# Hyperspectral remote sensing technology for water quality monitoring: knowledge graph analysis and Frontier trend

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Water environment health assessment is one of the vital fields closely related to the quality of human life. The change of material contained in water will lead to the reflectance change of hyperspectral remote sensing data. According to this phenomenon, the water quality parameters are calculated to achieve the purpose of water quality monitoring. Series knowledge graphs in this field are drawn after analyzing 564 publications from WOS (Web of Science) and EI (The Engineering Index) databases since 1994 with the support of VOSviewer and CiteSpace. Including statistics of documents publication time, contribution analysis, the influence of publications and journals, and the influence of funding institutions. It is concluded that the research trend of hyperspectral water quality monitoring is the machine learning algorithm based on UAV (Unmanned Aerial Vehicle) hyperspectral instrument data by analyzing scientific research cooperation, keyword analysis, and research hotspots. The whole picture of the research is obtained in this field from four subfields: application scenarios, data sources, water quality parameters, and monitoring algorithms in this paper. It is summarized that the miniaturization, integration, and intelligence of hyperspectral sensors will be the research trend in the next 10 years or even longer. The conclusions have significant reference values for this field.

KEYWORDS

hyperspectral remote sensing, water quality monitoring, knowledge graph analysis, VOSviewer, CiteSpace, Bibliometrics

## 1 Introduction

Water is called the source of life, which makes protecting water resources, preventing water pollution and rational using water resources hot issues of concern to all mankind (Hou et al., 2022). In the summer of 2022, the water level of rivers dropped sharply, and the residents had difficulty drinking water in many countries both in Europe and Asia, making the public pay more attention to water resources (Zhang et al., 2022). Remote sensing technology has been applied to water environment monitoring for more than 40 years

(Mueksch, 1994). It is generally believed that remote sensing technology can play a vital role in water boundary, water depth, water temperature, and water quality evaluation (Leuven et al., 2002; Calderón et al., 2013; Rotkiske and Jr, 2018). With the increase in the number of bands and the optimization of the algorithm, more and more water quality parameters can be quantified, especially in water quality evaluation (Mbuh, 2018). Early water color remote sensing was mainly used in a wide range of marine applications (Herut et al., 1999; Wolny et al., 2020). While more and more advanced sensors are recently applied to water quality monitoring with the aggravation of inland water quality problems (Qian et al., 2017; Cao et al., 2018; Niu et al., 2021; Lu et al., 2022).

The application scenario of remote sensing technology has gradually transitioned from the ocean and river to the study of lakes and urban water networks, which proves that remote sensing technology has steadily developed from macroscopic observation to microscopic monitoring (Delegido et al., 2014). Regarding monitoring data sources, from satellite and airborne to UAV and water surface buoy data (Zhang et al., 2022). The data showed a change in law from multispectral to hyperspectral integration. The water quality parameters monitored by remote sensing technology gradually transition from chlorophyll and cyanobacteria to calculate more than ten chemical parameters (Govender et al., 2007). The application range is progressively developed from optical parameters to non-optical parameters. And the research of monitoring algorithms has made rapid progress, from regression and correlation algorithms to artificial intelligence and machine learning algorithms (Maier and Keller, 2019; Sarigai et al., 2021). As a result, the efficiency and accuracy of data calculation are constantly improving.

Although hyperspectral remote sensing technology is one of the irreplaceable technologies for water quality monitoring and has become the scientific community's consensus, there is no mature theory and method to replace the traditional chemical reagent method completely, and many studies are still in the exploratory stage. Therefore, it is of great significance for the follow-up research to fully evaluate the application status of remote sensing technology in the water environment (Lee et al., 2008; Zhang et al., 2009; Harmel et al., 2012; Song et al., 2012). Some publications on Hyperspectral water quality monitoring and analysis have appeared in different disciplines since 1994 (Mueksch, 1994). It is not difficult to find that the existing research mainly focuses on limited fields such as atmospheric correction, data preprocessing, modeling algorithms, and application case analysis through the investigation of publications in this field (Salama and Monbaliu, 2002; Reuter et al., 2017). There are few publications on application scenarios, data sources, monitoring indicators, and algorithm trends. Only Joyce et al. researched the publication's analysis of multisensor technology for water quality monitoring in catchment areas through literature metrology analysis and knowledge mapping analysis (O'Grady et al., 2021).

Other publications discuss single indicators, such as chlorophyll and total phosphorus, but rarely involve a systematic analysis of water quality parameters combined with hyperspectral technology (Maier and Keller, 2019; Li et al., 2020). In addition, there is almost no comprehensive study on the development trend of water quality parameter calculation methods. Considering that the data platform of Science Network (WOS) is more scientific research papers, and the EI data platform includes engineering application publications based on summarizing previous studies, this paper searches the two data platforms of WOS and EI to provide a more comprehensive information. Therefore, this paper conducts a bibliometric analysis on 564 selected publications, quantifies the literature performance, and analyzes highly cited literature by using the data analysis function of WOS and EI databases. Meanwhile, in the knowledge map in the visual software of VOSviewer, CiteSpace, and Excel, the knowledge transformation is carried out on the data involved, the knowledge composition and development trend in this field is clarified, the potential research hotspots are explored, and the development direction of future technology is predicted (Govender et al., 2007; O'Grady et al., 2021). And the technical system of hyperspectral remote sensing water quality monitoring is systematically summarized from four subfields (scene, data source, parameter, and algorithm). In the end, the paper discusses the Frontier technologies such as miniaturization, intellectualization, and interdisciplinary application potential of the instrument for reference by production and scientific research institutions.

# 2 Data sources and methods

## 2.1 Data collation

The full name of WOS is Web of Science, which is Clarivate's product (formerly Thomson Reuters intellectual property and Technology). WOS includes three famous Citation Index Databases (SCI, SSCI, and A & HCI) and collects authoritative and influential journals in various disciplines. WOS, as a document retrieval tool due to its strict selection criteria and citation index mechanism, has also become one of the essential basic evaluation tools of bibliometrics and scientific metrology. WOS can retrieve relevant papers in various ways, such as keywords, authors, topics, DOI, *etc.* And it can enable authors or researchers to find the articles and data efficiently. EI is the citation abbreviation of the Engineering Index, a largescale comprehensive retrieval tool with the most extended history, and was founded by the American Federation of Engineers in 1884 (Palmer et al., 2015; Li et al., 2020). EI enjoys a high reputation worldwide in the academic, engineering, and information circles and is a critical retrieval tool commonly recognized by scientific and technological circles (Aasen et al., 2015). The content includes the research results of all engineering disciplines and engineering activities.

According to the statement of "TS = (hyperspectral AND water quality AND monitor)", Retrieve relevant papers in the WOS and EI databases. The data source is set to "search in web of science core collection" in the WOS platform (Hilton et al., 2012). Then, select the citation index as "Editions: All", select the document field as "Topic" and set the retrieval time as "Publication: All years (1994–2022)". Six hundred thirtytwo records were retrieved from WOS. Select the retrieval time from "all years" to "till now", and 404 records are extracted in the EI platform. Two hundred fiftyone publications are retrieved by the two databases simultaneously, and 221 publications are irrelevant. Finally, 564 practical items were obtained after selection.

FIGURE 1
Time distribution of number of publication and citation frequency from 1994 to 2022.
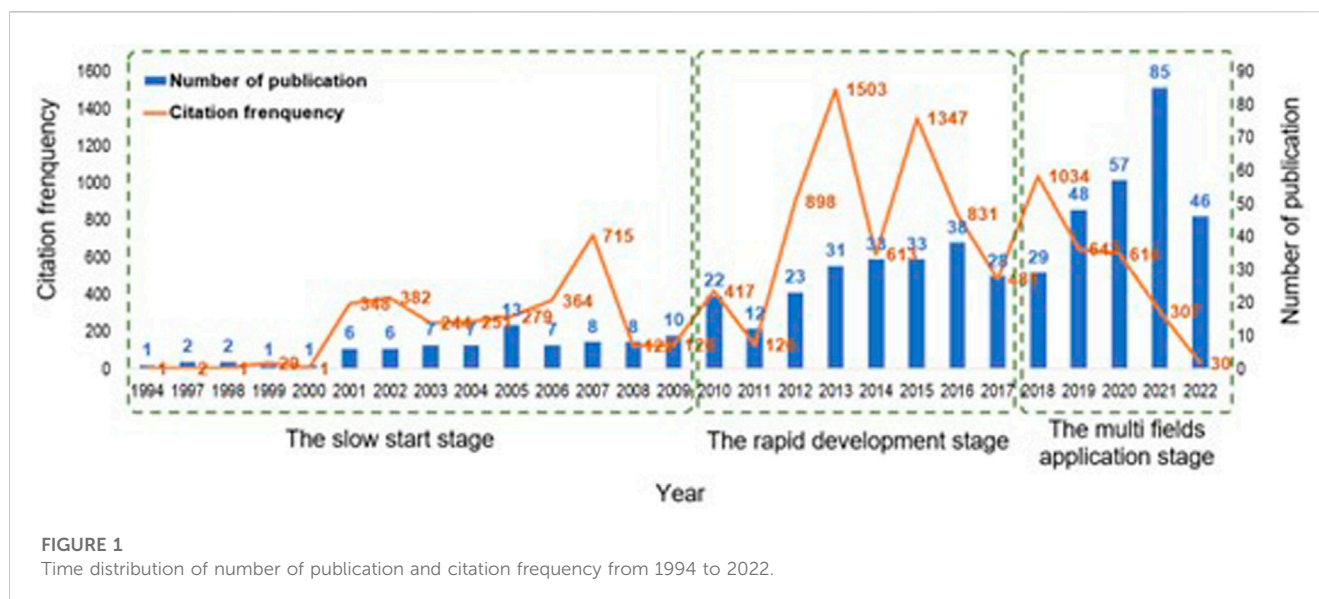
## 2.2 Data collation

The bibliometric analysis aims to summarize a series of results by describing publications objectively, systematically, and quantitatively. It is generally divided into four steps: sampling, recording entries, cataloging, and metrics. The first three steps are to record the titles, author, keywords, publication time, main methods, quoted data, *etc.*, of the publication through reasonable rules to form standardized data. Then, the metrics are realized to extract and analyze the hidden information in all publications, which can provide a direction for future research. The above work is more standardized and efficient with the support of software represented by VOSviewer and CiteSpace (Govender et al., 2007). VOSviewer is a free software based on Java developed by the Centre for Science and Technology Studies (CWTS) of Leiden University in the Netherlands in 2009 (Ben-Dor et al., 2002). It is mainly adapted to the mock examination undirected network analysis and focuses on the visualization of scientific knowledge. CiteSpace, known as "citation space", is a citation visual analysis software that focuses on analyzing the potential knowledge contained in scientific analysis and is gradually developed under the background of scient metrics and data visualization (O'Grady et al., 2021). This paper analyzes the scientific research status and trend in the field of water quality hyperspectral monitoring from four aspects with the support of the above software. The research scheme includes word counting, concept classification, spatial analysis, and semantic intensity analysis.

## 3 Results

## 3.1 Statistics of documents publication time

It can be concluded that the water quality monitoring work based on hyperspectral technology is generally divided into three research stages according to the statistics of the number of

publications and citation frequency in the last 30 years (Figure 1).

### 3.1.1 The first stage is the slow start stage (1994–2009)

The satellite (Mueksch, 1994; Östlund et al., 2001; Duan et al., 2009) and airborne hyperspectral (Barducci and Pippi, 1997; Herut et al., 1999; Kallio et al., 2001) data are gradually applied from exploration experiments, which are used to the evaluation of nutrient elements in water, especially the calculation of chlorophyll concentration (Flink et al., 2001). It has attracted European scholars' attention, particularly in assessing the eutrophication of water. The atmospheric correction algorithm suitable for water area is studied, and the concept of water leaving reflectivity is proposed in hyperspectral preprocessing (Salama and Monbaliu, 2002). The number of documents in this stage has increased from 12 to more than 5. The main reason is that the rapid development of airborne sensor technology has solved the difficulties of hyperspectral data sources (Barducci and Pippi, 1997). The number of citations reached 2,00,800, and the scope of research ranged from eutrophication monitoring (Jiao et al., 2006), hyperspectral data preprocessing (Kohler et al., 2004), and sensor development (Lee et al., 2011) to water quality inversion model realization (Song et al., 2005), and water quality monitoring (Kutser et al., 2006). New concepts, such as the combined use of hyperspectral and GIS technologies (Leuven et al., 2002) and the comprehensive monitoring of multiscale remote sensing data (Schmid et al., 2004), have been developed, especially after 2000. It has been further integrated with environmental science (Xie et al., 2006; Gong et al., 2008) and proposed the solution of coastal survey (Hlaing et al., 2010) and quantitative hyperspectral (Tong et al., 2010; Xiong et al., 2012) after 2007.

### 3.1.2 The second stage is rapid development (2011–2017)

The research focuses on three cores: environmental pollution monitoring, multisource data collaboration, and research on single

FIGURE 2
National cooperation network knowledge graph.
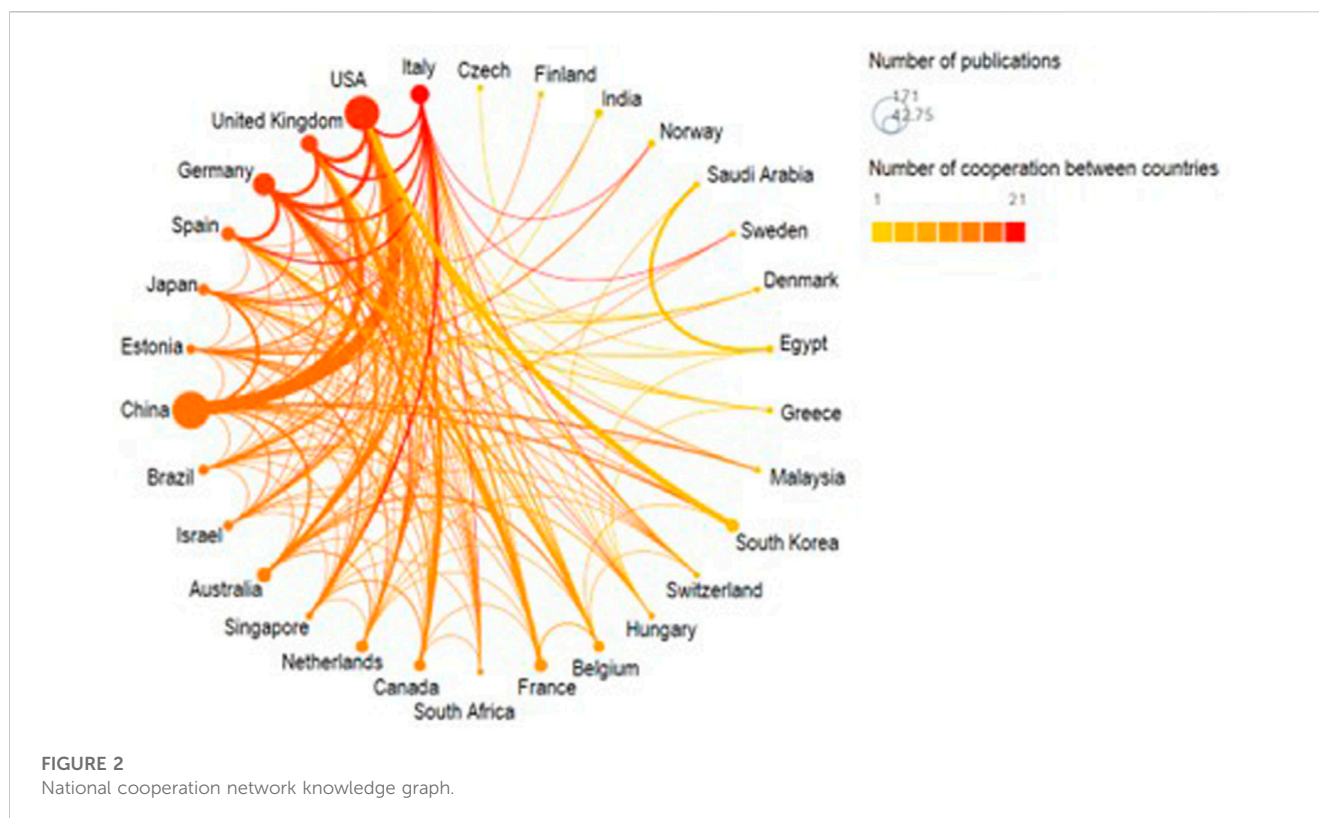
water quality parameter extraction with the continuous maturity of sensor technology. Airborne and satellite hyperspectral remote sensing data can be used to provide accurate records of water quality changes in pollution monitoring, such as total nitrogen concentration inversion (Pan et al., 2011), water bloom warning (Song Y. et al., 2010), suspended matter concentration calculation (Shen et al., 2011), seawater intrusion (SONG et al., 2011), and organic matter calculation (Zhu and Yu, 2013). These publications generally take a river or lake as an example of numerical analysis and mapping and gradually introduce water quality hyperspectral technology into environmental pollution monitoring. It is generally concluded that hyperspectral technology can solve the water pollution problems of departments, but not all in the application process. Collaborative processing and comprehensive application of multiple sensors have become significant achievements in this research stage to improve data availability further. Satellite hyperspectral and water surface *in situ* data (Augusto-Silva et al., 2014; Keith et al., 2014), satellite hyperspectral and airborne hyperspectral (Ahmed et al., 2011), polarization technology and hyperspectral technology (Harmel et al., 2012), hyperspectral and thermal infrared data (Calderón et al., 2013), satellite hyperspectral and satellite multispectral data (Chang et al., 2014), hyperspectral technology and fluorescence technology (Chen et al., 2015), and other data collaborative processing research (Beck et al., 2016; Reuter et al., 2017), which makes more scholars in cross fields understand hyperspectral technology, and try to get more innovative results after the introduction. The number of published papers has increased to a certain extent at this stage, but the frequency of citations has increased significantly. The number of sources in 2013 and

2015 exceeded 1,300, reflecting the phenomenon of cross integration in this field. The third research focus is on the exploration of individual water quality indicators. A precise spectral mechanism and calculation algorithm are given for indicators such as total suspended solids (Haji Gholizadeh et al., 2016), total phosphorus (Stal et al., 2016), chromogenic dissolved organic matter (CDOM) (Chen et al., 2015), chlorophyll a (Hunter et al., 2010), water color (Watanabe et al., 2016), and water acidity (Qian et al., 2017). The research and development of small-scale special instruments (Piegari et al., 2011) have been enlightened, and relevant research has been gradually developed to verify the accuracy of individual indicators.

### 3.1.3 The third stage is the multi fields application stage (2018–2022)

The number of publications has increased steadily, from 48 in 2018 to 85 in 2021, and there is a high probability will exceed 100 in 2022. The research in the past 5 years has indicated two significant characteristics. Firstly, the data sources are more abundant, especially the rapid development of hyperspectral technology of UAV, which has dramatically reduced the application threshold of hyperspectral technology in the field of water quality monitoring; Secondly, machine learning algorithm has become the mainstream method to calculate water quality indicators. Hyperspectral data is integrated into the cloud, facilitating data acquisition and rapid calculation of results under this idea. The representative research results of the former include, the realization method of UAV hyperspectral push scan imager for ecological monitoring (Arroyo-Mora et al., 2019; Becker et al., 2019; Buters et al., 2019), the inversion of water quality parameters of typical river
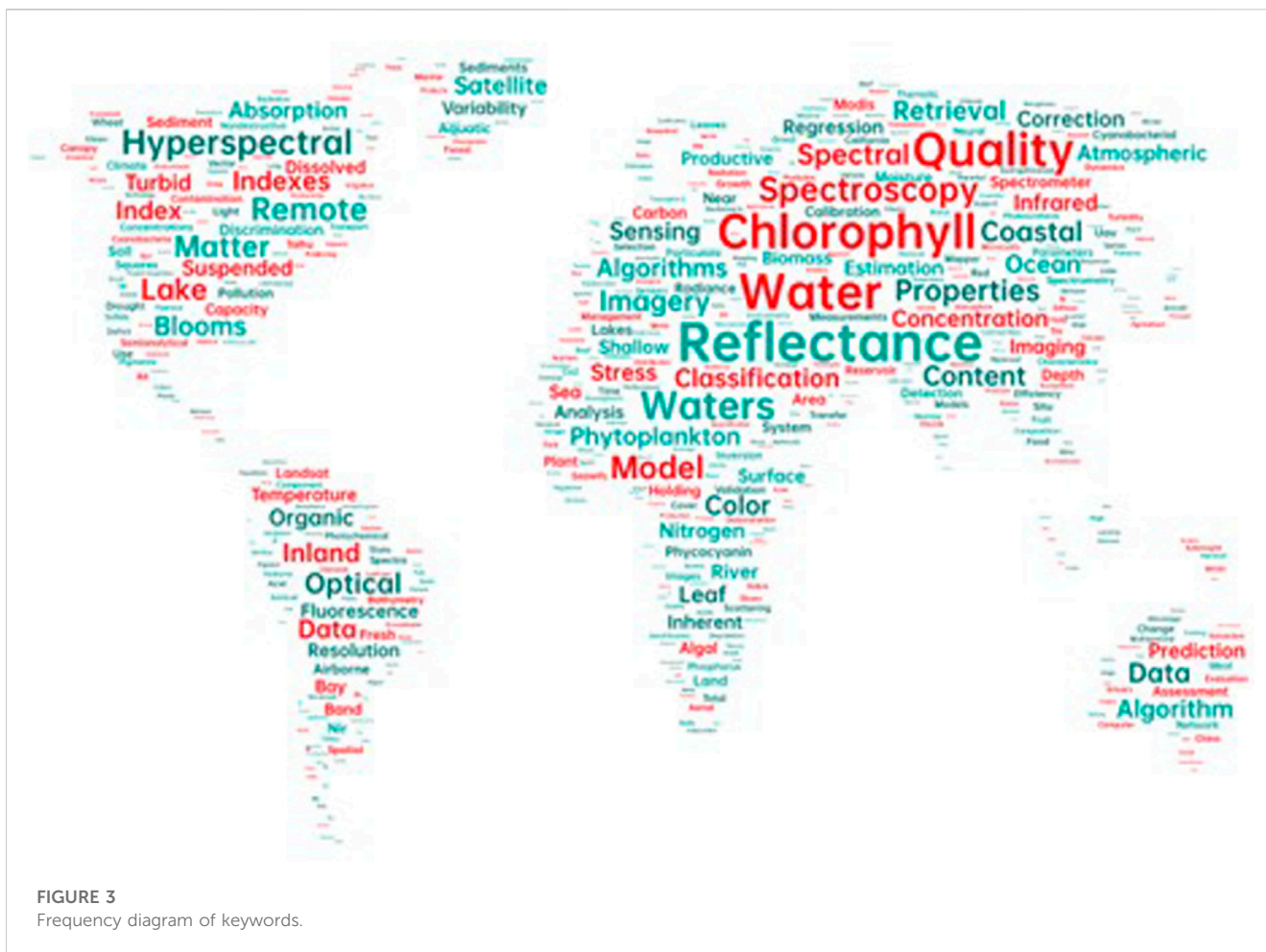
**FIGURE 3**
Frequency diagram of keywords.

**TABLE 1 Top 10 highfrequency keywords.**

| Number | Keywords | Count | Year | Number | Keywords | Count | Year |
|---|---|---|---|---|---|---|---|
| 1 | Reflectance | 182 | 2006 | 11 | Imagery | 55 | 2008 |
| 2 | Water | 154 | 2015 | 12 | Optical | 53 | 2018 |
| 3 | Chlorophyll | 142 | 2012 | 13 | Spectral | 50 | 2010 |
| 4 | Hyperspectral | 138 | 2015 | 14 | Coastal | 50 | 2012 |
| 5 | Quality | 97 | 2017 | 15 | Content | 50 | 2015 |
| 6 | Waters | 76 | 2006 | 16 | Data | 49 | 2016 |
| 7 | Remote | 71 | 2008 | 17 | Retrieval | 46 | 2015 |
| 8 | Model | 65 | 2016 | 18 | Blooms | 45 | 2017 |
| 9 | Matter | 63 | 2017 | 19 | Color | 44 | 2012 |
| 10 | Lake | 55 | 2017 | 20 | Inland | 44 | 2009 |

sections (LIN Jian-yuan et al.), water turbidity (Cao et al., 2018), algae pigments (Pyo et al., 2022), and cyanobacteria assessment (Moradinejad et al., 2019). UAV images in cities have been applied to the monitoring of black and odorous water (Huang and Zheng, 2019), transparency (Giardino et al., 2019), and water depth (Liu et al., 2020). The representative research achievements of the latter include the construction of several basic platforms, including the cloud network infrastructure (Mishra et al., 2018), the river system monitoring and early warning system (Esse et al., 2018), the shallow water color automatic observation system (Marcello et al., 2018),
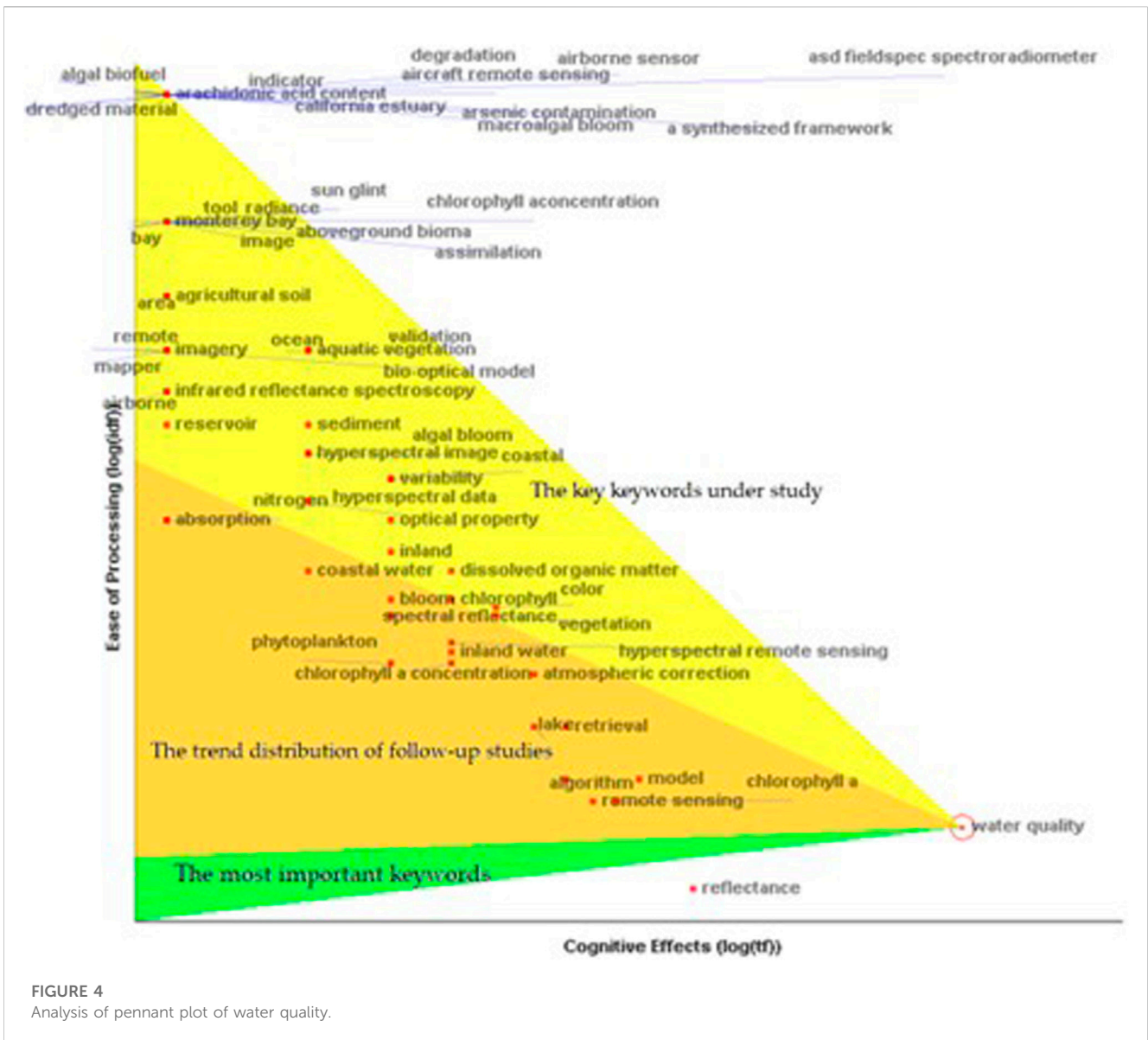
**FIGURE 4**
Analysis of pennant plot of water quality.

and the water quality of vulnerable inland ecosystems (Eugenio et al., 2019), which can monitor the global spread of harmful cyanobacterial blooms. In the calculation of chlorophyll concentration (Maier and Keller, 2019; Wang et al., 2020), total nitrogen concentration (Li et al., 2020), water quality parameters of urban rivers (Wei et al., 2019; 2020; Sarigai et al., 2021), river turbidity (Hong et al., 2021), and estimation of inactive inland water quality parameters (Niu et al., 2021) after integrating the machine learning algorithm.

## 3.2 Analysis of scientific research cooperation

Statistics on the number of books published by all countries can reflect the significant international cooperation countries in water quality hyperspectral research. The larger the circle, the greater the number of publications (Figure 2). Discharge the number of

publications in a clockwise direction. The number of publications in 18 countries exceeded 8. The country with the largest international cooperation papers is China, with 157 publications. The following four countries are the United States (133), Germany (56), Italy (38), and the United Kingdom (33). According to the 2021 China Water Resources Bulletin, the total amount of water resources in China in 2021 was 2963.82 billion cubic meters. As stated by the US Environmental Protection Agency, the United States has approximately 300,000 freshwater lakes, 5,200 rivers, and thousands of miles of coastline. Germany has abundant groundwater and surface water resources, most of which are used for water supply and agricultural irrigation. Italy has abundant freshwater resources, including about 61,000 km of rivers, lakes, and groundwater reserves. According to the UK Environment Agency, the UK has some large reservoirs and water supply systems to meet the country's water demand, as well as many small rivers and lakes. China and the United States have coauthored publications with most countries, representing the

**TABLE 2 Keywords mutation analysis.**

| Keywords | Strength | Begin | End | Research hotspot period |
|---|---|---|---|---|
| Airborne | 2.11 | 2009 | 2015 | |
| Model | 2.01 | 2010 | 2012 | |
| Bloom | 1.92 | 2010 | 2012 | |
| Water quality | 2.98 | 2011 | 2012 | |
| Spectral reflectance | 2.15 | 2011 | 2018 | |
| Turbid productive water | 3.50 | 2013 | 2017 | |
| Infrared reflectance spectroscopy | 2.74 | 2013 | 2015 | |
| Coastal water | 2.26 | 2013 | 2014 | |
| Thematic mapper | 1.92 | 2013 | 2016 | |
| Nitrogen | 1.84 | 2013 | 2014 | |
| Water holding capacity | 2.65 | 2015 | 2016 | |
| Inland water | 2.50 | 2015 | 2016 | |
| Color | 2.43 | 2015 | 2018 | |
| Least squares regression | 2.09 | 2015 | 2017 | |
| Optical property | 2.95 | 2016 | 2019 | |
| Spectroscopy | 1.98 | 2016 | 2018 | |
| Atmospheric correction | 3.53 | 2017 | 2018 | |
| Suspended particulate matter | 2.09 | 2018 | 2020 | |
| Ocean color | 2.09 | 2018 | 2020 | |
| Regression | 2.98 | 2019 | 2020 | |
| Hyperspectral Imagery | 2.43 | 2019 | 2022 | |
| UAV | 1.91 | 2019 | 2022 | |
| River | 4.18 | 2020 | 2022 | |
| Machine learning | 3.49 | 2020 | 2022 | |

highest level in water quality hyperspectral research. One notable feature is that these two countries are the first to conduct relevant research. The results of other countries are delayed for about 2 years compared with China and the United States. The support for new technologies and the spirit of exploring new fields are the main reasons for the two countries' outstanding development in this field.

## 3.3 Keyword analysis

Drawing the frequency diagram of keywords and calculating their occurrence times after counting the keywords of all publications (Figure 3). It is worth noting that this is a "cloud words picture", which is a visual highlight of the key words that appear frequently in the paper. The more they appear, the larger the font is displayed, the more prominent the keyword is. The color here is only used to distinguish from adjacent words, and has no representational meaning. The distribution of words is random and has no direct relationship with the geographical location of the response. The main research points and technologies of hyperspectral water quality monitoring can be obtained from the keywords (Table 1). The application scenario of hyperspectral technology for water quality monitoring, the organization format of hyperspectral data, the target of water quality monitoring, and the main algorithm ideas can be learned according to the top 20 words that appear most frequently. Firstly, the keywords "Water", "Quality", "Waters", "Lake", "Coastal" and "Inland" indicate that the application scenario of hyperspectral technology has covered the main water types on the Earth's surface, including lakes, oceans, and rivers. The scholars designed the technical process of each field and drew valuable conclusions according to the needs of the application. Secondly, the keywords such as "Reflection", "Hyperspectral", "Remote", "Imagery", "Optical", "Spectral", "Data" indicate that as passive remote sensing technology, the image data format is mainly used in water quality monitoring application. Image data is acquired primarily through the spectrometer mounted on three platforms, such as satellite, airborne or UAV. In addition, the
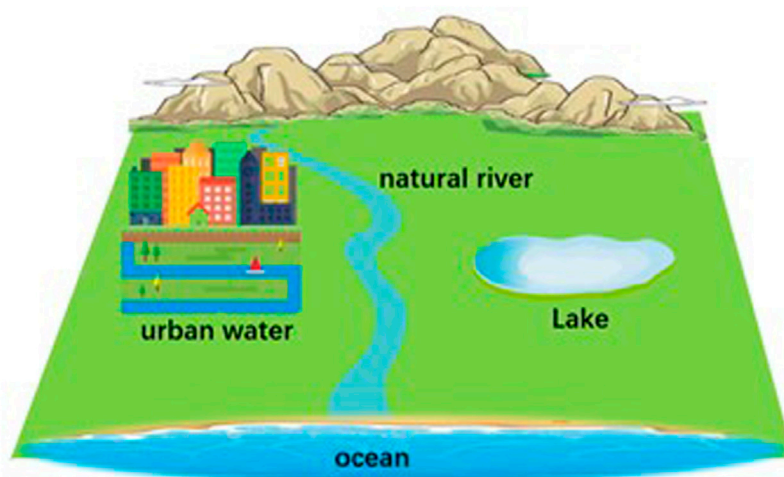
**FIGURE 5**
Main application scenarios of hyperspectral water quality monitoring.

spectral range is visible to nearinfrared, which is the response band of the main substances in the water (Zhang D. et al., 2021). Thirdly, the keywords "Chlorophyll", "Matter", "Content", "Blooms", and "Color" indicate the material information that has been proved can be accurately extracted by hyperspectral technology repeatedly. Chlorophyll content has been widely studied as the most common substance in water. The study of water bloom and color, closely related to chlorophyll concentration, has also indirectly become a research hotspot (Song K. et al., 2010). The former mainly focuses on the distribution law in natural waters, while the latter focuses on urban malodorous black river water research. In addition, the research on total nitrogen, total phosphorus, ammonia nitrogen, and other substances has also yielded many results that can be popularized. Fourthly, the keywords "model" and "retrieval" indicate that the algorithm of hyperspectral technology is still based on inversion technology. Largearea information extraction combines limited *in-situ* data and spectral data to establish a correlation model has become a mainstream method (Wang et al., 2005). The machine learning algorithm has become the core of the new modeling algorithm and has received a lot of new research in this process.

## 3.4 Analysis of Frontier trend

Draw a pennant plot with "water quality" as the goal, and infer the research trend according to the keywords (Figure 4). The idf value is an algorithm calculation result of tag words after clustering, which is used to infer mainstream research methods. The main contents of the literature are generated into cluster labels, and the research intensity of each research field is obtained after the weighted calculation. Usually, the idf is plotted after calculating the logarithm (Jianguang et al., 2005; Yan et al., 2005; Yan et al., 2006). Green, orange, and yellow in the figure, respectively, represent the most important keywords, the key

keywords under study, and the trend distribution of follow-up studies taking idf value as the evaluation index. Keywords with higher idf values depend more on keywords with lower idf values. It can be obtained from the figure that spectral reflectance is one of the fundamental technologies for water quality monitoring, and subsequent research is developed based on the optical mechanism of water. It can be concluded from the orange area that the current research mainly focuses on specific application scenarios, including lakes, water colors, internal roads, and water bodies. The essential research difficulties are leaf green extraction, atmospheric correction, and inversion algorithm. The follow-up research trend shows an explosive state, with many keywords in the yellow area in the figure. In addition, some more complex issues have been paid attention to, including the research and development of optical instruments, the extraction of micro materials, the application of reservoirs, the application of UAV remote sensing, the development of fluorescence technology, and the research of numerical simulation technology (Lee et al., 2007). On the whole, the pennant plot shows the divergent research rules of water quality remote sensing monitoring from the spectroscopy principle to the application of different scenarios and then to the study of complex problems (Bresciani et al., 2017).

Burst chart can show the mutation law of keywords in the field of water quality hyperspectral monitoring (Table 2). The mutation represents the whole process that the research frequency of scholars began to increase over some time, and gradually tended to be stable and cool with time. The red line in the figure represents the rise and continuation of research. The results of calculating the top 24 keywords of the last 15 years indicate that.

(1) Data: Airborne sensors represented by CASI were the primary data acquisition form from 2009 to 2015 on the platform of hyperspectral sensors. Airborne sensors can obtain hyperspectral data of thousands of square kilometers within a few hours, making remarkable

TABLE 3 Typical cases of hyperspectral water quality monitoring scenarios.

| Scenarios | References | Purpose | Research idea | Conclusion |
|---|---|---|---|---|
| Urban water | Hou et al. (2022) | Water quality parameters estimation | Exploring the feasibility of using hyperspectral monitoring technology instead of laboratory physical and chemical index test and evaluates the prediction effect of inversion model on water quality change | Machine learning has obvious overall advantages, making it more suitable for classified inversion prediction of urban river water quality parameters |
| | Wei et al. (2019) | Monitoring the pollution level of urban water | Research on the largescale monitoring of black-odor water, especially the cases of using unmanned aerial vehicle (UAV) to efficiently and accurately monitor the spatial distribution of urban river pollution | The technical effectiveness of using UAV hyperspectral technology to monitor the distribution of urban pollution sources is confirmed |
| | Lin et al., 2019 | Retrieval of water quality parameters | Came up with an improved algorithm suitable for water of inland urban river network to obtain the inherent optical parameters of water | The distribution of chlorophyll-a and suspended solids obtained from the retrieval was consistent with the characteristics and actual conditions of the urban river network |
| | Zhang et al. (2022) | Monitoring water quality parameters of urban rivers | A new monitoring mode is designed, which installs the hyperspectral imager on the UAV and places a buoy spectrometer on the river | Spatial–spectral differences should be fully considered when comparing test data for hyperspectral data combination of spectroscopy and optical imaging |
| Lake | Seidel et al. (2020) | Estimating optically active substances of underwater | Underwater hyperspectral imaging could thus facilitate future water monitoring efforts through the acquisition of consistent spectral reflectance measurements or derived water quality parameters along the water column | Improved the link between above surface proximal and remote sensing observations and in-situ point-based water probe measurements for ground truthing |
| | Elsayed et al. (2021) | Assess some water quality indicators of Qaroun lake | Using hyperspectral reflectance indices and partial least square regression (PLSR) models to assess the water quality of Qaroun Lake | Total dissolved solids (TDS), transparency, total suspended solids (TSS), chlorophyll-a (Chl-a), and total phosphorus (TP), can be monitored accurately, timely, and nondestructively |
| | Sharp et al. (2021) | Quantifying the cyanobacteria in eutrophic lake | Evaluated a satellite remote sensing tool for estimating coarse cyanobacteria distribution with coincident, in situ measurements at varying scales and resolutions | Satellite-based remote sensing tools are vital to researchers and water managers as they provide consistent, high-coverage data at a low cost and sampling effort |
| | Zhang et al. (2021a) | Lake bathymetry by spectral information | A multiband linear model with successive projections algorithm was developed to retrieve the bathymetry of Qinghai Lake | Bathymetry estimation obtained using remotely sensed hyperspectral data is an effective detection method and can provide largescale, rapid monitoring data to the relevant decision-making departments |
| Natural river | Pyo et al. (2021) | Cyanobacteria cell prediction | A convolutional neural network model with a convolutional block attention module was developed to predict cyanobacterial cell concentrations by using the observed cell data from field monitoring, chlorophyll-a distribution map from hyperspectral image sensing, and simulated water quality outputs from a hydrodynamic model | A deep learning model with data assemblage is practically feasible for predicting the presence of harmful algae in inland water |
| | Ahn et al. (2021) | Predicting cyanobacterial blooms | Presenting an optimal method of applying hyperspectral images to establish the Environmental Fluid Dynamics Code-National Institute of Environment Research (EFDCNIER) model initial conditions | Hyperspectral images allow detailed initial conditions to be applied in the EFDCNIER, which can reduce uncertainties in water quality (cyanobacteria) modeling |
| | Premkumar et al. (2021) | Calculating the chlorophyll-a concentration | The calibrated results between the in-situ chlorophyll*a and in-situ remote sensing reflectance based on the development of an empirical band ratio algorithm | The satellite-based approach provides a good correlation with in-situ data, which was helped in monitoring and retrieval of Chl-a concentration |
| | Gu et al. (2020) | River turbidity measurement | Proposing a novel river turbidity measurement model based on random forest ensemble | Experiments corroborate the superiority of proposed model over state-of-the-art competitors and its simplified counterparts |
| Ocean | Arabi et al. (2020) | Retrieval of water constituent concentrations | From simulations with the new model, called Water Sea Bottom (WSB) model, it was observed that bands 750 nm and 900 nm, is nearly insensitive to the Water Constituent Concentrations (WCCs) | The application of proposed NIBEI on satellite images requires only Top of Atmosphere (TOA) radiances at 750 nm and 900 nm and does not depend on atmospheric correction and ancillary local input data |

**TABLE 3 (*Continued*) Typical cases of hyperspectral water quality monitoring scenarios.**

| Scenarios | References | Purpose | Research idea | Conclusion |
|---|---|---|---|---|
| | Guillaume et al. (2020) | Determine the seabed composition | A subsurface mixing model is presented, based on a recently proposed oceanic radiative transfer model that accounts for seabed adjacency effects in the water column | The algorithm is effective for the local analysis of the benthic habitats |
| | Harringmeyer et al. (2021) | Detection and Sourcing of CDOM | Developed a new fluorescence-based indicator of effluent-derived chromophore-c dissolved organic matter (CDOM) helped demonstrate the feasibility of remotely detecting CDOM from wastewater | The UV-visible imaging spectrometers can facilitate coastal CDOM-related water quality monitoring and expand its range of applications |
| | Ma et al. (2021) | Inversion of ocean color constituents | Observing the three constituents of ocean color chlorophyll-a, suspended sediment concentration, and chromophore-c dissolved organic matter to indicate water eutrophication, and the inversion model of three constituents of ocean color is constructed | Airborne remote sensing has a very important role in developing refined observations for specific areas, and can more quickly and effectively monitor the ecological environment and evaluate pollution |

achievements in inland water and reservoir water quality monitoring. However, the high data acquisition costs limit this technology's largescale promotion (Fenocchi et al., 2015). A large number of micro spectrometers have been studied from 2016 to 2019. Micro spectrometers have played a good role in monitoring cities' odorous water bodies and coastal zones. Sensors mounted on UAVs can obtain hyperspectral data flexibly and at a low cost, becoming the most important data source with the promotion of UAV technology from 2019 to 2022.

(2) Algorithm: attention was paid to modeling spectral data and water quality parameters from 2010 to 2012. The traditional algorithm represented by the expression of the little square was studied from 2015 to 2020 to draw the thematic map of water pollution. Algorithms that can solve large data volumes have strong applicability and high computational efficiency and have become research hotspots with the increase of data volume and more and more hyperspectral water quality monitoring scenarios. The machine learning algorithm is undoubtedly the research hotspot in the last 3 years.

(3) Water quality parameters: people initially used hyperspectral technology to monitor water blooms due to the problem of water eutrophication from 2010 to 2012, and excellent application results were achieved. Subsequently, the research was transferred to calculating water quality parameters to obtain the total phosphorus, total nitrogen, and other parameters leading to water bloom (Villa et al., 2017). Therefore, the total nitrogen, turbidity, and suspended solids have been continuously emphasized from 2013 to 2020. As a result, a series of achievements have been made in applying inland water and ocean in this process. As a result, the research intensity of rivers closely related to human production and life, whether it is odorous water monitoring in cities or river pollution monitoring in rural areas, has been continuously enhanced in the last 3 years.

# 4 Discussion

The core elements of hyperspectral water quality monitoring can be summarized into four points: scenarios, data sources, parameters,

and algorithms. Each scholar tries to provide innovative solutions in four points. It can meet the application requirements through complex combinations. For example, excellent accuracy might be obtained by satellite, airborne or UAV platforms to calculate water quality parameters and select various algorithms in a fixed scenario (a reservoir). However, the error may be substantial with the same solution applied in lakes when monitoring urban water quality parameters, even if the data source, water, and algorithms are fixed. Magnanimous research needs to be researched to solve these problems, which is the difficulty of hyperspectral water quality monitoring and the significance of this work.

## 4.1 Monitoring scenarios

The main application scenarios can be classified as urban water, lake, natural river and ocean after the hyperspectral remote sensing technology is introduced into the water quality monitoring demand (Figure 5). The monitoring needs of urban water are concentrated on the assessment of reservoir water quality (Song K. et al., 2010), black-odor water management (Wei et al., 2019), sewage discharge monitoring (Pascucci et al., 2012), and flood warning (Lin et al., 2019). Hyperspectral data are acquired mainly by UAV and ground sensors, which meet the requirements of information extraction at the microscale. Lake's monitoring needs are significantly different, and the study core is the chlorophyll evaluation (Katlane et al., 2020). In particular, a large number of studies have been carried out on the rapid identification of cyanobacteria outbreaks because the lake water body is close to the territory of human production and living, and the water flow is relatively poor, which is prone to water bloom (Pyo et al., 2021). The research on natural rivers is more complicated than in the previous two scenarios. The critical point of the study is how to make hyperspectral technology partially or entirely replace the traditional *in-situ* assay method (Hong et al., 2021). Although more than ten indicators are considered adequate, the leading indicators reported in academic publications are total phosphorus, total nitrogen, ammonia nitrogen, and dissolved organic matter. The most complex application scenario is the ocean. The water quality monitoring accuracy is insufficient only through hyperspectral technology due to the interference of salinity and sea waves. Lidar, fluorescence, and ultraviolet sensors are also

TABLE 4 Basic information of water quality hyperspectral monitoring sensors.

| Platform | References | Sensors | Wavelength range (μm) | Spatial resolution (m) | | Country or region |
|---|---|---|---|---|---|---|
| Satellite | Lu et al. (2022) | ZY1-02D | 0.40–2.50 | 30.00 | | China |
| | Lee et al. (2011) | COMIS | 0.40–1.05 | 30.00 | | South Korea |
| | Liu et al. (2020) | GF5 | 0.40–2.50 | 30.00 | | China |
| | Santini et al. (2010) | PRISMA | 0.40–2.50 | 30.00 | | Italy |
| | Hafeez et al. (2021) | Himawari8 | 0.46–1.61 | 500.00 | | Japan |
| | Dall'Olmo et al. (2005) | SeaWiFS | 0.40–0.89 | 1100.00 | | United States |
| | Chang et al. (2014) | MODIS | 0.62–14.39 | 250.00 | | United States |
| | Zhang et al. (2021b) | OHS | 0.40–1.00 | 10.00 | | China |
| | Hlaing et al. (2010) | HICO | 0.36–1.08 | 90.00 | | United States |
| | Pan et al. (2011) | HJ-1A | 0.43–0.90 | 30.00 | | China |
| | Palacios et al. (2015) | HyspIRI | 0.38–2.50 | 30.00 | | United States |
| | Lee et al. (2007) | CHRIS | 0.40–1.05 | 17.00 | | European Union |
| Airborne | Delegido et al. (2014) | CASI | 0.35–1.05 | 0.50 | | Canada |
| | Simone et al. (2013) | TASI-600 | 8.00–14.00 | 1.00 | | Canada |
| | Mbuh (2018) | ARCHER | 0.40–2.50 | 1.00 | | United States |
| | Blanco et al. (2003) | AVIRIS | 0.37–2.51 | 20.00 | | United States |
| | Barducci and Pippi (1997) | MIVIS | 0.43–12.7 | 5.00 | | Italy |
| | Riaza et al. (2015) | HyMap | 0.40–2.50 | 1.00 | | Australia |

(Continued on following page)

TABLE 4 (*Continued*) Basic information of water quality hyperspectral monitoring sensors.

| Platform | References | Sensors | Wavelength range (μm) | Spatial resolution (m) | | Country or region |
|---|---|---|---|---|---|---|
| UAV | Aasen et al. (2015) | Cubert UHD185 | 0.45–0.95 | 0.45 | | Germany |
| | Jianguang et al. (2005) | Gaia-Skymini | 0.40–1.00 | 0.25 | | China |
| | Wenzl (2018) | Hyspex | 0.40–1.05 | 0.30 | | Norway |
| | Zhang et al. (2022) | Nano | 0.40–1.00 | 0.25 | | United States |
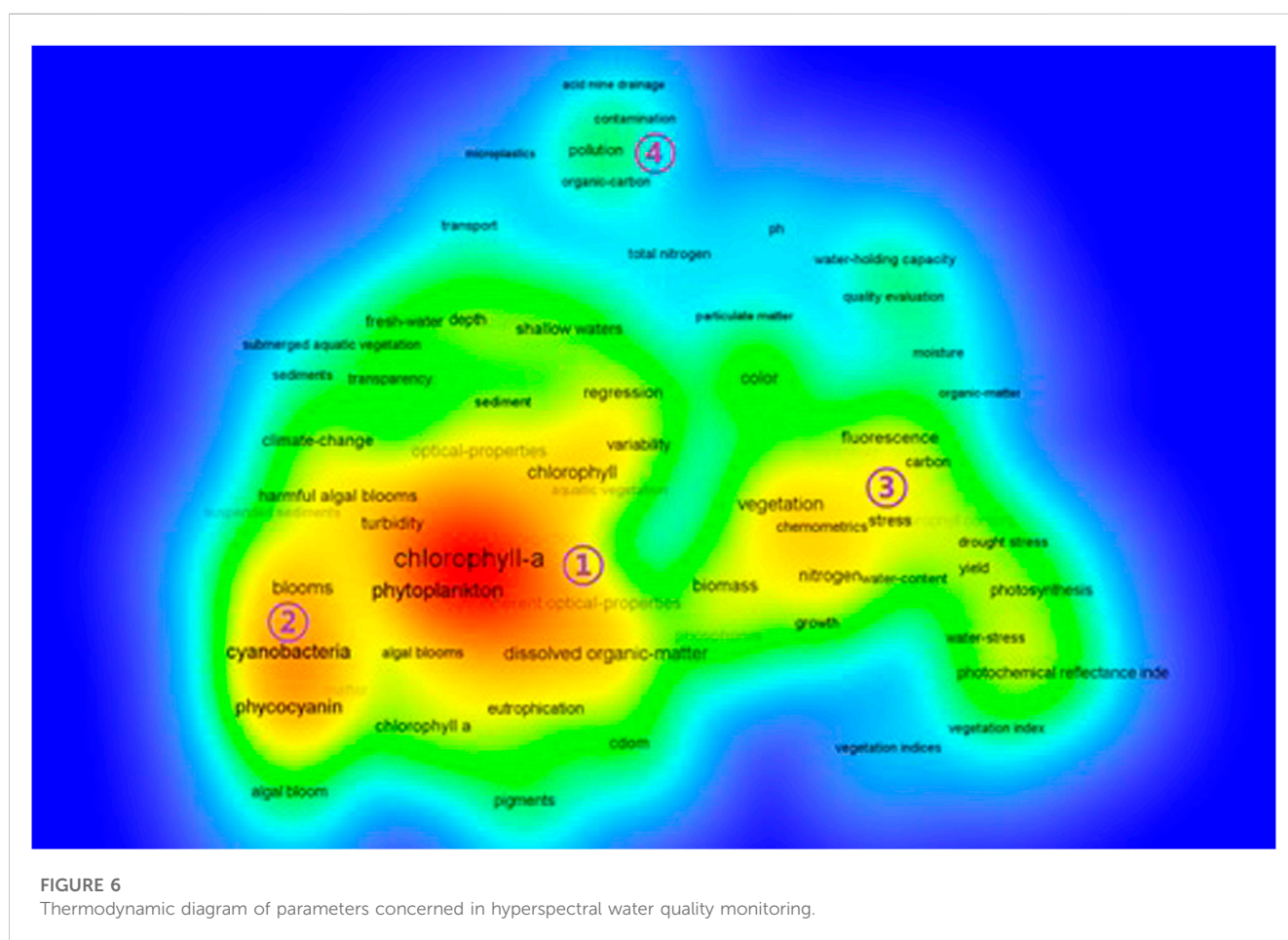


FIGURE 6
Thermodynamic diagram of parameters concerned in hyperspectral water quality monitoring.

introduced to realize the joint monitoring of multiple sensors (Gorkavyi et al., 2021). Good results have been achieved in monitoring seawater conductivity, water depth, and algae. Representative typical cases are listed in Table 3.

## 4.2 Monitoring data sources

The hyperspectral sensors mentioned in the publication can be divided into three platforms: satellite, airborne, and UAV,

according to statistics. Most of the higher-solution spectrometers are not specially designed for monitoring the water environment except for a few sensors. Spectral resolution refers to the ability of the sensor to distinguish different wavelengths, usually expressed in microns (μm). The main spectrum range is 0.401 μm and 0.402 μm, considering the application needs of vegetation, rock mining, and cities. All sensors covering a spectrum range of 0.400 μm can play a role in water quality monitoring since it is the main spectral response band of water quality parameters (Mielke et al., 2014). UAV

**TABLE 5 Typical cases of hyperspectral water quality monitoring parameters.**

| References | Location | Parameters | Application | Conclusion |
|---|---|---|---|---|
| Premkumar et al. (2021) | Hooghly River, India | Chlorophyll-a | Using satlantic hyperspectral ocean color radiometer and developing the regional algorithm for retrieval for chlorophyll-a concentration | The satellite-based approach provides a good correlation with *in-situ* data |
| Wolny et al. (2020) | Chesapeake Bay, United States of America | Blooms | using multispectral data products from the Ocean and Land Color Imager (OLCI) sensor on the Sentinel3 satellites and identified based on *in situ* phytoplankton data and ecological associations | Presenting a framework in which satellite data products could aid resource managers with monitoring water quality and protecting shellfish resources |
| Niu et al. (2021) | Guanhe River, China | Total phosphorus | Thematic maps of the water quality classification results and water parameter concentrations were generated and the overall water quality and pollution sources were analyzed | The deep learning-based regression models show a good performance in the feature extraction and image understanding of high-dimensional data |
| Zhang et al. (2021a) | Qinghai Lake, China | Lake bathymetry | A multiband linear model with successive projections algorithm was developed to retrieve the bathymetry of Qinghai Lake | Using remotely sensed hyperspectral data is an effective detection method |



**FIGURE 7**
Frequency and intensity of algorithm research.
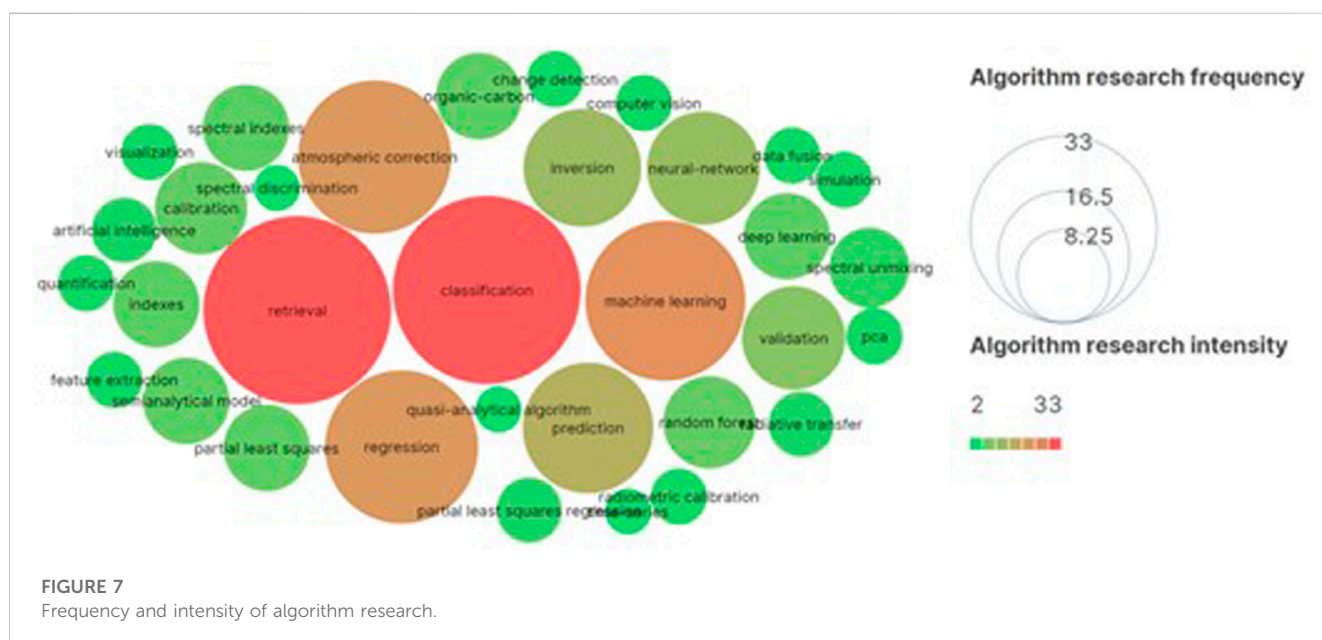
hyperspectral sensors can usually reach the submeter level, and airborne sensors can get the meter level in spatial resolution. While the highest answer of hyperspectral satellite data is the OHS sensor of China Orbita company, which reaches 10 m. And the mainstream spatial resolution of other satellite sensors is 30 m, which is the result of balancing data transmission efficiency and monitoring effect. Various countries are actively launching new hyperspectral sensors, and there is a lot of research and development of sensors on multiple platforms. Therefore, the number of sensor classes is much more than those listed in Table 4.

## 4.3 Monitoring parameters

Hyperspectral water quality monitoring parameters can be obtained by making statistics on the research objects of all publications and drawing thermodynamic maps. The more the color in the figure tends to be red, the higher the research concentration. Four clusters can be formed like "islands", corresponding to the monitoring focus of different fields (Figure 6). Firstly, research about geometrical optics of water bodies. The research target generally has a significant characteristic spectrum based on the analysis of the optical mechanism of water, such as chlorophyll-a, phytoplankton, dissolved organic matter, CDOM, turbidity, segments, and water color. These indicators can significantly show different characteristics in the visible band with additional water content, so they have been studied extensively. Mature research technology, sufficient theoretical basis, and reliable conclusions are the characteristics of these studies. Secondly, research about water bloom outbreak monitoring. Focusing on monitoring cyanobacteria, phycocyanin, algal and suspended sectors, and the water quality changes in different seasons are focused. Multiperiod

TABLE 6 Typical cases of hyperspectral water quality monitoring algorithms.

| References | Research content | Model used | Method | Conclusion |
|---|---|---|---|---|
| Hou et al. (2022) | Water quality parameters estimation | Partial least squares | Introducing partial least squares to calculate the turbidity, suspended substance, chemical oxygen demand, NH4N, total nitrogen, and total phosphorus models | Machine learning has obvious overall advantages, making it more suitable for classified inversion prediction of urban river water quality parameters |
| Wenzl (2018) | Dissolved organic matter | Multiple linear regression | Facilitating the remote sensing of chromophore-c dissolved organic matter in optically complex waters to improve the coastal water quality monitoring | Optimal performance was reached when combining 365nm, 400nm, and 700 nm as predictors of in a multiple linear regression |
| Pyo et al. (2022) | Pigments | Neural network | Based on the reflectance and absorption coefficient spectral inputs, a one-dimensional convolutional neural network (1DCNN) was developed to estimate the concentrations of the major and minor pigments | The model provided explicit algal biomass information using the estimated major pigments and implicit taxonomical information using accessory pigments such as green algae, diatoms, and cyanobacteria |
| Hong et al. (2021) | Harmful algal blooms | Deep learning | Appling a deep neural network model to monitor the vertical distribution of Chlorophyll-a, phycocyanin, and turbidity using drone-borne hyperspectral imagery, in-situ measurement, and meteoroidal data | The explainable deep learning model has the potential to show influential features that contribute to describing the vertical profile phenomena |

remote sensing data is generally used to identify the dynamic changes of water bloom in the water area. The rivers and lakes near the urban are the main areas of study. The transparency and water depth of the water area are evaluated. Thirdly, research about chemical parameters of water quality. It belongs to the quantitative analysis of water quality parameters. The indicators studied include carbon, fluorescence, organic matter, particulate matter, total phosphorus, biomass, vegetation indicators, pH, and temperature. The water-holding capacity of the water body is evaluated to guide the development of water quality based on the calculated content value. Fourthly, research about water quality evaluation and management. The water pollution investigation technology is studied under the premise of the first three explorations, including organic carbon, acid mine drainage, microplastics, and contamination. These pollutants have attracted worldwide attention, and hyperspectral technology is becoming one of the effective technologies (Table 5).

## 4.4 Monitoring algorithms

The algorithms used in all publications are counted to obtain the most commonly used algorithms (Figure 7). The research generally requires a lot of preprocessing and pre-analysis of spectral data, "classification", "atmospheric correction", "spectral indexes" and "radial transfer" have appeared in abundant publications to illustrate this point. Cause accurate spectral identification and atmospheric correction can ensure the correctness of spectral data and provide data sets for water quality parameter modeling. After spectral preprocessing, the algorithms for calculating water quality parameters can be divided into regression and machine learning methods. The most commonly used regression methods are semiempirical models based on limited in-situ data. "Partial least squares", "multiple linear regression", "principal component analysis", and "random forest" are all commonly used methods. The keywords that appear most frequently in machine learning methods include "neural network", "artificial intelligence", and "deep learning". In recent years, machine learning is the most studied method. In addition, the terms of "calibration", "visualization", "prediction", and

"verification" also show that scholars attach importance to the accuracy of the algorithm (Table 6).

## 5 Conclusion

Spectrum refers to the pattern of dichroic light arranged according to the wavelength or frequency after being separated by the dispersion system (Tong et al., 2010; Wang et al., 2020). It can reflect the diagnostic absorption difference caused by the internal electronic transition and molecular vibration of matter, and it represents the intrinsic characteristics of objects. There were 4,852 satellites in orbit according to the USC (Union of concerned scientists) satellite database up to 30 March 2022. Three thousand one hundred thirty-four communication satellites (64%), 1,050 Earth observation satellites (21%), 411 technical experimental satellites (8%), 154 navigation and positioning satellites (3%), 124 Earth science satellites (2.5%), and 76 space observation satellites (1.5%) among them. Among the 1,050 Earth observation satellites, 32 are hyperspectral satellites, accounting for less than 4%. At present, the technical advantages have not been fully brought into play, and the application potential of hyperspectral satellites is huge (Xiong et al., 2012). There are two difficulties in the hyperspectral technology for water quality monitoring. Firstly, water's material composition is complex, making it difficult to determine the transmission mechanism of spectral data. There are complex interaction processes such as superposition or subtraction among water quality parameters, and the interference of waves makes the extraction conclusions based on hyperspectral data lacking exact mechanism (Sarigai et al., 2021). This limits the model's generalizability, making it challenging to form industrial technical standards. Secondly, traditional data processing and analysis techniques take weeks to reach a conclusion because hyperspectral data is a high-dimensional matrix with tremendous data volume, leading to the result that it cannot meet the real-time demand of water quality monitoring obviously (Rotkiske and Jr, 2018). Scholars have introduced machine learning

algorithms, which can quickly calculate the water quality parameters concerned under the support of tag data, and have achieved initial success.

There are three development directions of hyperspectral technology for water quality monitoring under the guidance of difficulties. (1) the miniaturization of spectral instruments provides technical support for portable water quality monitoring. In 2015, Texas Instruments (TI) announced at Pittcon that it had added a new member to its near infrared (NIR) chipset product portfolio the industry's first fully programmable micro electro mechanical system (MEMS) chipset, which supports ultraportable spectral analysis in the wavelength range of 700–2500 nm. In 2022, Shenzhen Hyper-Nano officially mass-produced the first generation of micro hyperspectral imaging MEMS chip, which is only one-thousandth of the volume of traditional products. There was a strong demand for miniaturization, portability, and onsite spectral instruments in the late last century to adapt to the global development situation, and the trend of miniaturization of spectral instruments has emerged. The research and development of miniaturized spectral instruments have become the focus of various countries' scientific and technological departments and industrial departments. With the support of a microchip set, Tianjin Progoo Information Technology Co., Ltd. has developed a series of water quality monitoring hyperspectral products. The development of water quality monitoring technology urgently requires portable spectrometers for rapid onsite monitoring, which will obviously become the research and development focus of countries worldwide in the next few years. (2) Research on highly integrated technology of spectral technology and modern science. The achievements of modern science and technology in highly integrated device technology (such as chip technology), sensors, micro devices, and silicon technology are changing with each passing day. Modern information theory, mathematical processing methods, and computing software systems are also developing. These achievements will soon be absorbed into the continuous development process of new optical spectrum instruments. The spectrum instrument industry will continue to develop high-precision, multifunctional largescale spectrum analysis and detection instruments or corresponding systems to meet the analysis and detection requirements in modern aerospace, environmental and ecological protection, and global infectious disease control. More and more new practical spectrum instruments or systems that can work on the site, production lines, battlefields, unattended, and networked will appear, becoming online measurement and control. It is an indispensable analysis and detection means in environmental monitoring and other fields. The spectrum instrument must be out of the laboratory equipment, capable of withstanding the harsh working environment of the field and the area (including space) and the robust, chaotic, and changeable interference, unattended, long-term work away from the power grid, automatic monitoring, automatic adjustment of the best working state, and automatic network exchange of information. Therefore, largescale precision research and practical level spectrometers or systems for onsite and online measurement and control will be valued and significantly developed in the next 10 or 20 years. (3) The application of spectrum technology in water quality monitoring is a challenging broad band. In the future, the spectrum instrument will continue to develop in the direction of broadening and transferring the application area. It will expand from the traditional water quality indicator monitoring to the fields directly related to water safety, such as over-standard alarm, multi equipment linkage, water resource evaluation, pollution early warning and so on. The application of spectral water quality detection will be constantly updated under great development in many fields. The vast number of spectral analysis users will develop various new spectral analysis methods and put forward new application requirements and development requirements for new spectral instruments. We will be faced with an unprecedented situation of continuous development in which the spectral instrument industry continues to obtain new application results in all aspects of water quality monitoring. In brief, a more compact and stable instrument, coupled with a wide range of algorithms and more applications, will become the research trend in the future field of hyperspectral water quality monitoring.

Hyperspectral water quality monitoring is a technical process for measuring the types, concentrations, and changing trends of pollutants in water bodies to evaluate water quality. The monitoring scope includes natural water bodies at risk of pollution and having been polluted, as well as artificial water bodies discharged by industry, agriculture, and commerce (Fenocchi et al., 2015). Traditional water quality monitoring requires *in-situ* sampling, laboratory analysis, and rectification reports. The accuracy is guaranteed, but there are certain limitations, such as the event belongs to post-event monitoring, the spatial belongs to local monitoring, and the time belongs to cross-section monitoring (Mbuh, 2018). Modern hyperspectral technology can make up for these shortcomings partially. According to the research results in the past 30 years, it is indicated that the use of UAV technology to monitor the water quality of rivers has become a research hotspot through the analysis of all keywords, and the machine learning algorithm is the most concerning water quality parameter calculation method.

The research progress and trends in the four key subfields of hyperspectral water quality monitoring, including scene, data source, parameters, and algorithm, are sorted out on this basis. The difficulties encountered in each subfield and potential solutions are described and discussed. In conclusion, many studies have proved the method's feasibility and reliability in hyperspectral water quality monitoring. As a result, it will become one of the mainstream technologies in the field of water quality monitoring with the continuous reduction of hardware cost and the constant iteration of the information extraction algorithm.

# Author contributions

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# Conflict of interest

DZ, YH, LZ, XS, and ZL were employed by the Tianjin Progoo Information Technology Co. Ltd. LZ was employed by the Xinjiang Production and Construction Corps. WG was employed by the Shenzhen Intelligence. Ally Technology Co. Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

# Publisher's note

# Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2023.1133325/full#supplementary-material

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