).

Neural networks and supervised machine learning algorithms performed strongly due to their stability, speed and limited overfitting. Stacked machine learning models achieved higher R^2 values than single models (Zhang et al., 2020a; Zhang et al., 2020b), but may be susceptible to overfitting. This overfitting issue suggests that stacked models may become overly specialised in the training data, failing to generalise effectively to new data. Therefore, using stacked models with caution on small datasets is crucial to avoid becoming too focused on specific dataset characteristics rather than learning underlying patterns and relationships (Rocha et al. 2017; Wang et al. 2019).

4.3. Gaps, challenges and opportunities

Research on mapping chl-a in small water bodies using UAVs has been gaining momentum in recent years, driven by advancements in UAV sensor technologies. This study extensively reviewed existing literature and identified several key gaps, challenges and opportunities related to using UAVs for chl-a mapping in small water bodies.

Previous studies of chl-a estimation using UAV-remotely sensed have not done any work in Africa. This may have been impeded by the high costs of UAVs and piloting licenses, as well as legal restrictions on UAV usage in many African countries (Rhee et al. 2018; Wang et al. 2020; Sibanda et al. 2021). Most affordable UAVs are also designed for recreational use, rather than research (Sibanda et al. 2021).

In addition to the geographical gap, literature revealed that the mapping and monitoring chl-a in small inland reservoirs is still rudimentary. This is because inland small reservoirs are too small, making them challenging to map using satellite remote sensing with coarse-resolution sensors. However, UAV-borne hyperspectral and multispectral sensors could address this gap by acquiring ultra-high resolution suitable for mapping chl-a in small reservoirs.

Moreover, several studies have successfully used UAVs to monitor chl-a in small water bodies. However, several challenges hinder the effectiveness of UAVs in chl-a mapping, such as the lack of robust models that can be trusted across multiple studies. While several models (EBS, Chen method, PSO-LSSVM, GA_ABR, GA_XGB, AELR, GBRT, ERT, GA_PLS and SSNN) have shown strong predictive power ($R^2>0.7$), each has only been evaluated in a single study, raising concerns about their reliability and generalisability. Furthermore, the limited number of comparative studies makes it difficult to determine the best-performing algorithm.

The use of thirteen different cameras, ten different UAV platforms, several different algorithms and overall methodology study by study highlights UAVs' flexibility and customised application in estimating chl-a for different geographical settings. While this is a merit, it also reveals a lack of standardisation in the processes involved in UAV-based remote sensing of chl-a. A solution to this will be to provide a standardised framework and simplified inversion models (Shen et al. 2012) for different case scenarios (based on the type of water body and size of the water body). This will assist in reducing the time spent testing and evaluating multiple UAVs, sensors and algorithms.

The performance of some algorithms may have been affected by single-date or single-image approach disadvantages because a small sample size can affect the algorithm's accuracy (Wasehun et al. 2024). Few studies collected data across multiple times or seasons, highlighting the need for more robust datasets to improve model accuracy. This review emphasises the importance of multi-temporal data collection to enhance the reliability of water quality predictions.

4.4. Limitations of the study

Some articles were unavailable in full text/length, limiting the review's comprehensiveness. Non-English articles were excluded, which may negatively impact the total number of studies reviewed on estimating chl-a concentrations. The accuracy of remote sensing data is crucial for reliability. This review used R^2 values as the primary measure for accuracy, which was limiting. Different studies used various accuracy measures with non-universal and variable International System of Units (SI unit). Additionally, R^2 values are influenced by factors such as sample size, sensor type, algorithm used and vegetation indices applied. These factors should be considered in the final analysis. However, since only peer-reviewed studies were included, it is assumed that the accuracy measures used in each study have been verified and deemed credible by peer reviewers.

Acknowledgements

The authors gratefully acknowledge the Water Resources Commission of South Africa for funding this research.

Disclosure statement

The authors declare no conflict of interest.

Funding

This research was funded by the Water Research Commission of South Africa under the project C2022/2023-00912, titled "*Assessing the utility of drone technology in monitoring water availability and quality in irrigation canals and dams for improving crop water productivity and enhancing precision agriculture in smallholder farms*".

Data availability statement

Data will be made available on request.

References

Adejimi OE, Sadhasivam G, Schmilovitch Z, Shapiro OH, Herrmann I. 2023. Applying hyperspectral transmittance for inter-genera classification of cyanobacterial and algal cultures. Algal Research. 71: 103067. doi: 10.1016/j.algal.2023.103067.

Adjovu GE, Stephen H, James D, Ahmad S. 2023. Overview of the application of remote sensing in effective monitoring of water quality parameters. Remote Sens. 15(7):1938. doi: 10.3390/rs15071938.

Ahn JM, Kim B, Jong J, Nam G, Park LJ, Park S, Kang T, Lee J-K, Kim J. 2021. Predicting cyanobacterial blooms using hyperspectral images in a regulated river. Sensors. 21(2):530. doi: 10.3390/s21020530.

Aranda YN, Bhatt P, Ates N, Engel BA, Simsek H. 2023. Cyanophage-cyanobacterial interactions for sustainable aquatic environment. Environ Res. 229:115728. doi: 10.1016/j.envres.2023.115728.

Arango JG, Nairn RW. 2019. Prediction of optical and non-optical water quality parameters in oligotrophic and eutrophic aquatic systems using a small unmanned aerial system. Drones. 4(1):1. doi: 10.3390/drones4010001.

Arias-Rodriguez LF, Duan Z, Díaz-Torres J, Basilio Hazas M, Huang J, Kumar BU, Tuo Y, Disse M. 2021. Integration of remote sensing and Mexican water quality monitoring system using an extreme learning machine. Sensors. 21(12):4118. doi: 10.3390/s21124118.

Bangira T, Matongera TN, Mabhaudhi T, Mutanga O. 2024. Remote sensing-based water quality monitoring in African reservoirs, potential and limitations of sensors and algorithms: a systematic review. Phys Chem Earth, Parts A/B/C. 134:103536. doi: 10.1016/j.pce.2023.103536.

Batur E, Maktav D. 2018. Assessment of surface water quality by using satellite images fusion based on PCA method in the Lake Gala, Turkey. IEEE Trans Geosci Remote Sens. 57(5):2983–2989. doi: 10.1109/TGRS.2018.2879024.

Becker RH, Sultan MI, Boyer GL, Twiss MR, Konopko E. 2009. Mapping cyanobacterial blooms in the Great Lakes using MODIS. J Great Lakes Res. 35(3):447–453. doi: 10.1016/j.jglr.2009.05.007.

Becker RH, Sayers M, Dehm D, Shuchman R, Quintero K, Bosse K, Sawtell R. 2019. Unmanned aerial system based spectroradiometer for monitoring harmful algal blooms: a new paradigm in water quality monitoring. J Great Lakes Res. 45(3):444–453. doi: 10.1016/j.jglr.2019.03.006.

Belgiu M, Drăguţ L. 2016. Random forest in remote sensing: a review of applications and future directions. ISPRS J Photogramm Remote Sens. 114:24–31. doi: 10.1016/j.isprsjprs.2016.01.011.

Biggs J, Williams P, Whitfield M, Nicolet P, Weatherby A. 2005. 15 years of pond assessment in Britain: results and lessons learned from the work of Pond Conservation. Aquatic Conservation. 15(6):693–714. doi: 10.1002/aqc.745.

Breiman L. 2001. Random forests. Machine Learning. 45(1):5–32. doi: 10.1023/A:1010933404324.

Bunyon CLF, Benjamin T, McQuaid A, Congalton RG. 2023. Using imagery collected by an unmanned aerial system to monitor cyanobacteria in New Hampshire, USA, Lakes. Remote Sensing. 15(11):2839. doi: 10.3390/rs15112839.

Cai X, Wu L, Li Y, Lei S, Xu J, Lyu H, Li J, Wang H, Dong X, Zhu Y, et al. 2023. Remote sensing identification of urban water pollution source types using hyperspectral data. J Hazard Mater. 459:132080. doi: 10.1016/j.jhazmat.2023.132080.

Cao Z, Ma R, Duan H, Pahlevan N, Melack J, Shen M, Xue K. 2020. A machine learning approach to estimate chlorophyll-a from Landsat-8 measurements in inland lakes. Remote Sens Environ. 248: 111974. doi: 10.1016/j.rse.2020.111974.

Carlberg C, Carlberg CG. 2014. Statistical analysis: Microsoft Excel 2013. Pearson Education.

Chen B, Mu X, Chen P, Wang B, Choi J, Park H, Xu S, Wu Y, Yang H. 2021. Machine learning-based inversion of water quality parameters in typical reach of the urban river by UAV multispectral data. Ecol Indic. 133:108434. doi: 10.1016/j.ecolind.2021.108434.

Chen P, Wang B, Wu Y, Wang Q, Huang Z, Wang C. 2023. Urban river water quality monitoring based on self-optimizing machine learning method using multi-source remote sensing data. Ecol Indic. 146: 109750. doi: 10.1016/j.ecolind.2022.109750.

Chien W-H, Wang T-S, Yeh H-C, Hsieh T-K. 2016. Study of NDVI application on turbidity in reservoirs. J Indian Soc Remote Sens. 44(5):829–836. doi: 10.1007/s12524-015-0533-6.

Choo Y, Kang G, Kim D, Lee S. 2018. A study on the evaluation of water-bloom using image processing. Environ Sci Pollut Res Int. 25(36):36775–36780. doi: 10.1007/s11356-018-3578-6.

Ciężkowski WF, Magdalena K, Ignacy P, Wiktoria Chormański J. 2023. Cyanobacteria risk and water quality assessment in Inland Głuszyńskie Lake Poland using field and UAV spectroscopy. IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium, p. 3752–3754. IEEE.

Cillero Castro C, Domínguez Gómez JA, Delgado Martín J, Hinojo Sánchez BA, Cereijo Arango JL, Cheda Tuya FA, Díaz-Varela R. 2020. An UAV and satellite multispectral data approach to monitor water quality in small reservoirs. Remote Sensing. 12(9):1514. doi: 10.3390/rs12091514.

Cook KV, Beyer JE, Xiao X, Hambright KD. 2023. Ground-based remote sensing provides alternative to satellites for monitoring cyanobacteria in small lakes. Water Res. 242:120076. doi: 10.1016/j.watres.2023.120076.

De Keukelaere LM, Knaeps R, Sterckx E, Reusen S, De Munck I, Simis D, Constantinescu SGH, Scrieciu AM, Katsouras A, Mertens G, et al. 2023. Airborne drones for water quality mapping in inland, transitional and coastal waters-MapEO water data processing and validation. Remote Sensing. 15(5):1345. doi: 10.3390/rs15051345.

Dekker AG. 1993. Detection of optical water quality parameters for eutrophic waters by high-resolution remote sensing. Available from: https://research.vu.nl/ws/portalfiles/portal/62846616/complete+dissertation.pdf

Douglas Greene SB, LeFevre GH, Markfort CD. 2021. Improving the spatial and temporal monitoring of cyanotoxins in Iowa lakes using a multiscale and multi-modal monitoring approach. Sci Total Environ. 760:143327. doi: 10.1016/j.scitotenv.2020.143327.

El-Alem A, Chokmani K, Venkatesan A, Rachid L, Agili H, Dedieu J-P. 2021. How accurate is an unmanned aerial vehicle data-based model applied on satellite imagery for chlorophyll-a estimation in freshwater bodies? Remote Sensing. 13(6):1134. doi: 10.3390/rs13061134.

Fournier C, Quesada A, Cirés S, Saberioon M. 2024. Discriminating bloom-forming cyanobacteria using lab-based hyperspectral imagery and machine learning: validation with toxic species under environmental ranges. Sci Total Environ. 932:172741. doi: 10.1016/j.scitotenv.2024.172741.

Fu B, Li S, Lao Z, Yuan B, Liang Y, He W, Sun W, He H. 2023. Multi-sensor and multi-platform retrieval of water chlorophyll a concentration in karst wetlands using transfer learning frameworks with ASD, UAV, and Planet CubeSate reflectance data. Sci Total Environ. 901:165963. doi: 10.1016/j.scitotenv.2023.165963.

Gao Y, Gao J, Yin H, Liu C, Xia T, Wang J, Huang Q. 2015. Remote sensing estimation of the total phosphorus concentration in a large lake using band combinations and regional multivariate statistical modeling techniques. J Environ Manage. 151:33–43. doi: 10.1016/j.jenvman.2014.11.036.

Gilerson AA, Gitelson AA, Zhou J, Gurlin D, Moses W, Ioannou I, Ahmed SA. 2010. Algorithms for remote estimation of chlorophyll-a in coastal and inland waters using red and near infrared bands. Opt Express. 18(23):24109–24125. doi: 10.1364/OE.18.024109.

Gitelson A. 1992. The peak near 700 nm on radiance spectra of algae and water: relationships of its magnitude and position with chlorophyll concentration. Int J Remote Sens. 13(17):3367–3373. doi: 10.1080/01431169208904125.

Gitelson AA, Gritz Y, Merzlyak MN. 2003. Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves. J Plant Physiol. 160(3):271–282. doi: 10.1078/0176-1617-00887.

Gregor J, Marsálek B. 2004. Freshwater phytoplankton quantification by chlorophyll a: a comparative study of in vitro, in vivo and in situ methods. Water Res. 38(3):517–522. doi: 10.1016/j.watres.2003.10.033.

Guimarães T, Veronez M, Koste E, Gonzaga L, Bordin F, Inocencio L, Larocca A, De Oliveira M, Vitti D, Mauad F. 2017. An alternative method of spatial autocorrelation for chlorophyll detection in water bodies using remote sensing. Sustainability (Switzerland). 9(3):416. doi: 10.3390/su9030416.

Gurlin D, Gitelson AA, Moses WJ. 2011. Remote estimation of chl-a concentration in turbid productive waters—return to a simple two-band NIR-red model? Remote Sens Environ. 115(12):3479–3490. doi: 10.1016/j.rse.2011.08.011.

Herrera VM, Khoshgoftaar TM, Villanustre F, Furht B. 2019. Random forest implementation and optimization for Big Data analytics on LexisNexis's high performance computing cluster platform. J Big Data. 6(1):1–36. doi: 10.1186/s40537-019-0232-1.

Hong SM, Abbas A, Kim S, Kwon DH, Yoon N, Yun D, Lee S, Pachepsky Y, Pyo J, Cho KH. 2023. Autonomous calibration of EFDC for predicting chlorophyll-a using reinforcement learning and a real-time monitoring system. Environ Model Software. 168:105805. doi: 10.1016/j.envsoft.2023.105805.

Hong SM, Cho KH, Park S, Kang T, Kim MS, Nam G, Pyo J. 2022. Estimation of cyanobacteria pigments in the main rivers of South Korea using spatial attention convolutional neural network with hyperspectral imagery. GIScience Remote Sens. 59(1):547–567. doi: 10.1080/15481603.2022.2037887.

Horsley T, Dingwall O, Sampson M. 2011. Checking reference lists to find additional studies for systematic reviews. Cochrane Database Syst Rev. 2011(8):MR000026. doi: 10.1002/14651858.MR000026.pub2.

Hunter P, Tyler A, Presing M, Kovacs A, Preston T. 2008. Spectral discrimination of phytoplankton colour groups: the effect of suspended particulate matter and sensor spectral resolution. Remote Sens Environ. 112(4):1527–1544. doi: 10.1016/j.rse.2007.08.003.

Jang SWY, HJ, Kwak S, Nam, Sohn BY, Kim SG, Kim DH. 2016. Algal bloom monitoring using UAVs imagery. Adv Sci Technol Lett. 138 30–33. doi: 10.14257/astl.2016.138.08.

Johan FB, Jafri MZBM, San LH, Omar WMW, Ho TC. 2018. Chlorophyll a concentration of fresh water phytoplankton analysed by algorithmic based spectroscopy. J Phys: Conf Ser. 1083:12015. doi: 10.1088/1742-6596/1083/1/012015.

Jung S, Cho H, Kim D, Kim K, Han J-I, Myung H. 2017. Development of algal bloom removal system using unmanned aerial vehicle and surface vehicle. IEEE Access. 5:22166–22176. doi: 10.1109/ACCESS.2017.2764328.

Kim E-J, Nam S-H, Koo J-W, Hwang T-M. 2021. Hybrid approach of unmanned aerial vehicle and unmanned surface vehicle for assessment of chlorophyll-a imagery using spectral indices in Stream, South Korea. Water. 13(14):1930. doi: 10.3390/w13141930.

Kim H-M, Yoon H-J, Jang SW, Kwak SN, Sohn BY, Kim SG, Kim DH. 2016. Application of unmanned aerial vehicle imagery for algal bloom monitoring in river basin. IJCA. 9(12):203–220. doi: 10.14257/ijca.2016.9.12.18.

Kirk JT. 1994. Light and photosynthesis in aquatic ecosystems. Cambridge: Cambridge University Press.

Koh PW, Liang P. 2017. Understanding black-box predictions via influence functions. International Conference on Machine Learning. 1885–1894. PMLR.

Kolluru S, Tiwari SP. 2022. Modeling ocean surface chlorophyll-a concentration from ocean color remote sensing reflectance in global waters using machine learning. Sci Total Environ. 844:157191. doi: 10.1016/j.scitotenv.2022.157191.

Kolluru S, Gedam SS, Chander S, Sahay A. 2023. Development of chlorophyll-a concentration estimation algorithm for turbid productive inland waters in India. Geocarto International. 38(1):2171143. doi: 10.1080/10106049.2023.2171143.

Kuhn C, de Matos Valerio A, Ward N, Loken L, Sawakuchi HO, Kampel M, Richey J, Stadler P, Crawford J, Striegl R, et al. 2019. Performance of Landsat-8 and Sentinel-2 surface reflectance products for river remote sensing retrievals of chlorophyll-a and turbidity. Remote Sens Environ. 224:104–118. doi: 10.1016/j.rse.2019.01.023.

Kutser T. 2009. Passive optical remote sensing of cyanobacteria and other intense phytoplankton blooms in coastal and inland waters. Int J Remote Sens. 30(17):4401–4425. doi: 10.1080/01431160802562305.

Kwon YS, Pyo J, Kwon Y-H, Duan H, Cho KH, Park Y. 2020. Drone-based hyperspectral remote sensing of cyanobacteria using vertical cumulative pigment concentration in a deep reservoir. Remote Sens Environ. 236:111517. doi: 10.1016/j.rse.2019.111517.

Lai Y, Zhang J, Song Y, Gong Z. 2021. Retrieval and evaluation of chlorophyll-a concentration in reservoirs with main water supply function in Beijing, China, based on landsat satellite images. Int J Environ Res Public Health. 18(9):4419. doi: 10.3390/ijerph18094419.

Lee J, Kim M, Im J, Han H, Han D. 2021. Pre-trained feature aggregated deep learning-based monitoring of overshooting tops using multi-spectral channels of GeoKompsat-2A advanced meteorological imagery. GIScience Remote Sens. 58(7):1052–1071. doi: 10.1080/15481603.2021.1960075.

Li Z, Zhu X, Wu Z, Sun T, Tong Y. 2023. Recent advances in cyanotoxin synthesis and applications: a comprehensive review. Microorganisms. 11(11):2636. doi: 10.3390/microorganisms11112636.

Lins RC, Martinez J-M, Motta Marques DD, Cirilo JA, Fragoso CR. Jr, 2017. Assessment of chlorophyll-a remote sensing algorithms in a productive tropical estuarine-lagoon system. Remote Sens. 9(6):516. doi: 10.3390/rs9060516.

Liu H, Yu T, Hu B, Hou X, Zhang Z, Liu X, Liu J, Wang X, Zhong J, Tan Z, et al. 2021. Uav-borne hyperspectral imaging remote sensing system based on acousto-optic tunable filter for water quality monitoring. Remote Sens. 13(20):4069. doi: 10.3390/rs13204069.

Liu W, Qiu R. 2007. Water eutrophication in China and the combating strategies. J of Chemical Tech & Biotech. 82(9):781–786. doi: 10.1002/jctb.1755.

Lo Y, Fu L, Lu T, Huang H, Kong L, Xu Y, Zhang C. 2023. Medium-sized lake water quality parameters retrieval using multispectral UAV image and machine learning algorithms: a case study of the Yuandang Lake, China. Drones. 7(4):244. doi: 10.3390/drones7040244.

Logan RDT, Madison A, Feijó-Lima R, Colman BP, Valett HM, Shaw JA. 2023. UAV-based hyperspectral imaging for river algae pigment estimation. Remote Sensing. 15(12):3148. doi: 10.3390/rs15123148.

Lu Q, Si W, Wei L, Li Z, Xia Z, Ye S, Xia Y. 2021. Retrieval of water quality from UAV-borne hyperspectral imagery: a comparative study of machine learning algorithms. Remote Sensing. 13(19):3928. doi: 10.3390/rs13193928.

Maravilla RMG, Quinalayo JP, Blanco AC, Candido CG, Gubatanga EV, Ticman KDV. 2019. Estimation of chlorophyll-a concentration in sampaloc lake using uas multispectral remote sensing and regression. Int Arch Photogramm Remote Sens Spatial Inf Sci. XLII-4/W19:297–303. International Society for Photogrammetry and Remote Sensing. doi: 10.5194/isprs-archives-XLII-4-W19-297-2019.

Markogianni V, Kalivas D, Petropoulos GP, Dimitriou E. 2018. An appraisal of the potential of Landsat 8 in estimating chlorophyll-a, ammonium concentrations and other water quality indicators. Remote Sensing. 10(7):1018. doi: 10.3390/rs10071018.

Matthews MW. 2011. A current review of empirical procedures of remote sensing in inland and near-coastal transitional waters. Int J Remote Sens. 32(21):6855–6899. doi: 10.1080/01431161.2010.512947.

Mishra S, Mishra DR. 2012. Normalized difference chlorophyll index: a novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. Remote Sens Environ. 117:394–406. doi: 10.1016/j.rse.2011.10.016.

Mobley C. 1994. Light and water: radiative transfer in natural waters. San Diego, CA: Academic Press.

Modiegi M, Rampedi IT, Tesfamichael SG. 2020. Comparison of multi-source satellite data for quantifying water quality parameters in a mining environment. J Hydrol. 591:125322. doi: 10.1016/j.jhydrol.2020.125322.

Morgan BJ, Stocker MD, Valdes-Abellan J, Kim MS, Pachepsky Y. 2020. Drone-based imaging to assess the microbial water quality in an irrigation pond: a pilot study. Sci Total Environ. 716:135757. doi: 10.1016/j.scitotenv.2019.135757.

Moses WJ, Gitelson AA, Perk RL, Gurlin D, Rundquist DC, Leavitt BC, Barrow TM, Brakhage P. 2012. Estimation of chlorophyll-a concentration in turbid productive waters using airborne hyperspectral data. Water Res. 46(4):993–1004. doi: 10.1016/j.watres.2011.11.068.

O'Reilly JE, Maritorena S, Siegel DA, O'Brien MC, Toole D, Mitchell BG, Kahru M, Chavez FP, Strutton P, Cota GF. 2000. Ocean color chlorophyll a algorithms for SeaWiFS, OC2, and OC4: version 4. SeaWiFS postlaunch calibration and validation analyses part. 3:9–23.

Olivetti D, Cicerelli R, Martinez J-M, Almeida T, Casari R, Borges H, Roig H. 2023. Comparing unmanned aerial multispectral and hyperspectral imagery for harmful algal bloom monitoring in artificial ponds used for fish farming. Drones. 7(7):410. doi: 10.3390/drones7070410.

O'Reilly JE, Werdell PJ. 2019. Chlorophyll algorithms for ocean color sensors-OC4, OC5 & OC6. Remote Sens Environ. 229:32–47. doi: 10.1016/j.rse.2019.04.021.

O'Reilly JE, Maritorena S, Mitchell BG, Siegel DA, Carder KL, Garver SA, Kahru M, McClain C. 1998. Ocean color chlorophyll algorithms for SeaWiFS. J Geophys Res. 103(C11):24937–24953. doi: 10.1029/98JC02160.

Paerl HW, Barnard MA. 2020. Mitigating the global expansion of harmful cyanobacterial blooms: moving targets in a human-and climatically-altered world. Harmful Algae. 96:101845. doi: 10.1016/j.hal.2020.101845.

Paerl HW, Hall NS, Calandrino ES. 2011. Controlling harmful cyanobacterial blooms in a world experiencing anthropogenic and climatic-induced change. Sci Total Environ. 409(10):1739–1745. doi: 10.1016/j.scitotenv.2011.02.001.

Pal M. 2005. Random forest classifier for remote sensing classification. Int J Remote Sens. 26(1):217–222. doi: 10.1080/01431160412331269698.

Pamula AS, Gholizadeh H, Krzmarzick MJ, Mausbach WE, Lampert DJ. 2023. A remote sensing tool for near real-time monitoring of harmful algal blooms and turbidity in reservoirs. J American Water Resour Assoc. 59(5):929–949. doi: 10.1111/1752-1688.13121.

Pokrzywinski K, Johansen R, Reif M, Bourne S, Hammond S, Fernando B. 2022. Remote sensing of the cyanobacteria life cycle: a mesocosm temporal assessment of a Microcystis sp. bloom using coincident unmanned aircraft system (UAS) hyperspectral imagery and ground sampling efforts. Harmful Algae. 117:102268. doi: 10.1016/j.hal.2022.102268.

Pulliainen J, Kallio K, Eloheimo K, Koponen S, Servomaa H, Hannonen T, Tauriainen S, Hallikainen M. 2001. A semi-operative approach to lake water quality retrieval from remote sensing data. Sci Total Environ. 268(1–3):79–93. doi: 10.1016/S0048-9697(00)00687-2.

Pyo JC, Ligaray M, Kwon YS, Ahn M-H, Kim K, Lee H, Kang T, Cho SB, Park Y, Cho KH. 2018. High-spatial resolution monitoring of phycocyanin and chlorophyll-a using airborne hyperspectral imagery. Remote Sensing. 10(8):1180. doi: 10.3390/rs10081180.

Pyo J, Hong SM, Jang J, Park S, Park J, Noh JH, Cho KH. 2022. Drone-borne sensing of major and accessory pigments in algae using deep learning modeling. GIScience and Remote Sensing. 59(1):310–332. doi: 10.1080/15481603.2022.2027120.

Raghavendra NS, Deka PC. 2014. Support vector machine applications in the field of hydrology: a review. Appl Soft Comput. 19:372–386. doi: 10.1016/j.asoc.2014.02.002.

Rankinen K, Bernal JEC, Holmberg M, Vuorio K, Granlund K. 2019. Identifying multiple stressors that influence eutrophication in a Finnish agricultural river. Sci Total Environ. 658:1278–1292. doi: 10.1016/j.scitotenv.2018.12.294.

Rhee DS, Kim YD, Kang B, Kim D. 2018. Applications of unmanned aerial vehicles in fluvial remote sensing: an overview of recent achievements. KSCE J Civ Eng. 22(2):588–602. doi: 10.1007/s12205-017-1862-5.

Ritchie JC, Zimba PV, Everitt JH. 2003. Remote sensing techniques to assess water quality. Photogramm Eng Remote Sensing. 69(6):695–704. doi: 10.14358/PERS.69.6.695.

Rocha AD, Groen TA, Skidmore AK, Darvishzadeh R, Willemen L. 2017. The Naïve Overfitting Index Selection (NOIS): a new method to optimize model complexity for hyperspectral data. ISPRS J Photogramm Remote Sens. 133:61–74. doi: 10.1016/j.isprsjprs.2017.09.012.

Salmi P, Eskelinen MA, Leppänen MT, Pölönen I. 2021. Rapid quantification of microalgae growth with hyperspectral camera and vegetation indices. Plants. 10(2):341. doi: 10.3390/plants10020341.

Schalles JF. 2006. Optical remote sensing techniques to estimate phytoplankton chlorophyll a concentrations in coastal waters with varying suspended matter and CDOM concentrations. Remote Sensing of Aquatic Coastal Ecosystem Processes: science and Management Applications. 27–79.

Shafique NA, Fulk F, Autrey BC, Flotemersch J. 2003. Hyperspectral remote sensing of water quality parameters for large rivers in the Ohio River basin. First interagency conference on research in the watershed, Benson, AZ, p. 216–221. Citeseer.

Sharp SL, Forrest AL, Bouma-Gregson K, Jin Y, Cortés A, Schladow SG. 2021. Quantifying scales of spatial variability of cyanobacteria in a large, Eutrophic lake using multiplatform remote sensing tools. Front Environ Sci. 9:612934. doi: 10.3389/fenvs.2021.612934.

Shen L, Xu H, Guo X. 2012. Satellite remote sensing of harmful algal blooms (HABs) and a potential synthesized framework. Sensors (Basel). 12(6):7778–7803. doi: 10.3390/s120607778.

Sibanda M, Mutanga O, Chimonyo VG, Clulow AD, Shoko C, Mazvimavi D, Dube T, Mabhaudhi T. 2021. Application of drone technologies in surface water resources monitoring and assessment: a systematic review of progress, challenges, and opportunities in the global south. Drones. 5(3):84. doi: 10.3390/drones5030084.

Silveira Kupssinskü L, Thomassim Guimarães T, Menezes de Souza E, C. Zanotta D, Roberto Veronez M, Gonzaga L, Jr., Mauad FF. 2020. A method for chlorophyll-a and suspended solids prediction through remote sensing and machine learning. Sensors. 20(7):2125. doi: 10.3390/s20072125.

Son G, Kim D, Kim YD, Lyu S, Kim S. 2020. A forecasting method for harmful algal bloom (HAB)-prone regions allowing preemptive countermeasures based only on acoustic doppler current profiler measurements in a large river. Water. 12(12):3488. doi: 10.3390/w12123488.

Søndergaard M, Larsen SE, Jørgensen TB, Jeppesen E. 2011. Using chlorophyll a and cyanobacteria in the ecological classification of lakes. Ecol Indic. 11(5):1403–1412. doi: 10.1016/j.ecolind.2011.03.002.

Song Z, Xu W, Dong H, Wang X, Cao Y, Huang P, Hou D, Wu Z, Wang Z. 2022. Research on cyanobacterial-bloom detection based on multispectral imaging and deep-learning method. Sensors. 22(12):4571. doi: 10.3390/s22124571.

Sothe C, De Almeida CM, Schimalski MB, La Rosa LEC, Castro JDB, Feitosa RQ, Dalponte M, Lima CL, Liesenberg V, Miyoshi GT, et al. 2020. Comparative performance of convolutional neural network, weighted and conventional support vector machine and random forest for classifying tree species using hyperspectral and photogrammetric data. GIScience & Remote Sensing. 57(3):369–394. doi: 10.1080/15481603.2020.1712102.

Stengel VG, Trevino JM, King TV, Ducar SD, Hundt SA, Hafen KC, Churchill CJ. 2023. Near real-time satellite detection and monitoring of aquatic algae and cyanobacteria: how a combination of chlorophyll-a indices and water-quality sampling was applied to north Texas reservoirs. J Appl Rem Sens. 17(4):44514. doi: 10.1117/1.JRS.17.044514.

Stoyneva-Gärtner MPU, Blagoy A, Descy J-P, Gärtner G, Draganova PH, Borisova CI, Pavlova V, Mitreva M. 2019. Pilot application of drone observations and pigment marker detection by HPLC in studies of cyanobacterial harmful algal blooms in Bulgarian inland waters. Mar Freshwater Res. 71(5):606–616. doi: 10.1071/MF18383.

Su TC. 2017. A study of a matching pixel by pixel (MPP) algorithm to establish an empirical model of water quality mapping, as based on unmanned aerial vehicle (UAV) images. Int J Appl Earth Obs Geoinf. 58:213–224. doi: 10.1016/j.jag.2017.02.011.

Su T-C, Chou H-T. 2015. Application of multispectral sensors carried on unmanned aerial vehicle (UAV) to trophic state mapping of small reservoirs: a case study of Tain-Pu reservoir in Kinmen, Taiwan. Remote Sensing. 7(8):10078–10097. doi: 10.3390/rs70810078.

Tian S, Guo H, Xu W, Zhu X, Wang B, Zeng Q, Mai Y, Huang JJ. 2023. Remote sensing retrieval of inland water quality parameters using Sentinel-2 and multiple machine learning algorithms. Environ Sci Pollut Res Int. 30(7):18617–18630. doi: 10.1007/s11356-022-23431-9.

Topp SN, Pavelsky TM, Jensen D, Simard M, Ross MR. 2020. Research trends in the use of remote sensing for inland water quality science: moving towards multidisciplinary applications. Water. 12(1):169. doi: 10.3390/w12010169.

Tóth VZ, Grósz J, Ladányi M, Jung A. 2021. A new lake algae detection method supported by a drone-based multispectral camera. Lakes & Reservoirs. 26(3):e12377. doi: 10.1111/lre.12377.

Van Eck NJ, Waltman L. 2007. VOS: a new method for visualizing similarities between objects. Advances in Data Analysis: Proceedings of the 30th Annual Conference of the Gesellschaft Für Klassifikation eV, Freie Universität Berlin, March 8–10, 2006, p. 299–306. Springer.

Wang EK, Wang F, Sun R, Liu X. 2019. A new privacy attack network for remote sensing images classification with small training samples. Math Biosci Eng. 16(5):4456–4476. doi: 10.3934/mbe.2019222.

Wang L, Yue X, Wang H, Ling K, Liu Y, Wang J, Hong J, Pen W, Song H. 2020. Dynamic inversion of inland aquaculture water quality based on UAVs-WSN spectral analysis. Remote Sens. 12(3):402. doi: 10.3390/rs12030402.

Wang W, Shi K, Zhang Y, Li N, Sun X, Zhang D, Zhang Y, Qin B, Zhu G. 2022. A ground-based remote sensing system for high-frequency and real-time monitoring of phytoplankton blooms. J Hazard Mater. 439:129623. doi: 10.1016/j.jhazmat.2022.129623.

Warren MA, Simis SGH, Selmes N. 2021. Complementary water quality observations from high and medium resolution sentinel sensors by aligning chlorophyll-a and turbidity algorithms. Remote Sens Environ. 265:112651. doi: 10.1016/j.rse.2021.112651.

Wasehun ET, Hashemi Beni L, Di Vittorio CA. 2024. UAV and satellite remote sensing for inland water quality assessments: a literature review. Environ Monit Assess. 196(3):277. doi: 10.1007/s10661-024-12342-6.

Wisser D, Frolking S, Douglas EM, Fekete BM, Schumann AH, Vörösmarty CJ. 2010. The significance of local water resources captured in small reservoirs for crop production–a global-scale analysis. J Hydrol. 384(3–4):264–275. doi: 10.1016/j.jhydrol.2009.07.032.

Wu C, Wu J, Qi J, Zhang L, Huang H, Lou L, Chen Y. 2010. Empirical estimation of total phosphorus concentration in the mainstream of the Qiantang River in China using Landsat TM data. Int J Remote Sens. 31(9):2309–2324. doi: 10.1080/01431160902973873.

Wu D, Li R, Zhang F, Liu J. 2019. A review on drone-based harmful algae blooms monitoring. Environ Monit Assess. 191(4):211. doi: 10.1007/s10661-019-7365-8.

Wu D, Jiang J, Wang F, Luo Y, Lei X, Lai C, Wu X, Xu M. 2023. Retrieving eutrophic water in highly urbanized area coupling UAV multispectral data and machine learning algorithms. Water. 15(2):354. doi: 10.3390/w15020354.

Xiang T-Z, Xia G-S, Zhang L. 2019. Mini-unmanned aerial vehicle-based remote sensing: techniques, applications, and prospects. IEEE Geosci Remote Sens Mag. 7(3):29–63. doi: 10.1109/MGRS.2019.2918840.

Xiao Y, Chen J, Xu Y, Guo S, Nie X, Guo Y, Li X, Hao F, Fu YH. 2023. Monitoring of chlorophyll-a and suspended sediment concentrations in optically complex inland rivers using multisource remote sensing measurements. Ecol Indic. 155:111041. doi: 10.1016/j.ecolind.2023.111041.

Xiao Y, Guo Y, Yin G, Zhang X, Shi Y, Hao F, Fu Y. 2022. UAV multispectral image-based urban river water quality monitoring using stacked ensemble machine learning algorithms—a case study of the Zhanghe River, China. Remote Sensing. 14(14):3272. doi: 10.3390/rs14143272.

Yang H, Kong J, Hu H, Du Y, Gao M, Chen F. 2022. A review of remote sensing for water quality retrieval: progress and challenges. Remote Sensing. 14(8):1770. doi: 10.3390/rs14081770.

Yang W, Fu B, Li S, Lao Z, Deng T, He W, He H, Chen Z. 2023. Monitoring multi-water quality of internationally important karst wetland through deep learning, multi-sensor and multi-platform remote sensing images: a case study of Guilin, China. Ecol Indic. 154:110755. doi: 10.1016/j.ecolind.2023.110755.

Yao H, Qin R, Chen X. 2019. Unmanned aerial vehicle for remote sensing applications—a review. Remote Sensing. 11(12):1443. doi: 10.3390/rs11121443.

Yi L, Zhang G, Zhang B. 2023. Application of UAV push-broom hyperspectral images in water quality assessments for inland water protection: a case study of Zhang Wei Xin River in Dezhou Distinct, China. Remote Sensing. 15(9):2360. doi: 10.3390/rs15092360.

Yu G, Yang W, Matsushita B, Li R, Oyama Y, Fukushima T. 2014. Remote estimation of Chlorophyll-a in inland waters by a NIR-Red-based algorithm: validation in Asian lakes. Remote Sensing. 6(4):3492–3510. doi: 10.3390/rs6043492.

Zaludin Z, Harituddin ASM. 2019. Challenges and trends of changing from hover to forward flight for a converted hybrid fixed wing vtol uas from automatic flight control system perspective. 2019 IEEE 9th International Conference on System Engineering and Technology (ICSET), 247–252. IEEE. doi: 10.1109/ICSEngT.2019.8906483.

Zeng C, Richardson M, King DJ. 2017. The impacts of environmental variables on water reflectance measured using a lightweight unmanned aerial vehicle (UAV)-based spectrometer system. ISPRS J Photogramm Remote Sens. 130:217–230. doi: 10.1016/j.isprsjprs.2017.06.004.

Zhang D, Zhang L, Sun X, Gao Y, Lan Z, Wang Y, Zhai H, Li J, Wang W, Chen M, et al. 2022. A new method for calculating water quality parameters by integrating space–ground hyperspectral data and spectral-in situ assay data. Remote Sens. 14(15):3652. doi: 10.3390/rs14153652.

Zhang Y, Wu L, Deng L, Ouyang B. 2021. Retrieval of water quality parameters from hyperspectral images using a hybrid feedback deep factorization machine model. Water Res. 204:117618. doi: 10.1016/j.watres.2021.117618.

Zhang Y, Wu L, Ren H, Deng L, Zhang P. 2020a. Retrieval of water quality parameters from hyperspectral images using hybrid Bayesian probabilistic neural network. Remote Sens. 12(10):1567. doi: 10.3390/rs12101567.

Zhang Y, Wu L, Ren H, Liu Y, Zheng Y, Liu Y, Dong J. 2020b. Mapping water quality parameters in urban rivers from hyperspectral images using a new self-adapting selection of multiple artificial neural networks. Remote Sensing. 12(2):336. doi: 10.3390/rs12020336.

Zhao X, Li Y, Chen Y, Qiao X. 2022a. A method of cyanobacterial concentrations prediction using multispectral images. Sustainability. 14(19):12784. doi: 10.3390/su141912784.

Zhao X, Li Y, Chen Y, Qiao X, Qian W. 2022b. Water chlorophyll a estimation using UAV-based multispectral data and machine learning. Drones. 7(1):2. doi: 10.3390/drones7010002.