drones

MDPI

Systematic Review

Assessing Drone-Based Remote Sensing for Monitoring Water Temperature, Suspended Solids and CDOM in Inland Waters: A Global Systematic Review of Challenges and Opportunities

Shannyn Jade Pillay [1,*], Tsitsi Bangira [2], Mbulisi Sibanda [3], Seifu Kebede Gurmessa [1], Alistair Clulow [4] and Tafadzwanashe Mabhaudhi [1,2,5]

[1] Centre for Water Resources Research, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Private Bag X01, Scottsville, Pietermaritzburg 3209, South Africa
[2] Centre for Transformative Agricultural and Food Systems, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Scottsville, Pietermaritzburg 3209, South Africa
[3] Department of Geography, Environmental Studies and Tourism, University of the Western Cape, Private Bag X17, Bellville 7535, South Africa
[4] Discipline of Agro-Meteorology, School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Scottsville, Pietermaritzburg 3209, South Africa
[5] Centre on Climate Change and Planetary Health, London School of Hygiene and Tropical Medicine, London WC1E 7HT, UK
* Correspondence: 218059937@stu.ukzn.ac.za

Abstract: Monitoring water quality is crucial for understanding aquatic ecosystem health and changes in physical, chemical, and microbial water quality standards. Water quality critically influences industrial, agricultural, and domestic uses of water. Remote sensing techniques can monitor and measure water quality parameters accurately and quantitatively. Earth observation satellites equipped with optical and thermal sensors have proven effective in providing the temporal and spatial data required for monitoring the water quality of inland water bodies. However, using satellite-derived data are associated with coarse spatial resolution and thus are unsuitable for monitoring the water quality of small inland water bodies. With the development of unmanned aerial vehicles (UAVs) and artificial intelligence, there has been significant advancement in remotely sensed water quality retrieval of small water bodies, which provides water for crop irrigation. This article presents the application of remotely sensed data from UAVs to retrieve key water quality parameters such as surface water temperature, total suspended solids (TSS), and Chromophoric dissolved organic matter (CDOM) in inland water bodies. In particular, the review comprehensively analyses the potential advancements in utilising drone technology along with machine learning algorithms, platform type, sensor characteristics, statistical metrics, and validation techniques for monitoring these water quality parameters. The study discusses the strengths, challenges, and limitations of using UAVs in estimating water temperature, TSS, and CDOM in small water bodies. Finally, possible solutions and remarks for retrieving water quality parameters using UAVs are provided. The review is important for future development and research in water quality for agricultural production in small water bodies.

Keywords: unmanned aerial vehicles; water quality monitoring; TSS; CDOM; machine learning algorithm; remote sensing

check for updates

Citation: Pillay, S.J.; Bangira, T.; Sibanda, M.; Kebede Gurmessa, S.; Clulow, A.; Mabhaudhi, T. Assessing Drone-Based Remote Sensing for Monitoring Water Temperature, Suspended Solids and CDOM in Inland Waters: A Global Systematic Review of Challenges and Opportunities. *Drones* **2024**, *8*, 733. https://doi.org/10.3390/drones8120733

Academic Editor: Yangquan Chen

Received: 31 October 2024
Revised: 22 November 2024
Accepted: 29 November 2024
Published: 3 December 2024

1. Introduction

Storage water bodies are vital to human and aquatic life since they support ecosystem services that sustain water for agricultural irrigation, human and animal consumption, industrial uses, and biodiversity conservation [1–6]. However, rapid population growth, urbanisation, industrial and agricultural activities, and climate change have increasingly threatened water quality in vulnerable regions such as Southern Africa [5,7].

According to Mangadzea et al. [8] and Namugize et al. [9], aquatic ecosystems in Southern Africa are stressed due to unsustainable land use—land cover changes, deforestation of catchments, pollution, contaminated runoff from mines and agricultural pesticides, and inadequate catchment management and water laws. The demand for suitable water resources has prompted efforts from policymakers, the public and researchers to monitor and manage water quality in water bodies to ensure sustainable use [10] and to achieve the targets of sustainable development goal 6 (SDG 6), which advocates for clean water and sanitation for all by 2030 [11].

Traditional in situ water sampling and ground measurements are time-consuming, costly and labour-intensive [12,13]. In contrast, satellite-based remote sensing provides an alternative by integrating remotely sensed data acquired by multispectral and thermal sensors for large-scale monitoring of spatial and temporal changes in water quality parameters in inland water bodies [14–17]. Different sensors on satellites measure the radiation at various wavelengths reflected from the water surface. These reflections can be used directly or indirectly to detect different water quality indicators. The optically active parameters, including total suspended solids (TSS), Chromophoric dissolved organic matter (CDOM), temperature and chlorophyll-a, can be directly derived from remote sensing reflection [5,18].

Conversely, non-optically active substances such as chemical oxygen demand, total nitrogen, electrical conductivity, pH, metals, and *Escherichia coli* (*E. coli*), which have no direct optical properties, can be derived using proxies or artificial intelligence [19,20]. The principle behind water quality remote-sensing inversion is first to build a model using empirical data from water quality monitoring and corresponding data from remote sensing images (forward modelling), then use the model to obtain the temporal and spatial distribution of water quality parameters [21,22]. Although positive outcomes have been achieved by estimating optically active parameters in small water bodies using Landsat [23], MODIS [24], MERIS [25], and Sentinel satellites [26], limitations still arise. Coarse spatial resolutions hinder the monitoring of small-scale water bodies, atmospheric interferences such as the presence of clouds, long revisit times, and data accessibility limitations, which have been mentioned in the literature as some of the challenges [14,27].

Unmanned aerial vehicles (UAVs) or drones have recently emerged as a viable solution, providing ultra-high spatial resolution data suitable for capturing detailed information on water quality parameters in small inland water bodies [6,28,29]. UAVs offer an advanced, practical, and near-real-time method for monitoring water quality parameters [28,30,31]. Since drone technology is fairly recent, studies such as Cillero Castro et al. [14] have utilised satellite data as a primary source of information and drone-based data as a form of validation when monitoring water quality in a reservoir in Spain. The performance of both platforms was evaluated, and there was an agreement when comparing the water quality parameter results from both platforms.

While agriculture is the major use for water stored in small water bodies [3], this review focuses on three major water quality indicators for water suitable for irrigation, considering that they can be measured using remote sensing techniques. This study focuses on surface water temperature, total suspended solids (TSS), and Chromophoric dissolved organic matter (CDOM). Water temperature is the measure of the kinetic energy of water, expressed as °C (degrees Celsius) and changes in water temperature stem from changing climates, precipitation and evaporation [5,32]. In agriculture, varying water temperatures from irrigated water sources lead to decreased crop yields since changing water temperatures directly impact soil temperatures, specifically for sensitive crops during growing stages [33]. Meanwhile, total suspended solids (TSS) are fine particles suspended in water, including bacteria, algae, mineral particles, and organic debris [34,35]. An increase in the TSS in reservoirs stems from increased soil erosion and runoff containing organic and inorganic pollutants flowing into the reservoir [34].

Consequently, significant amounts of suspended sediments can affect drip, centre pivot, and ditch irrigation methods [10]. Chromophoric dissolved organic matter (CDOM) is a fundamental subsection of dissolved organic matter (DOM). It comprises a combination of compounds, dissolved organic matter and nutrients stemming from polluted residential, agricultural and industrial runoff [36]. Zheng et al. [36] further, explain that CDOM reduces light penetration and limits the production of beneficial nutrients needed for crop growth. These parameters are crucial for assessing the physical, chemical, and microbial degradation of water quality, especially for agricultural use. Furthermore, given the prevalent challenges of water scarcity in Southern Africa, farmers require timely information on water quality to sustain agricultural production and avert hunger and poverty. This emphasises that the suitability of water needs to be monitored regularly to meet irrigation and environmental standards as well as human and animal consumption standards [30]. Subsequently, by utilising drone-derived high spatial resolution information, farmers can make educated decisions about how to conduct their everyday activities and early warning systems for timely intervention, leading to resilience building and enhancing productivity and economic benefits [6,30].

Therefore, this study aims to systematically review the literature on the utility of remotely sensed data for monitoring surface water temperature, TSS, and CDOM in small inland water bodies, particularly at a farm scale. The objectives are to evaluate the progress, challenges and opportunities associated with implementing and utilising UAV-based remote sensing to monitor water quality. This review is organised into several key sections. Following the introduction of Section 1, Section 2 focuses on the methodologies used to analyse the existing literature critically. Section 3 focuses on the results from the literature analysis, highlighting the progress made utilising drone-based remote sensing, spectral indices and machine learning algorithms for monitoring the water quality of inland water bodies. Finally, Section 4 synthesises the study's results and provides insight into the limitations, research gaps, and research directions for future work using UAV-based remote sensing for water quality monitoring.

2. Materials and Methods

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach and checklist were used to conduct a comprehensive literature search, reduce reporting biases, and provide an in-depth systematic review [37]. The methodology was split into three steps: the literature search, data extraction and analysis.

2.1. The Literature Search

The initial step of the literature search was to identify keywords, terms, and phrases about the scope of the intended study [38,39]. These keywords and phrases, along with Boolean operators such as "AND", "OR", and "NOT" to form search strings which retrieved relevant publications were put into five search engines, namely, SCOPUS, Web of Science, Google Scholar, IEEE Xplore, and Science Direct, and filtered to ensure the relevant literature about the mapping and monitoring of water quality in inland water bodies was retained [39]. The Boolean operators aided in determining inclusive/exclusive criteria for each search string, which were restricted to keywords, titles, and abstracts of the relevant literature. The search covered the period from 1980 to 2023, and 702 articles were retained from the five search engines (Table 1).

Table 1. Search strings for this review are made from keywords and Boolean operators.

Search Engine	Search Criterion	Total Number of Articles
Web of Science	TS = ("unmanned aerial vehicles" OR "drones" OR "UAVs" OR "remote sensing") AND ("water quality monitoring" OR "inland water quality") AND ("water bodies" OR "dams" OR "rivers" OR "reservoirs") AND ("TSS" OR "suspended sediment" OR "temperature" OR "CDOM") NOT ("sea water" OR "coastal water")	328
Google Scholar	("unmanned aerial vehicles" OR "drones" OR "UAVs" OR "UAS") AND ("water quality monitoring" OR "water quality assessment" OR "inland water quality") AND ("dams" OR "reservoirs") AND ("remote sensing") AND ("TSS" OR "CDOM" OR "temperature" OR "Chromophoric dissolved organic matter" OR "suspended sediments") AND ("machine learning algorithms" OR "regression algorithms") NOT ("coastal waters" OR "ocean water")	165
Scopus	(TITLE-ABS-KEY ("Unmanned aerial vehicles" OR "drones" OR "UAVs" OR "UAS") AND ("water quality monitoring" OR "water quality assessment" OR "inland water quality") AND ("water bodies" OR "dams" OR "reservoirs" OR "rivers") AND ("TSS" OR "suspended sediment" OR "CDOM" OR "Chromophoric dissolved organic matter" OR "temperature") AND NOT ("coastal waters" OR "groundwater")	136
Science Direct	(("unmanned aerial vehicles" OR "drones" OR 'UAVs") AND ("water quality imaging" OR "monitoring") AND ("TSS" OR "CDOM" OR "temperature") NOT ("seawater"))	57
IEEE Xplore	("All Metadata "unmanned aerial vehicles OR "All Metadata "drones OR "All Metadata "UAVs) AND ("All Metadata "water quality monitoring OR "All Metadata "inland water quality) AND ("All Metadata "TSS OR "All Metadata "CDOM OR "All Metadata "temperature) AND ("All Metadata "remote sensing) NOT ("All Metadata": ocean water)	16
	Total number of Articles retained	**702**

All the retrieved literature was exported into Endnote for further screening processes. The screening process was conducted in five stages. Firstly, 68 duplicates were removed since similar search terms can result in the same papers appearing across multiple search engines. The second step involved excluding 12 papers not written in English and 43 papers not identified as journal articles (such as conference proceedings). Thirdly, the abstracts of the remaining articles were read. A total of 282 papers which conducted predictive modelling, observed coastal regions and those which did not fit the scope of the study were excluded. Finally, 297 full-length articles were downloaded and exported into an Excel spreadsheet for further screening. Upon the last stage of screening, the inclusion criteria focused on selecting articles which:

1. Monitored any of the three specific parameters of TSS, CDOM, or temperature.
2. Involved in utilising unmanned aerial vehicles as a platform to aid remote sensing techniques.

This resulted in 247 articles being excluded (Figure 1) since they focused solely on satellite-based remote sensing, on monitoring other water quality parameters outside of the specified parameters, or utilised UAVs for groundwater monitoring, and numerous articles which utilised UAVs to collect water samples rather than a platform for remote sensing sensors. After that, the final 50 articles were thoroughly read, and valuable characteristics were extracted and recorded.

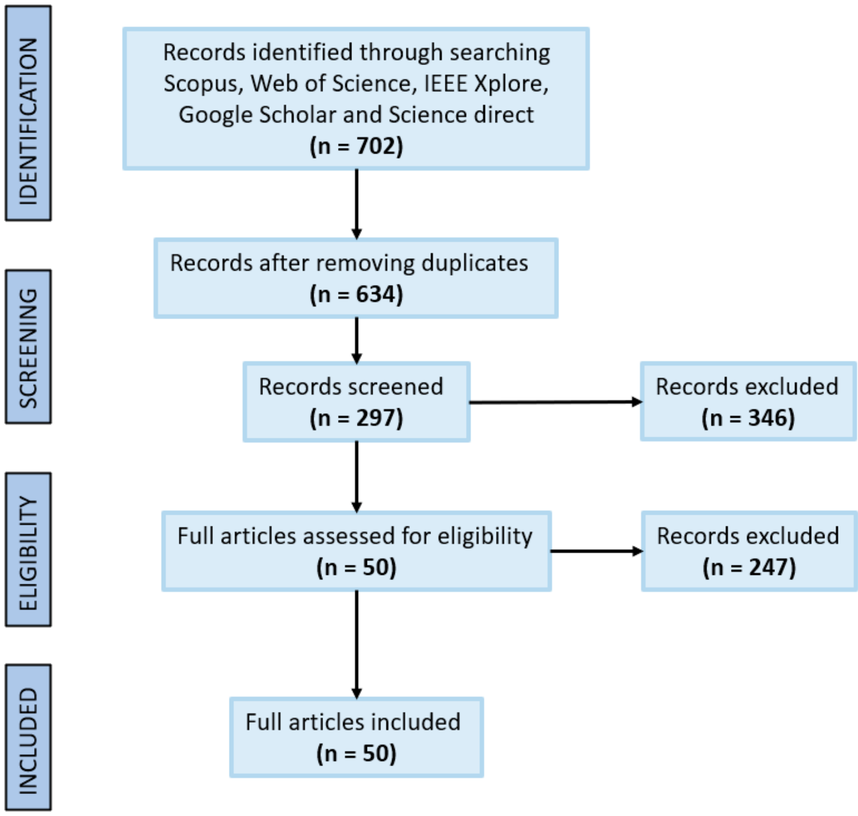

Figure 1. Selection of the studies considered in this review.

2.2. Data Extraction

During the data extraction process, the previously created spreadsheet was used to record bibliometric data such as author names, year of publication, title of article, abstract and keywords from each article, along with characteristics such as the study site or country, type of water body, scale of water body, water quality parameter, platform type, sensor type, in situ validation techniques, algorithms or models, and statistical metrics used. This captured information highlighted the existing gaps, and the progress made when referring to the use of UAVs in water quality monitoring at a regional scale.

2.3. Data Analysis

Both quantitative and qualitative analyses were performed on the identified literature. A simple frequency analysis was performed for the quantitative assessment, while trend analysis was used to determine the qualitative characteristics of the literature. Additionally, this method was carried out to evaluate the advancements of UAVs for monitoring water quality by statistically assessing the occurrence and co-occurrence of key terms using VOS viewer (version 1.6.20) software [38]. The VOS viewer software was adopted for text mining and displaying bibliometric maps of key terms relating to the use of drone technology for water quality monitoring [40]. Studies that have utilised the software, such as Bangira [6], explain that it is advantageous in showcasing the current status of water quality research, developing trends, and most cited authors. It is useful for forecasting the future direction of disciplines and research themes. Once the screening and data extraction processes were complete, the articles' titles, keywords and abstracts were imported into the VOS viewer programme to commence text mining. These results highlighted recurring key terms throughout the selected literature.

3. Results

3.1. Spatial Distribution of UAV-Based Literature for Water Quality Monitoring

The spatial distribution of the identified literature is depicted in Figure 2. More research has been conducted in the USA, Latin America, Europe, and South-East Asia compared to Africa and Southern Africa. The USA and China had the highest number of 12 UAV-based articles monitoring TSS, temperature, and CDOM. This was followed by Brazil having four articles, Spain having three, India and South Korea having two, and countries such as South Africa, Namibia, Zimbabwe, Malawi, The United Kingdom and Chile having one article. Figure 2 also displays that the region of Southern Africa only accounted for 6.3% of the selected literature compared to South Asia, which accounted for 50%, and North and South America, which accounted for 25% and 10.4%, respectively. It is also apparent that no study in Africa's West, North, and Central regions used UAV-based remote sensing to monitor TSS, temperature, and CDOM in water sources.

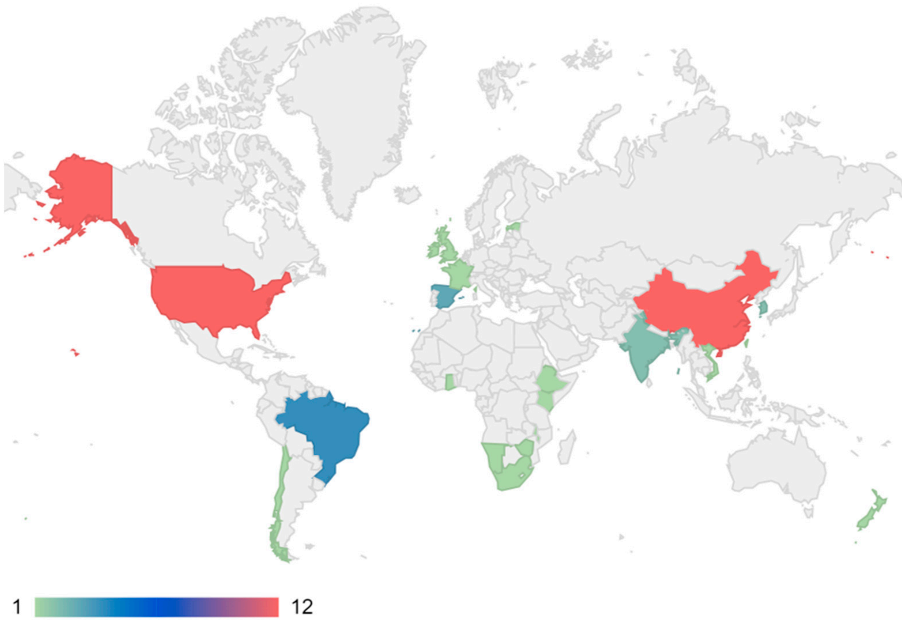

Figure 2. Spatial distribution of UAV-based remote sensing studies focused on monitoring surface water temperature, TSS and CDOM.

3.2. Keyword Analysis

Figure 3 highlights the important terms from the selected articles' titles, keywords and abstracts. Text mining was used to illustrate the evolution and direction of research, and four clusters were evident. Looking at each cluster in depth, it is visible that the keywords from cluster 1 are 'parameter', 'Unmanned Aerial Vehicle', 'machine learning' and 'random forest', which highlight what aspect of water quality is being measured, the remote sensing platform used as well as the processes used to understand and interpret UAV derived data. Cluster 2 highlights keywords such as 'performance', 'water sample', 'lake', 'drone', 'UAV', 'RMSE' (Root Mean Square Error), 'USA' and 'temperature'. This suggests linkages between the performance of drone technology and in situ data taken from water samples. It also highlights the major drone technology advancements in the United States of America compared to the rest of the world. Cluster 3 emphasises words such as 'sensor', 'reservoir', 'estimation', 'mapping', 'TSS', 'case study' and 'chlorophyll', suggesting links to water quality monitoring and highlighting the most optically active water quality parameters which can be detected by remote sensing. Finally, cluster 4 highlights keywords like 'water', 'sentinel', 'Landsat', 'correlation', 'total nitrogen', 'total phosphorus', 'organic matter' and 'human activity'. This emphasised the use of satellite-based remote sensing to determine water quality parameters. Satellite remote sensing terminology stems from studies that observed UAV and satellite-derived data to analyse the selected water quality parameters. In such cases, UAV-based data were validated against satellite data from Sentinel and Landsat.

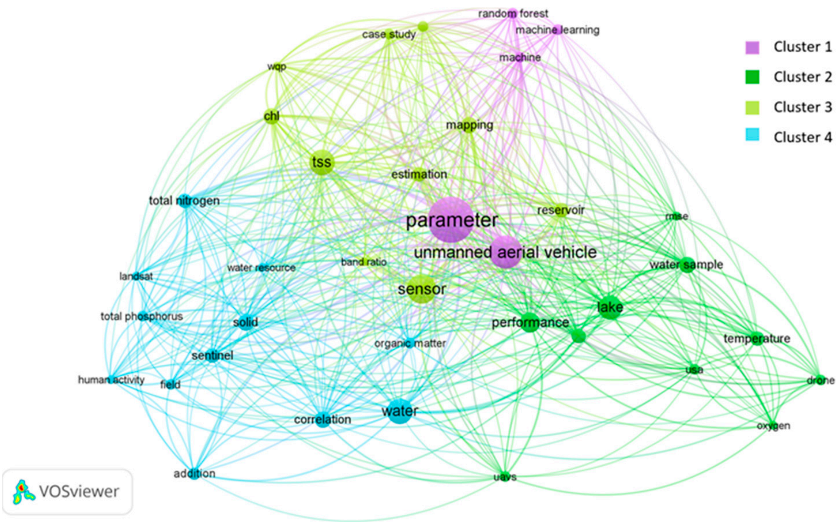

Figure 3. Topical concepts in monitoring water quality utilising UAV-derived remotely sensed data using information from abstracts, titles and keywords from literature.

3.3. Progress of Remotely Sensed Water Quality Monitoring

Primarily, this review focused on using UAV-derived remotely sensed data to monitor surface water temperature, TSS, and CDOM. However, several studies utilising satellite-based remote sensing and comparing it with UAV-based remote sensing were selected, as they highlighted valuable techniques regarding temperature, TSS, and CDOM. In these studies, UAV-based data, in situ sampling, measurements, and laboratory analysis were used to validate satellite data. Figure 4 illustrates that there has been much focus on the mapping and modelling water quality using both remotely sensed satellite and UAV data, with the number of studies steadily increasing. Although remote sensing techniques have been popular since the 20th century and the selected range for this literature search was from 1980 to 2023, it is evident that there had only been a steep increase in published literature utilising UAV data since 2012. Before this, remote sensing was primarily conducted via satellites. When observing Figure 4, it is evident that Landsat 8 OLI has appeared more frequently within the selected studies and accounted for 13% of the total selected studies since UAV data were used for validation. For instance, a study by Xiao [41] to monitor TSS across a lake utilised UAV-based data to calibrate satellite-based models directly. The results of this study exclaimed that the UAV-based data improved the satellite-based models due to the advances in spatial resolutions.

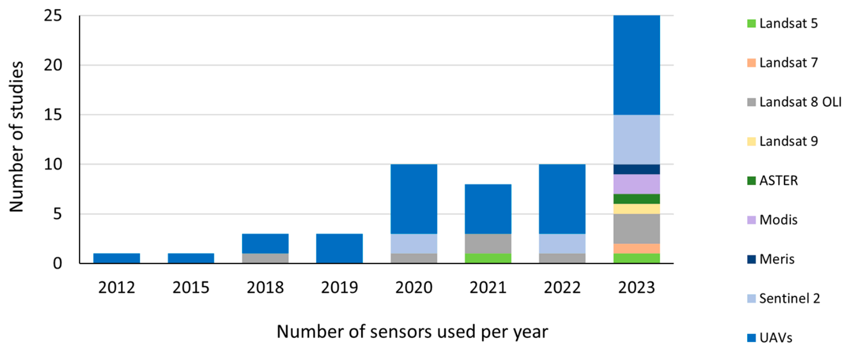

Figure 4. The frequency of studies per year based on both satellite sensors and UAVs.

Additionally, 2021 and 2023 accounted for the remaining studies using UAV and satellite-based sensors such as Landsat 5, 7, and 9, ASTER, MODIS, MERIS, and Sentinel 2. Alternately, Figure 4 highlights the significant increase in studies that ventured solely into using UAV-based data for mapping and monitoring water quality parameters. From 2020 to 2023, it is evident that there has been a significant increase in UAV-based studies, with 47% of the selected studies being found in this period. Additionally, the average number of UAV-based articles for these four years was eight articles per year.

Figure 5 illustrates the parameters detected using UAV-based remote sensing only and the percentage they account for within the selected studies. Many studies focused on more than one parameter in conjunction with temperature, TSS, and CDOM. For example, Womber et al. [42] measured TSS with Turbidity and Secchi Disk Depth (SDD) in a large lake in Ethiopia. The authors found that changes in TSS concentrations influence Turbidity and SDD measurements, such that increased TSS resulted in increased turbidity in the lake. Furthermore, since the main objective of this review focused on TSS, surface water temperature and CDOM, these parameters appeared more frequently within the studies (Figure 5). Figure 5 shows that turbidity accounted for 13.6%, chlorophyll was 12%, temperature was 11.2%, TSS was 10.4%, CDOM was 4%, etc. These parameters occurred more frequently in studies since they are said to be more 'optically active' than other water quality parameters. This means their particles scatter more light, making them easily detectable via UAV sensors [43]. Parameters that accounted for less than 4% of the total studies were combined to form the 'other' category. These included salinity, total dissolved solids, algae content, dissolved organic carbon, and Secchi Disk Depth, which comprised 10.4% combined. Temperature, TSS, and CDOM formed a combined total of 25.6% of the selected literature.

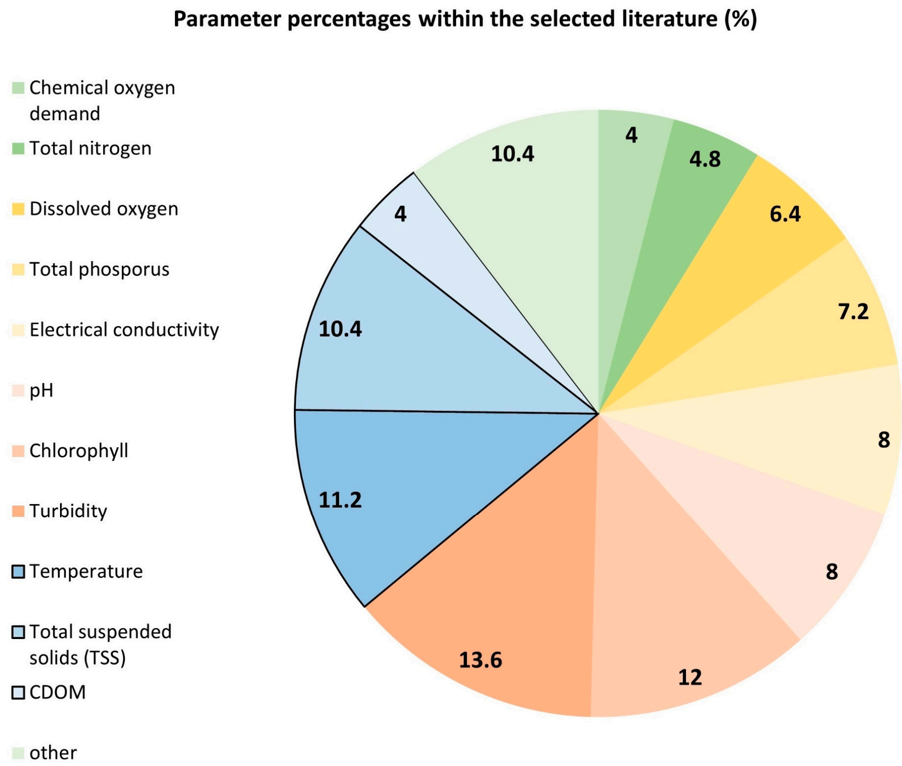

Figure 5. Percentage of each water quality parameter from the total number of selected studies.

3.4. Characteristics of Sensors and UAV Platforms

Figure 6 shows that various UAV platform types have been utilised throughout the years, including the DJI, the Octocopter, and the Sense fly eBee. The multicopter DJI UAV platform was dominantly used and accounted for 76% of the selected studies. For example, Lo [18] utilised a DJI drone to estimate the temperature in a lake in China. It has been a popular choice of platform since 2020. The reason for the dominance of the DJI platform is that it is more compatible with many types of sensors and is better suited to surface water resource mapping, according to Brito [44]. The DJI platforms are also more cost-effective, and their taking-off and landing systems are advantageous. Conversely, the MD4-1000, Sense fly eBee, Hexacopter, Octocopter, and 3DRSolo accounted for 4.8% individually.

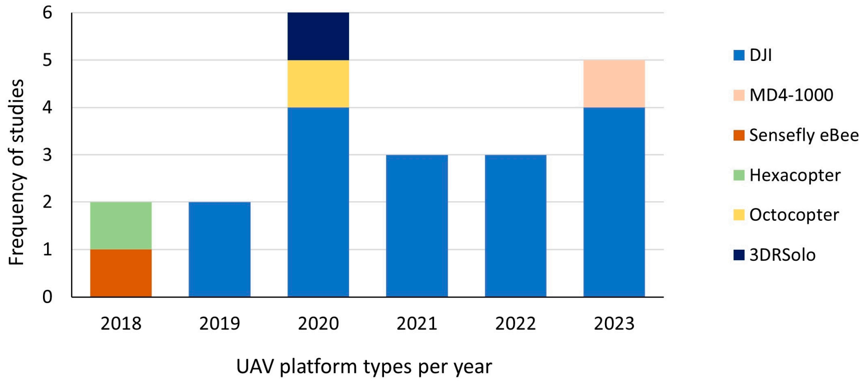

Figure 6. Frequency of studies relating to UAV platform types across a temporal scale.

Regarding sensor types, it is apparent that multispectral sensors appeared more frequently than thermal or hyperspectral sensors when characterising surface water temperature, TSS and CDOM (Figure 7). The multispectral sensor is cost-effective compared to the hyperspectral sensor and observes more multiple spectral bands than the thermal sensor. Thus, they are widely used. The multispectral sensor captures imagery within the visible spectrum, at red, green, and blue bands and outside of the visible spectrum at the near-infrared, red-edge, and thermal infrared portions of the electromagnetic spectrum. Furthermore, while water temperature can be monitored using thermal infrared bands, CDOM uses blue and green bands, while TSS uses red and near-infrared bands, which is further emphasised by Figure 7. Multispectral sensors were used to detect all three water quality parameters; however, thermal sensors were used mainly to detect water temperature and TSS. Multispectral and hyperspectral sensors were used for CDOM since they fall within the blue and green bands of the electromagnetic spectrum, and for TSS, they fall within the red and near-infrared bands.

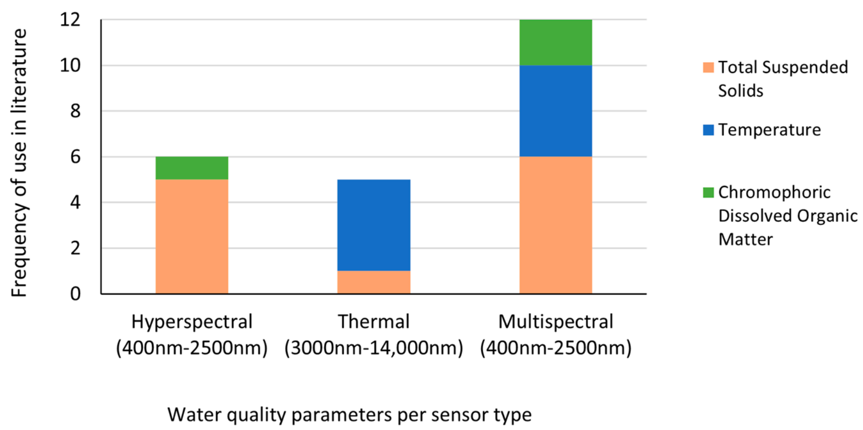

Figure 7. Frequency of sensor types used onboard drone platforms for detecting water temperature, TSS and CDOM.

3.5. Spectral Indices Used for Estimating Surface Water Temperature, TSS and CDOM in Inland Water Bodies Using Sensors Onboard UAVs

Studies have derived spectral indices algorithms using individual bands or multiple bands to predict the concentration of TSS, CDOM, and water temperature in inland water bodies. The combination of spectral indices and machine learning algorithms has significantly improved estimation and prediction models in estimating surface water temperature, TSS, and CDOM in small water bodies [45]. Figure 8 shows indices commonly used to retrieve biophysical information about a study site by differentiating landcover spectral values. For example, these spectral indices were used to delineate between a water body and its surrounding vegetation, which influences the concentrations of TSS or CDOM within the water body. Furthermore, it is evident in Figure 8 that NDVI and NDWI appeared in most studies, accounting for 41.2% and 11.8%, respectively. These two indices were more frequently utilised due to their common red and near-infrared wavebands [46].

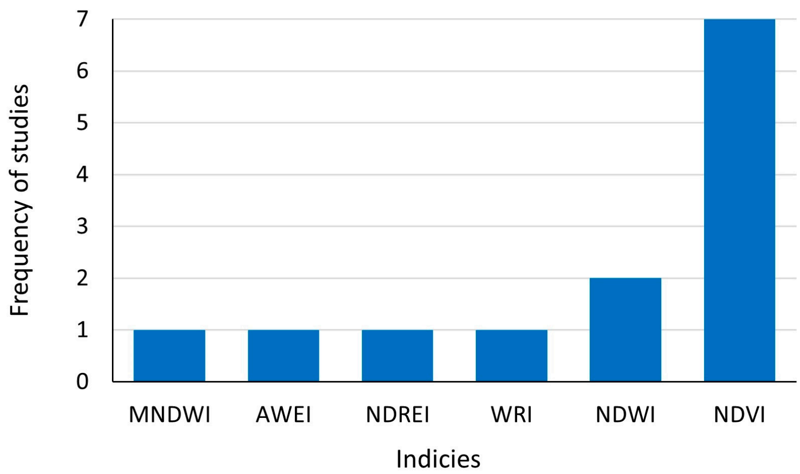

Figure 8. Indices used to delineate water bodies from surrounding vegetation. (NDVI = Normalised Difference Vegetation Index; NDWI = Normalised Difference Water Index; WRI = Water Ratio Index; NDREI = Normalised Difference Red Edge Index; AWEI = Automated Water Extraction Index; MNDWI = Modified Normalised Difference Water Index).

Table 2 presents indices for detecting TSS and CDOM in inland water bodies. These spectral indices were used to quantify the concentration of TSS and CDOM and were derived from reflected or absorbed wavelengths [45]. Spectral indices for TSS are typically derived from wavelengths from the red and near-infrared portions of the electromagnetic spectrum due to suspended particles reflecting scattered light. Spectral indices for CDOM are derived from wavelengths in the visible and ultraviolet portions of the electromagnetic spectrum due to light absorption [26,47]. Table 2 presents spectral indices found in the literature and their R^2 value. It is evident that for TSS, indices from Veronez et al. [48] and Rahul [26] obtained the highest R^2 values, indicating strong performances when quantifying TSS concentrations, while Kutser et al. [49] and Fan [50] obtained the highest R^2 values when quantifying CDOM concentrations. These high R^2 values can be attributed to feature enhancement since variations in spectral bands highlight specific TSS and CDOM characteristics [45].

Furthermore, these spectral indices, used to identify spectral changes and bands, can be combined with machine learning algorithms to produce models for testing and validating drone-derived data. A study conducted by Veronez et al. [48] made use of spectral indices, utilising red and near-infrared portions of the electromagnetic spectrum as well as the Artificial Neural Network machine learning algorithm to predict the correlation between the indices and TSS and CDOM concentration values in an artificial lake. The results in Table 2 were in agreement such that TSS × NDVI had an R^2 value of 0.65, TSS × NDWI had a value of 0.76, CDOM × NDVI had a value of 0.54, and CDOM × NDWI had a value of 0.59. Additionally, it can be noted that in the literature, indices used to estimate surface water temperature were scarce since only thermal bands are used, compared to TSS and CDOM, which utilise a range of spectral bands.

Table 2. Spectral indices utilised in the literature to characterise TSS and CDOM.

Water Quality Parameter	Formula	R^2	Characteristics of the Study Area	Author and Year
TSS	$TSS = 45.4 \times NDVI^2 + 43.1 \times NDVI + 20.9$	0.65	Small artificial lake in the South of Brazil	Veronez et al. [48]
	$TSS = 68.7 \times NDWI^2 - 111.2 \times NDWI + 56.1$	0.76		
	$TSS = 151.2 + (384 \times (RE)) + (173.9 \times \left(\frac{G}{R}\right))$ Where G is the green band (480–520 nm) and R is the red band (640–680 nm)	0.60	Stream is located in Alabama, USA	Larson [47] Prior [51]
	$TSS = 142.7 - (53.8 \times (\frac{R}{RE}))$ Where R is the red band (640–680 nm) and RE is the red-edge band (730–740 nm)	0.60		
	$TSS = 8133.15 - 11002.9 \times \frac{B7}{(B6+B8A)}$ Where B7 is 783 nm, B6 is 740 nm and B8A is 865 nm	0.73	Lake situated in Tamil Nadu, India	Rahul [26]
CDOM	$CDOM = 244.9 \times NDVI^3 + 186.2 \times NDVI^2 + 7 \times NDVI + 21.8$	0.54	Small artificial lake in the South of Brazil	Veronez et al. [48]
	$CDOM = 2119.5 \times NDWI^3 + 4559.1 \times NDWI^2 - 2760.4 \times NDWI + 603.6$	0.59		
	$aCDOM\ (420) = 5.20x^{-2.76}$ Where aCDOM (420) is the absorption of CDOM at 420 nm	0.84	Lake located in Finland	Kutser et al. [49]
	$CDOM = 0.89 \times \frac{\rho 700\ nm}{\rho 450\ nm} - 0.15$ Where ρ is the spectral reflectance at wavelengths 700 nm and 450 nm	0.83	River, located in the USA	Fan [50]

3.6. Machine Learning Algorithms

Machine learning algorithms offer great opportunities for assessing, classifying, and predicting surface water temperature, TSS, and CDOM in water quality studies for small inland water bodies using remotely sensed data acquired by sensors onboard UAVs. Figure 9 shows that linear regression (LR), empirical methods, random forest classification (RF), support vector machines (SVM), artificial neural networks (ANN), XGBoost, deep neural networks (DNN), and gradient boost decision trees (GBDT) were the most used algorithms. Linear regression appeared more frequently than other statistical methods in 27.5% of the total articles.

The random forest and empirical methods appeared in 12.5% of the total articles. SVM and ANN appeared in 11.25% and 10%, respectively, and each of the remaining algorithms, such as IMP-MPP, LSTM, Semi-empirical, Semi-analytical, LASSO, GBDT, DNN, and XG Boost, appeared in less than 7% of the total number of articles.

Fifty articles were chosen as case studies to identify further and explain algorithmic trends. Although the selected articles provided valuable information about monitoring surface water temperature, TSS and CDOM in small water bodies, not all of these articles solely utilised drone remotely sensed data or stated the validation techniques used. Approximately 35% of the selected articles utilised satellite-based remote sensing and only used drone-derived data as a validation technique. Moreover, 40% of the articles omitted information about in situ data collection approaches, the statistical methods used, or root mean square error (RMSE), resulting in the error assessment (R^2) being considered only. For this reason, these articles were excluded from the case studies (Table 3).

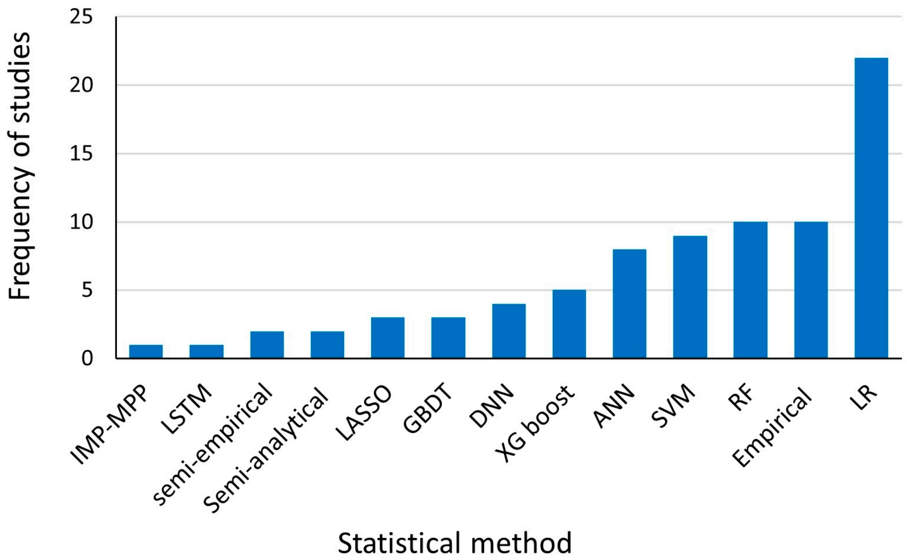

Figure 9. Machine learning algorithms used to detect and map surface water temperature, TSS, and CDOM. (IMP-MPP = improved matching pixel by pixel; LSTM = Long Short-Term Memory; LASSO = Least Absolute Shrinkage and Selection Operator; GBDT = Gradient Boost Decision Trees; DNN = Deep Neural Networks; ANN = Artificial Neural Networks; SVM = Support Vector Machines; RF = Random Forest; LR = Linear Regression).

Table 3. Case studies used to emphasise the statistical methods used for estimating temperature, TSS and CDOM from drone-derived data and their error assessment (R^2).

Title	Location of the Study	Parameter	In Situ Data Collection Technique	Statistical Technique	Fit Error Metric (R^2)	Author and Year
Evaluation of surface water quality of Ukkadam Lake in Coimbatore using UAV and Sentinel-2 multispectral data	India	TSS	Colorimeter	Linear regression	0.86	Rahul [26]
Evaluation of water quality based on UAV images and the IMP-MPP algorithm	China	TSS		IMP-MPP algorithm	0.825	Ying [52]
Low-Cost Unmanned Aerial Multispectral Imagery for Siltation Monitoring in Reservoirs	Brazil	TSS	TriOS RAMSES spectroradiometer	Empirical and semi-empirical models	0.94	Olivetti [53]
A method for chlorophyll-a and suspended solids prediction through remote sensing and machine learning	Brazil	TSS	APHA standard weighing method	RF	0.81	Silveira-Kupssinskü [54]
Machine learning models applied to TSS estimation in a reservoir using a multispectral sensor onboard to RPA	Brazil	TSS	APHA standard weighing method	SVM	0.869	Dias [55]
Proposal of a method to determine the correlation between total suspended solids and dissolved organic matter in water bodies from spectral imaging and artificial neural networks	Brazil	TSS	APHA standard weighing method	ANN	0.77	Vernonez [56]

Table 3. *Cont.*

Title	Location of the Study	Parameter	In Situ Data Collection Technique	Statistical Technique	Fit Error Metric (R^2)	Author and Year
Local algorithm for monitoring total suspended sediments in micro-watersheds using drone and remote sensing applications. Case study: Teusaca River, La Calera, Columbia	Columbia	TSS	Sampling and lab analysis	Linear regression	0.887	Saenz, et al. [57]
Machine learning algorithm inversion experiment and pollution analysis of water quality parameters in urban small and medium-sized rivers based on UAV multispectral data	Korea	TSS	APHA standard weighing method	RF	0.635	Hou [22]
Inland waters suspended solids concentration retrieval based on PSO-LSSVM for UAV-borne hyperspectral remote sensing imagery	China	TSS	Sampling and lab analysis	SVM	0.96	Wei et al. [58]
Drone with a thermal infrared camera provides high-resolution georeferenced imagery of the Waikite geothermal area, New Zealand	New Zealand	Temp		Linear regression	0.98	Harvey et al. [59]
Monitoring Phytoplankton Biomass and Surface Temperatures of Small Inland Lakes by Multispectral and Thermal UAS imagery	USA	Temp	Multiprobe	Linear regression	0.31	Bartel [60]
Medium-Sized Lake Water Quality Parameters Retrieval Using Multispectral UAV Image and Machine Learning Algorithms: A Case Study of the Yuandang Lake, China	China	Temp	Multiprobe	Gradient boosting	0.75	Lo [18]
Urban Land Surface Temperature Monitoring and Surface Thermal Runoff Pollution Evaluation Using UAV Thermal Remote Sensing Technology	China	Temp	Thermometer	Linear regression	0.83	Xu [61]
The impacts of environmental variables on water reflectance measured using a lightweight unmanned aerial vehicle (UAV)- based spectrometer system	Canada	CDOM	In situ sensor	Linear regression	0.61	Zeng et al. [62]
UAV Multispectral Image-Based Urban River Water Quality Monitoring Using Stacked Ensemble Machine Learning Algorithms—A Case Study of the Zhanghe River, China	China	CDOM	In situ sensor	XGBoost	0.92	Xiao [28]
Remote sensing Estimation of CDOM and DOC with the Environmental implications for Lake Khanka	China	CDOM	Spectrophotometer	GBDT	0.95	Qiang, et al. [63]

Table 3. *Cont.*

Title	Location of the Study	Parameter	In Situ Data Collection Technique	Statistical Technique	Fit Error Metric (R^2)	Author and Year
Estimation of the Biogeochemical and Physical Properties of Lakes Based on Remote Sensing and Artificial Intelligence Applications	Estonia	CDOM		XGBoost	0.92	Toming, et al. [64]
Underwater Use of a Hyperspectral Camera to Estimate Optically Active Substances in the Water Column of Freshwater Lakes	Germany	CDOM	Fluorometer	Empirical and semi-empirical models	0.47	Seidel, et al. [65]
Estimation of Water Quality Parameters in Oligotrophic Coastal Waters Using Uncrewed-Aerial-Vehicle-Obtained Hyperspectral Data	Croatia	CDOM	Fluorometer	Linear regression	0.92	Divi'c, et al. [66]
Autonomous learning of new environments with a robotic team employing Hyperspectral Remote sensing, Comprehensive in-situ sensing and machine learning	USA	CDOM	In situ sensor	Linear regression	0.97	Lary et al. [67]

Table 3 consists of case studies from various regions across the globe, emphasising the statistical methods used for estimating each of the three water quality parameters (temperature, TSS, and CDOM), as well as the in situ data collection technique used and the error assessment (R^2). For TSS, several studies were conducted in South America and across Asia. They used the APHA standard weighing method to analyse water samples taken in the field, colorimeters, and TriOS RAMSES for spectro-radiometric data. These techniques were utilised as validation techniques. Alternately, these studies used varying statistical methods and machine learning algorithms. For instance, a study by Wei et al. [58] utilised the support vector machine algorithm to estimate TSS from hyperspectral UAV imagery and produced an R^2 value of 0.96. Similarly, the study by Olivetti [53] utilised empirical and semi-empirical equations and models to estimate TSS from multispectral UAV imagery, resulting in an R^2 value of 0.94. Furthermore, Saenz et al. [57] used linear regression to produce an R^2 value of 0.887.

Studies on CDOM were conducted in North America, Europe, and Asia, where in situ measurements were primarily taken using sensors, fluorometers, and a spectrophotometer. Additionally, these studies utilised different statistical methods and algorithms such as linear regression, XGBoost, gradient boost decision trees (GBDT) and empirical methods. The studies compiled by Lary et al. [67], Divi'c et al. [66] and Zeng et al. [62] utilised linear regression to estimate CDOM from UAV imagery and resulted in an R^2 value of 0.97, 0.92, and 0.61, respectively. Following this, other studies utilised gradient boost decision trees, XGBoost, and empirical methods to estimate CDOM in water sources, producing values of 0.95, 0.92, and 0.92, respectively.

Finally, when looking at temperature, 50% of the studies took place in China and utilised in situ thermometers and multiprobes. Additionally, most studies utilised linear regression, resulting in the highest R^2 value of 0.98, as seen in the study by Harvey et al. [59]. Furthermore, Table 3 highlights the statistical methods most used for TSS, CDOM, and temperature estimation, which happens to be linear regression, emphasised in Figure 9. This is due to linear regression being easier to understand and implement. Additionally, this can be said for empirical methods that utilise spectral band rations and indices to assess water quality parameters based on remotely sensed data from drones. Furthermore,

Figure 10 was generated to assess the magnitude of performance of the most commonly used algorithms and statistical methods from the case studies.

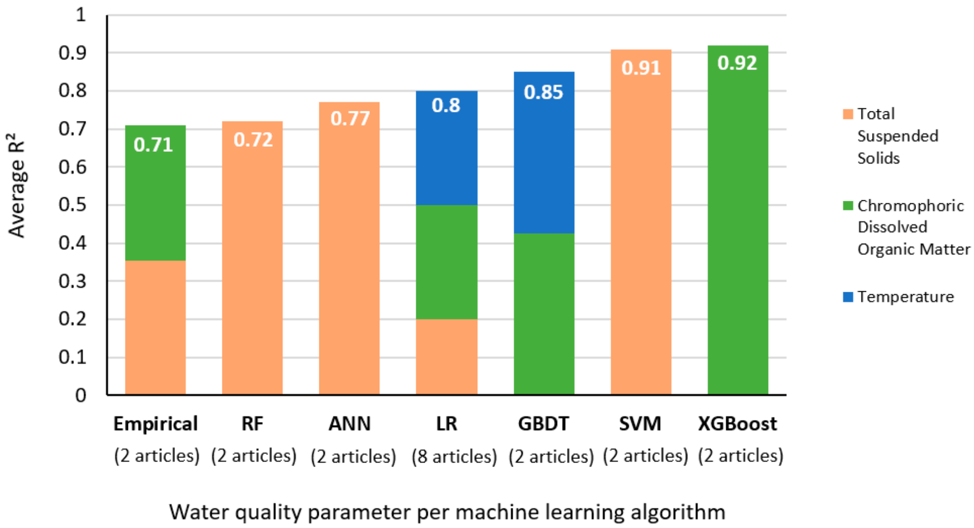

Figure 10. Average error assessment of machine learning algorithms.

Figure 10 highlights the average error assessment of machine learning algorithms, their use for estimating TSS, CDOM, and surface water temperature, and how many articles appeared. Linear regression was the most commonly used method, appearing in eight articles and was used to estimate all three water quality parameters and obtained an average error of assessment value of 0.8. This signifies a good correlation between the drone-derived and in situ data, utilising linear regression for further estimation. XGBoost obtained the highest average R^2 from the case studies with a value of 0.92 and was used in two articles for estimating CDOM. Alternately, SVM, ANN, and RF algorithms obtained average R^2 values of 0.91, 0.77, and 0.72, respectively, and these were used solely to estimate TSS in the case studies. GBDT and empirical methods obtained average values of 0.85 and 0.71, respectively, and were utilised to estimate CDOM. Furthermore, all algorithms and statistical methods obtained average error assessment values above 0.7. This indicates good performance since values closer to 1 represent higher estimation accuracies.

4. Discussion

4.1. Progress in the Remote Sensing of Temperature, TSS and CDOM Using Drone Technologies

In recent years, UAV-based remote sensing has significantly monitored TSS, CDOM and surface water temperature in small water bodies. However, when looking at the spatial distribution of these efforts, it is evident that there has been much effort in the USA and China (Figure 2) since the earliest drone technologies began in the 1850s in Europe, the USA, and China [38]. These are considered "technologically advanced" nations compared to many other regions, such as Africa, which lack the resources and skilled labour to conduct such research. However, the use of drone technology has spread worldwide over the past decade [38]. Furthermore, Sibanda et al. [38] emphasised that the utility of drone technology in Southern Africa was still rudimentary; however, a few years later, there has been significant progress illustrated by a sharp increase in the number of studies utilising drone technology for TSS, water temperature and CDOM, specifically in South Africa, Zimbabwe, and Namibia (Figure 2).

Over the past decades, satellite-based remote sensing has been the dominant and conventional earth observation approach [68]. However, using UAVSs has recently been demonstrated to be a more effective and reliable technique, especially when dealing with small inland water bodies, since they offer fine-resolution data in near real-time. For this reason, many identified sources in the literature compared satellite and drone-based techniques. These studies use drone-based data to validate satellite-based data for water temperature, TSS, and CDOM. As depicted in Figure 4, UAVs appeared more frequently in the literature since this review focused on the application of drone technologies. However, numerous widely used satellite sensors also appeared in conjunction with UAVs. These were predominantly Landsat, Sentinel 2 MSI, MODIS, and MERIS. When looking specifically at satellite sensors, it is evident that Landsat 8 operational land instrument (OLI) appeared in numerous studies compared to the other sensors (Figure 4). According to Gholizadeh et al. [43], this is due to Landsat being the longest free-supplying mission of remotely sensed data and being the best suited for identifying water quality parameters. Furthermore, satellite sensors are prone to limitations such as cloud cover and lagged return times. They produce coarser resolution images that are inadequate for water quality monitoring in small inland dams [69].

Subsequently, the results from this review suggest that the most commonly used UAV platform has been the DJI drone due to its compatibility and versatility (Figure 6). This platform is relatively affordable, with supplies available globally and is user-friendly for commercial UAV operations since it provides high-resolution images [70,71]. Along with this platform, multispectral imaging sensors are the most appropriate for water quality monitoring (Figure 7). However, the results indicated that several studies used hyperspectral imaging sensors compared to multispectral sensors. This is because hyperspectral sensors have hundreds of spectral bands compared to multispectral sensors' 4–6 bands. These multispectral bands are also narrower, allowing for increased sensitivity to water quality parameters such as TSS, CDOM, and surface water temperature [72]. However, hyperspectral is very costly and has a greater weight, thus requiring bigger UAV platforms.

Furthermore, remote sensing-based approaches for estimating temperature, as well as TSS and CDOM, involve establishing relations between these parameters and the spectral properties of remote sensing images. According to Adjovu [5], these main approaches include empirical, analytical, semi-empirical, and artificial intelligence methods. Adjovu [5] further explains each method, starting with empirical methods, which utilise linear statistical relationships derived from measured remote sensing spectral properties and water quality parameters. This simple and straightforward approach has been used to effectively estimate and retrieve water quality data. Analytical methods involve using bio-optical and transmission models to simulate how light is spread in water bodies and the relationship between water quality parameters and their reflection. Since this method utilises models, it is considered more complex than the empirical method. Semi-empirical methods are a combination of empirical and analytical methods. In this method, the spectral characteristics of the water quality parameters are known, and the appropriate combination of wavebands is used as a correlate. The spectral radiance is recalculated to values above the surface irradiance reflectance and then, through regression techniques, related to the water quality parameters. Finally, artificial intelligence (AI) methods utilise an implicit algorithm approach that differs from the three other approaches. AI applications capture linear and nonlinear relationships compared with conventional statistical approaches and are the most advanced and complex of the approaches [5].

Drawing from Table 3, a variety of algorithms/regression approaches were used in the case studies to determine TSS, surface water temperature, and CDOM. Regarding TSS, Support Vector Machines yielded the highest R^2 value of 0.96, followed by empirical and semi-empirical approaches, which yielded the second-highest R^2 value of 0.94. For Temperature, three of the four observed case studies utilised linear regression statistical approaches, yielding the highest R^2 values of 0.98. Furthermore, for CDOM, various techniques were used, including XGBoost, gradient boost decision trees (GBDT), and linear regression, which yielded the highest R^2 of 0.97. Therefore, moving forward, these techniques can be combined with spectral bands and indices to produce models for testing and validating drone-derived data, which can be considered for use in further research.

4.2. Limitations of Utilising Drone Technologies in Monitoring TSS, CDOM and Water Temperature in Small Water Bodies

Although drone technologies have been proven beneficial for monitoring water temperature, CDOM, and TSS, there are many limitations, specifically in Southern Africa. One of the limitations is the cost of equipment. Although this technique is low-cost, acquiring a licence, a suitable UAV platform, and various sensors can become costly, specifically when limited funding is available [5]. Furthermore, these costs raise concerns about security, theft, and damage to equipment, which lead to the limited use of drone technology. Additionally, since the use of drone technology is still a novel approach for water quality monitoring in Southern Africa, there is a lack of skilled and trained technicians who can operate the drones over water bodies as well as a lack of trained professionals who can interpret the collected data [5].

Further challenges include connectivity issues since many parts of Southern Africa lack network coverage. Technical challenges include limited battery efficiency, flight ranges, and limited altitudes of drones. Environmental challenges, such as the interference of drone technology on wildlife and challenges due to weather sensitivity, such as heavy rainfall periods experienced in Southern Africa during summer months, hinder drone flights. Furthermore, aviation restrictions and privacy concerns limit where drones can be flown.

4.3. Research Gaps

While drone-based remote sensing for monitoring inland water quality has made great progress in recent years, numerous research gaps are still evident in the literature. The first gap is the limited use of UAVs for monitoring water temperature, TSS, and CDOM in Africa. The literature highlighted that parameters such as chlorophyll content, total nitrogen and total phosphorus are more frequently monitored in small water bodies across other world regions. At the same time, only a limited number of studies were performed in Africa, particularly Southern Africa. This highlighted a gap which addresses the lack of variation in drone-based remote sensing performs across diverse climatic zones, natural disasters like droughts and water conditions such as turbidity, flow regimes, and vegetation interference. Additionally, most studies focused on large lakes, rivers, and coastal regions, with limited research on smaller inland water bodies such as reservoirs. Furthermore, there were evident gaps surrounding the lack of field validation studies. Numerous studies provided systematic reviews, overviews and reports regarding the advancements in drone technology; however, there is a shortage of field validation studies or case studies that have deployed drone technology to monitor water quality. This highlighted the underutilisation of advanced sensors such as LiDAR and Worldview2-3 to capture detailed water quality parameters and the lack of integration of in situ measurements coupled with remote sensing to improve accuracy and reliability. The limitations of drone technology, such as the cost, technical skills and regulatory challenges, limit real-time monitoring and reporting for immediate decision making in water resource management. Subsequently, this emphasises gaps regarding interdisciplinary and collaborative research approaches with minimal exploration of how drone-based remote sensing could be beneficial and accessible to farmers, local governments, and policymakers to generate actionable solutions for water management and water quality monitoring on a farm scale.

4.4. Future Research Directions

Future research should enhance field validation techniques by building on the identified research gaps. Research is needed to create robust and standardised protocols for validating drone-based data and to ensure consistency and accuracy for different applications and uses in various industries. Additionally, hybrid methods combining drone data with satellite imagery (from Worldview or Sentinel) and in situ measurements can produce a comprehensive, multiscale view of the studied water systems. Subsequently, increased research is needed to monitor less mainstream water quality parameters such as TSS and CDOM since these parameters are of great importance in the agricultural and industrial sectors. Additionally, understanding an array of water quality parameters provides a comprehensive understanding of water quality. Future research is needed to encourage interdisciplinary applications of drone-based remote sensing. This will enable collaborations between drone-based data and hydrological and environmental modelling, as well as water management and policy development. Long-term research is also needed to assess the scalability, repeatability, and cost-effectiveness of using drone-based monitoring that will aid in understanding real-time monitoring capabilities for emergencies such as pollution events or management of resolving harmful algal blooms. Since there is a lack of research conducted on small inland water bodies, future research is encouraged across these water bodies since they play a great role in the development of the region they occupy. These small water bodies are often utilised for agricultural and industrial purposes or for domestic uses and further research in monitoring these water bodies could have great socio-economic benefits. Lastly, increased research efforts in Africa would be highly beneficial due to the continent's unique climatic zones, addressing water quality challenges and environmental sustainability. Increased research and use of drone technologies are also beneficial for socio-economic efforts, aiding farmers with the management and production of crop yields and for capacity building since communities will be leaning and applying new skills.

5. Conclusions

This systematic review highlights the progress, advantages and disadvantages of utilising sensors onboard UAVs to monitor surface water temperature, TSS and CDOM in small inland water bodies. A comprehensive literature search was conducted by utilising the PRISMA guidelines and through a transparent screening process, the literature was critically assessed for relevance and quality. This identified the overall trend of publications and the interlinkages between the characteristics of the sensors, techniques and validation methods. The results indicated that while significant progress has been made globally, there has also been an increase in progress made within Southern Africa. The findings suggest that while the application of drone technologies in water quality monitoring is a fairly new technique, there is strong agreement when utilised as a validation technique along with satellite-based remote sensing. Throughout the case studies, linear regression appeared as the most used statistical method, while all the average error assessment values (R^2) were above 0.7 for several other algorithms. This signified high accuracies for estimating water temperature, TSS, and CDOM. Furthermore, this review synthesised the results and emphasised the importance of progress in water quality monitoring through UAV remote sensing techniques moving forward. Future research needs to account for the fact that effective mapping of water temperature, TSS, and CDOM using UAVs is still rudimentary and, therefore, more research is needed to overcome the limitations as mentioned earlier, including the development of explicit methods and techniques and fusion of data from many sources.

Author Contributions: Conceptualisation and design of the review, S.J.P., T.B., M.S., S.K.G., A.C. and T.M.; S.J.P. performed this research and drafted the manuscript, T.B., M.S. and S.K.G. edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Water Research Commission of South Africa. Project number C2022/2023-00912, 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: No new data were created or analysed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Matthews, M.W.; Bernard, S. Eutrophication and cyanobacteria in South Africa's standing water bodies: A view from space. *S. Afr. J. Sci.* **2015**, *111*, 1–8. [CrossRef] [PubMed]
2. Edokpayi, J.N.; Odiyo, J.O.; Durowoju, O.S. Impact of wastewater on surface water quality in developing countries: A case study of South Africa. *Water Qual.* **2017**, *10*, 10.5772.
3. Bangira, T.; Alfieri, S.M.; Menenti, M.; van Niekerk, A. Comparing Thresholding with Machine Learning Classifiers for Mapping Complex Water. *Remote Sens.* **2019**, *11*, 1351. [CrossRef]
4. Korsgaard, L.; Schou, J.S. Economic valuation of aquatic ecosystem services in developing countries. *Water Policy* **2010**, *12*, 20–31. [CrossRef]
5. Adjovu, G.E.; Stephen, H.; James, D.; Ahmad, S. Overview of the Application of Remote Sensing in Effective Monitoring of Water Quality Parameters. *Remote Sens.* **2023**, *15*, 1938. [CrossRef]
6. Bangira, T.; Matongera, T.N.; Mabhaudhi, T.; Mutanga, O. 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* **2024**, *134*, 103536. [CrossRef]
7. Duan, P.; Zhang, F.; Liu, C.; Tan, M.L.; Shi, J.; Wang, W.; Cai, Y.; Kung, H.-T.; Yang, S. High-Resolution Planetscope Imagery and Machine Learning for Estimating Suspended Particulate Matter in the Ebinur Lake, Xinjiang, China. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2023**, *16*, 1019–1032. [CrossRef]
8. Mangadze, T.; Dalu, T.; Froneman, P.W. Biological monitoring in southern Africa: A review of the current status, challenges and future prospects. *Sci. Total Environ.* **2018**, *648*, 1492–1499. [CrossRef]
9. Namugize, J.N.; Jewitt, G.; Graham, M. Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa. *Phys. Chem. Earth* **2018**, *105*, 247–264. [CrossRef]
10. El Bilali, A.; Taleb, A. Prediction of irrigation water quality parameters using machine learning models in a semi-arid environment. *J. Saudi Soc. Agric. Sci.* **2020**, *19*, 439–451. [CrossRef]
11. United Nations. *Transforming Our World: The 2030 Agenda for Sustainable Development*; United Nations, Department of Economic and Social Affairs: New York, NY, USA, 2015.
12. O'Grady, J.; Zhang, D.; O'Connor, N.; Regan, F. A comprehensive review of catchment water quality monitoring using a tiered framework of integrated sensing technologies. *Sci. Total Environ.* **2021**, *765*, 142766. [CrossRef] [PubMed]
13. Ahmed, U.; Mumtaz, R.; Anwar, H.; Mumtaz, S.; Qamar, A.M. Water quality monitoring: From conventional to emerging technologies. *Water Supply* **2020**, *20*, 28–45. [CrossRef]
14. Cillero Castro, C.; Domínguez Gómez, J.A.; Delgado Martín, J.; Hinojo Sánchez, B.A.; Cereijo Arango, J.L.; Cheda Tuya, F.A.; Díaz-Varela, R. An UAV and Satellite Multispectral Data Approach to Monitor Water Quality in Small Reservoirs. *Remote Sens.* **2020**, *12*, 1514. [CrossRef]
15. Azzam, A.; Uddin, H.; Mannan, U. Estimation of Suspended Sediment Concentration of Keenjhar Lake through Remote Sensing. *Eng. Proc.* **2022**, *22*, 20. [CrossRef]
16. Boamah, L.A.; Nyamekye, C.; Gyamfi, C.; Ballard, J.Q.; Anornu, G.K. Mapping and estimating water quality parameters in the Volta Lake's Kpong Headpond of Ghana using regression model and Landsat 8. *Cogent Eng.* **2024**, *11*, 2307165. [CrossRef]
17. Usali, N.; Ismail, M.H. Use of Remote Sensing and GIS in Monitoring Water Quality. *J. Sustain. Dev.* **2010**, *3*, 228. [CrossRef]
18. Lo, Y.; Fu, L.; Lu, T.; Huang, H.; Kong, L.; Xu, Y.; Zhang, C. Medium-Sized Lake Water Quality Parameters Retrieval Using Multispectral UAV Image and Machine Learning Algorithms: A Case Study of the Yuandang Lake, China. *Drones* **2023**, *7*, 244. [CrossRef]
19. Sun, D.; Qiu, Z.; Li, Y.; Shi, K.; Gong, S. Detection of Total Phosphorus Concentrations of Turbid Inland Waters Using a Remote Sensing Method. *Water Air Soil Pollut.* **2014**, *225*, 1953. [CrossRef]
20. El Din, E.S.; Zhang, Y.; Suliman, A. Mapping concentrations of surface water quality parameters using a novel remote sensing and artificial intelligence framework. *Int. J. Remote Sens.* **2017**, *38*, 1023–1042. [CrossRef]
21. Chen, B.; Mu, X.; Chen, P.; Wang, B.; Choi, J.; Park, H.; Xu, S.; Wu, Y.; Yang, H. Machine learning-based inversion of water quality parameters in typical reach of the urban river by UAV multispectral data. *Ecol. Indic.* **2021**, *133*, 108434. [CrossRef]
22. Hou, Y.; Zhang, A.; Lv, R.; Zhang, Y.; Ma, J.; Li, T. Machine learning algorithm inversion experiment and pollution analysis of water quality parameters in urban small and medium-sized rivers based on UAV multispectral data. *Environ. Sci. Pollut. Res.* **2023**, *30*, 78913–78932. [CrossRef] [PubMed]
23. Ciancia, E.; Campanelli, A.; Lacava, T.; Palombo, A.; Pascucci, S.; Pergola, N.; Pignatti, S.; Satriano, V.; Tramutoli, V. Modeling and Multi-Temporal Characterization of Total Suspended Matter by the Combined Use of Sentinel 2-MSI and Landsat 8-OLI Data: The Pertusillo Lake Case Study (Italy). *Remote Sens.* **2020**, *12*, 2147. [CrossRef]
24. Hamidi, S.A.; Hosseiny, H.; Ekhtari, N.; Khazaei, B. Using MODIS remote sensing data for mapping the spatio-temporal variability of water quality and river turbid plume. *J. Coast. Conserv.* **2017**, *21*, 939–950. [CrossRef]
25. Campbell, G.; Phinn, S.R.; Dekker, A.G.; Brando, V.E. Remote sensing of water quality in an Australian tropical freshwater impoundment using matrix inversion and MERIS images. *Remote Sens. Environ.* **2011**, *115*, 2402–2414. [CrossRef]
26. Rahul, T.S.; Brema, J.; Wessley, G.J.J. Evaluation of surface water quality of Ukkadam lake in Coimbatore using UAV and Sentinel-2 multispectral data. *Int. J. Environ. Sci. Technol.* **2023**, *20*, 3205–3220. [CrossRef]

27. Omondi, A.N.; Ouma, Y.; Kosgei, J.R.; Kongo, V.; Kemboi, E.J.; Njoroge, S.M.; Mecha, A.C.; Kipkorir, E.C. Estimation and mapping of water quality parameters using satellite images: A case study of Two Rivers Dam, Kenya. *Water Pract. Technol.* **2023**, *18*, 428–443. [CrossRef]
28. Xiao, Y.; Guo, Y.; Yin, G.; Zhang, X.; Shi, Y.; Hao, F.; Fu, Y. UAV Multispectral Image-Based Urban River Water Quality Monitoring Using Stacked Ensemble Machine Learning Algorithms—A Case Study of the Zhanghe River, China. *Remote Sens.* **2022**, *14*, 3272. [CrossRef]
29. Mishra, V.; Avtar, R.; Prathiba, A.P.; Mishra, P.K.; Tiwari, A.; Sharma, S.K.; Singh, C.H.; Yadav, B.C.; Jain, K. Uncrewed Aerial Systems in Water Resource Management and Monitoring: A Review of Sensors, Applications, Software, and Issues. *Adv. Civ. Eng.* **2023**, *2023*, 3544724. [CrossRef]
30. Nhamo, L.; Ndlela, B.; Nhemachena, C.; Mabhaudhi, T.; Mpandeli, S.; Matchaya, G. The Water-Energy-Food Nexus: Climate Risks and Opportunities in Southern Africa. *Water* **2018**, *10*, 567. [CrossRef]
31. Koutalakis, P.; Tzoraki, O.; Zaimes, G. UAVs for Hydrologic Scopes: Application of a Low-Cost UAV to Estimate Surface Water Velocity by Using Three Different Image-Based Methods. *Drones* **2019**, *3*, 14. [CrossRef]
32. Woolway, R.I.; Kraemer, B.M.; Lenters, J.D.; Merchant, C.J.; O'reilly, C.M.; Sharma, S. Global lake responses to climate change. *Nat. Rev. Earth Environ.* **2020**, *1*, 388–403. [CrossRef]
33. Wierenga, P.J.; Hagan, R.M. *Effects of Irrigation on Soil and Crop*; Division of Agricultural Science, University of California: Berkley, CA, USA, 1996.
34. Al-Abed, N.; Abdulla, F.; Zahrawi, R. Evaluation of irrigation water total suspended solids (TSS) on a farm scale. *Arch. Agron. Soil Sci.* **2009**, *53*, 345–353. [CrossRef]
35. Khouni, I.; Louhichi, G.; Ghrabi, A. Use of GIS based Inverse Distance Weighted interpolation to assess surface water quality: Case of Wadi El Bey, Tunisia. *Environ. Technol. Innov.* **2021**, *24*, 101892. [CrossRef]
36. Zheng, K.; Shao, T.; Ning, J.; Zhuang, D.; Liang, X.; Ding, X. Water quality, basin characteristics, and discharge greatly affect CDOM in highly turbid rivers in the Yellow River Basin, China. *J. Clean. Prod.* **2023**, *404*, 136995. [CrossRef]
37. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Int. J. Surg.* **2021**, *88*, 372. [CrossRef]
38. Sibanda, M.; Mutanga, O.; Chimonyo, V.G.; Clulow, A.D.; Shoko, C.; Mazvimavi, D.; Dube, T.; Mabhaudhi, T. Application of Drone Technologies in Surface Water Resources Monitoring and Assessment: A Systematic Review of Progress, Challenges, and Opportunities in the Global South. *Drones* **2021**, *5*, 84. [CrossRef]
39. Bangira, T.; Mutanga, O.; Sibanda, M.; Dube, T.; Mabhaudhi, T. Remote Sensing Grassland Productivity Attributes: A Systematic Review. *Remote Sens.* **2023**, *15*, 2043. [CrossRef]
40. Van Eck, N.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef]
41. Xiao, Y.; Chen, J.; Xu, Y.; Guo, S.; Nie, X.; Guo, Y.; Li, X.; Hao, F.; Fu, Y.H. Monitoring of chlorophyll-a and suspended sediment concentrations in optically complex inland rivers using multisource remote sensing measurements. *Ecol. Indic.* **2023**, *155*, 111041. [CrossRef]
42. Womber, Z.R.; Zimale, F.A.; Kebedew, M.G.; Asers, B.W.; DeLuca, N.M.; Guzman, C.D.; Tilahun, S.A.; Zaitchik, B.F. Estimation of Suspended Sediment Concentration from Remote Sensing and In Situ Measurement over Lake Tana, Ethiopia. *Adv. Civ. Eng.* **2021**, *2021*, 9948780. [CrossRef]
43. Gholizadeh, M.H.; Melesse, A.M.; Reddi, L. A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques. *Sensors* **2016**, *16*, 1298. [CrossRef] [PubMed]
44. Brito, R.C.; Lorencena, M.C.; Loureiro, J.F.; Favarim, F.; Todt, E. A comparative approach on the use of unmanned aerial vehicles kind of fixed-wing and rotative wing applied to the precision agriculture scenario. In Proceedings of the Computer Software and Applications Conference (COMPSAC), Milwaukee, WI, USA, 15–19 July 2019.
45. Sagan, V.; Peterson, K.T.; Maimaitijiang, M.; Sidike, P.; Sloan, J.; Greeling, B.A.; Maalouf, S.; Adams, C. Monitoring inland water quality using remote sensing: Potential and limitations of spectral indicies, bio-optical simulations, machine learning and cloud computing. *Earth Sci. Rev.* **2020**, *205*, 103187. [CrossRef]
46. Choi, B.; Lee, J.; Park, B.; Sungjong, L. A study of cyanobacterial bloom monitoring using unmanned aerial vehicles, spectral indices, and image processing techniques. *Heliyon* **2023**, *9*, e16343. [CrossRef]
47. Larson, M.D.; Milas, A.S.; Vincent, R.K.; Evans, J.E. Multi-depth suspended sediment estimation using high-resolution remote-sensing UAV in Maumee River, Ohio. *Int. J. Remote Sens.* **2018**, *39*, 5472–5489. [CrossRef]
48. Veronez, M.R.; Kupssinskü, L.S.; Guimarães, T.T.; Koste, E.C.; Da Silva, J.M.; De Souza, L.V.; Oliverio, W.F.M.; Jardim, R.S.; Koch, I.; De Souza, J.G.; et al. Proposal of a method to determine the correlation between total suspended solids and dissolved organic matter in water bodies from spectral imaging and artificial neural networks. *Sensors* **2018**, *18*, 159. [CrossRef]
49. Kutser, T.; Pierson, D.C.; Tranvik, L.; Reinart, A.; Sobek, S.; Kallio, K. Using Satellite Remote Sensing to Estimate the Colored Dissolved Organic Matter Absorption Coefficient in Lakes. *Ecosystems* **2005**, *8*, 709–720. [CrossRef]
50. Fan, C. Spectral analysis of water reflectance for hyperspectral remote sensing pf water quality in esturine water. *J. Geosci. Environ. Prot.* **2014**, *2*, 19–27.

51. Prior, E.M.; O'donnell, F.C.; Brodbeck, C.; Runion, G.B.; Shepherd, S.L. Investigating small unoccupied aerial systems (sUAS) multispectral imagery for total suspended solids and turbidity monitoring in small streams. *Int. J. Remote Sens.* **2021**, *42*, 39–64. [CrossRef]
52. Ying, H.; Xia, K.; Huang, X.; Feng, H.; Yang, Y.; Du, X.; Huang, L. Evaluation of water quality based on UAV images and the IMP-MPP algorithm. *Ecol. Inform.* **2021**, *61*, 101239. [CrossRef]
53. Olivetti, D.; Roig, H.; Martinez, J.-M.; Borges, H.; Ferreira, A.; Casari, R.; Salles, L.; Malta, E. Low-Cost Unmanned Aerial Multispectral Imagery for Siltation Monitoring in Reservoirs. *Remote Sens.* **2020**, *12*, 1855. [CrossRef]
54. Silveira Kupssinskü, L.; Thomassim Guimarães, T.; Menezes de Souza, E.; Zanotta, D.C.; Roberto Veronez, M.; Gonzaga Jr, L.; Mauad, F.F. A method for chlorophyll-a and suspended solids prediction through remote sensing and machine learning. *Sensors* **2020**, *20*, 2125. [CrossRef] [PubMed]
55. Dias, R.L.S.; da Silva, D.D.; Fernandes-Filho, E.I.; Amaral, C.H.D.; dos Santos, E.P.; Marques, J.F.; Veloso, G.V. Machine learning models applied to TSS estimation in a reservoir using multispectral sensor onboard to RPA. *Ecol. Inform.* **2021**, *65*, 101414. [CrossRef]
56. Guimarães, T.T.; Veronez, M.R.; Koste, E.C.; Souza, E.M.; Brum, D.; Gonzaga, L., Jr.; Mauad, F.F. Evaluation of Regression Analysis and Neural Networks to Predict Total Suspended Solids in Water Bodies from Unmanned Aerial Vehicle Images. *Sustainability* **2019**, *11*, 2580. [CrossRef]
57. Sáenz, N.A.; Paez, D.E.; Arango, C. Local algorithm for monitoring total suspended sediments in micro-watersheds using drone and remote sensing applications. Case study: Teusaca River, La Calera, Columbia. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2015**, *19*, 159–165. [CrossRef]
58. Wei, L.; Huang, C.; Zhong, Y.; Wang, Z.; Hu, X.; Lin, L. Inland Waters Suspended Solids Concentration Retrieval Based on PSO-LSSVM for UAV-Borne Hyperspectral Remote Sensing Imagery. *Remote. Sens.* **2019**, *11*, 1455. [CrossRef]
59. Harvey, M.C.; Rowland, J.V.; Luketina, K.M. Drone with thermal infrared camera provides high resolution georeferenced imagery of the Waikite geothermal area, New Zealand. *J. Volcanol. Geotherm. Res.* **2016**, *325*, 61–69. [CrossRef]
60. Bartelt, G. Monitoring Phytoplankton Biomass and Surface Temperatures of Small Inland Lakes by Multispectral and Thermal UAS Imagery. Master's Thesis, University of Minnesota, Minneapolis, MN, USA, 2021.
61. Xu, J.; Xu, Z.; Kuang, J.; Lin, C.; Xiao, L.; Huang, X.; Zhang, Y. An Alternative to Laboratory Testing: Random Forest-Based Water Quality Prediction Framework for Inland and Nearshore Water Bodies. *Water* **2021**, *13*, 3262. [CrossRef]
62. Zeng, C.; Richardson, M.; King, D.J. The impacts of environmental variables on water reflectance measured using a lightweight unmanned aerial vehicle (UAV)-based spectrometer system. *ISPRS J. Photogramm. Remote Sens.* **2017**, *130*, 217–230. [CrossRef]
63. Qiang, S.; Song, K.; Shang, Y.; Lai, F.; Wen, Z.; Liu, G.; Tao, H.; Lyu, Y. Remote Sensing Estimation of CDOM and DOC with the Environmental Implications for Lake Khanka. *Remote Sens.* **2023**, *15*, 5707. [CrossRef]
64. Toming, K.; Liu, H.; Soomets, T.; Uuemaa, E.; Nõges, T.; Kutser, T. Estimation of the Biogeochemical and Physical Properties of Lakes Based on Remote Sensing and Artificial Intelligence Applications. *Remote Sens.* **2024**, *16*, 464. [CrossRef]
65. Seidel, M.; Hutengs, C.; Oertel, F.; Schwefel, D.; Jung, A.; Vohland, M. Underwater Use of a Hyperspectral Camera to Estimate Optically Active Substances in the Water Column of Freshwater Lakes. *Remote Sens.* **2020**, *12*, 1745. [CrossRef]
66. Galešić Divić, M.; Kvesić Ivanković, M.; Divić, V.; Kišević, M.; Panić, M.; Lugonja, P.; Crnojević, V.; Andričević, R. Estimation of Water Quality Parameters in Oligotrophic Coastal Waters Using Uncrewed-Aerial-Vehicle-Obtained Hyperspectral Data. *J. Mar. Sci. Eng.* **2023**, *11*, 2026. [CrossRef]
67. Lary, D.J.; Schaefer, D.; Waczak, J.; Aker, A.; Barbosa, A.; Wijeratne, L.O.; Talebi, S.; Fernando, B.; Sadler, J.; Lary, T.; et al. Autonomous learning of new environments with a robotic team employing Hyper-spectral Remote sensing, Comprehensive in-situ sensing and machine learning. *Sensors* **2021**, *21*, 2240. [CrossRef] [PubMed]
68. Gitelson, A.; Garbuzov, G.; Szilagyi, F.; Mittenzwey, K.-H.; Karnieli, A.; Kaiser, A. Quantitative remote sensing methods for real-time monitoring of inland waters quality. *Int. J. Remote Sens.* **1993**, *14*, 1269–1295. [CrossRef]
69. Acharya, B.S.; Bhandari, M. Machine Learning and Unmanned Aerial Vehicles in Water Quality Monitoring. *Sustain. Horiz.* **2022**, *3*, 100019. [CrossRef]
70. Yoakum, C.; Cerreta, J. A review od DJI's Mavic Pro precision landing accuracy. *Int. J. Aviat. Aeronaut. Aerosp.* **2020**, *7*, 5.
71. Matrice, D.J.I. *Matrice 300 RTK User Manual*; DJI: Shenzhen, China, 2023.
72. Kim, J.; Jang, W.; Kim, J.H.; Lee, J.; Cho, K.H.; Lee, Y.G.; Chon, K.; Park, S.; Pyo, J.; Park, Y.; et al. Application of airborne hyperspectral imagery to retrieve spatiotemporal CDOM distribution using machine learning in a reservoir. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *114*, 103053. [CrossRef]