Application of remote sensing technology in water quality monitoring

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Abstract. Water is the source of life, and water quality is one of the world's significant environmental problems today; the current state of water quality problems is worrying. Traditional water quality monitoring methods usually use buoys to carry sensors or manual sampling for real-time field water quality monitoring. These methods, although the monitoring accuracy is high, are labor-intensive, expensive and time-consuming. Remote sensing technology now occupies an increasingly important position in water quality monitoring because of its low cost, wide range and fast response time. This study introduces the research status and development problems of water quality remote sensing monitoring neighborhood from water quality remote sensing principle, data source, indicators, and monitoring methods. Results show that the data source mainly contains satellite and emerging UAV data. The remote sensing indicators typically include FUI, suspended solids, CDOM, Chl-a, and TN; Traditional methods like empirical and semi-empirical methods, and developing methods like analytic method and the surging machine learning and automation methods.

Keywords: Water Quality, Remote Sensing, Satellite, Water Quality Indicators.

1. Introduction

Due to the advancement of industrialization and urbanization, human beings have long abandoned natural ecological health in favor of economic development, resulting in environmental problems that have begun to threaten the survival of human beings. Water is the source of life, and water quality is one of the main environmental problems in the world today, the countermeasures for water pollution are still far from the speed of industrial development today, and the current situation of water quality is worrying [1]. The discharge of urban sewage pollutants is inevitable due to industrialization and urbanization, which largely causes heavy metal pollution, eutrophication of water bodies, and other water pollution problems [2]. IUCN has regarded the water pollution control project as one of the top priorities in solving environmental problems.

Water quality refers to the common characteristics of water and its impurities, and its indicators are parameters to describe water quality, usually using the type of impurities in water and the proportion of each part to express. Traditional water quality monitoring methods usually use buoys to carry sensors or manual sampling for real-time field water quality monitoring. These methods, although the monitoring accuracy is high, are labor-intensive, expensive and time-consuming. Furthermore, when monitoring a small area, a single point of measurement station is difficult to represent the entire water quality situation [3]. Because of its low cost, wide range, fast response time and other advantages, remote sensing technology now occupies an increasingly important position in water quality monitoring. Remote sensing monitoring of water quality mainly uses various remote sensing data sources to build the inverse model of water quality indicators, to calculate the numerical changes of water quality indicators in real-time to reflect the changes in water quality [4].

This article will introduce the research status and problems of water quality remote sensing monitoring neighbourhood from water quality remote sensing data source, principle, indicators and monitoring methods.

2. Principle of water quality remote sensing

In essence, water quality remote sensing models the relationship between a water body's reflectance and the concentration of water quality parameters measured at the surface. Using remote sensing technologies to measure and analyze the spectral characteristics of the absorption and scattering of solar radiation energy by water bodies is the basis for remote sensing monitoring of water quality. Different components in the water body (such as phytoplankton, suspended solids and chromophoric dissolved organic matter) lead to different absorption and scattering of different wavelengths of light.They could cause changes in reflectivity, upward irradiation, color and other apparent parameters, and remote sensors can capture specific information about these parameters through the transmission of electromagnetic waves, which can be used as a basis for the inverse performance of various properties of the water body at this time. The radiative transfer process of electromagnetic waves interacting with the water body is shown in Figure 1 [5].

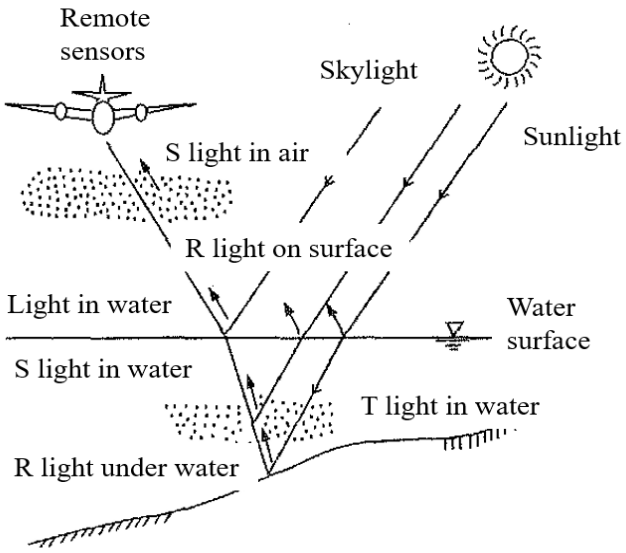


Figure 1. The transmission process of electromagnetic waves between water bodies. T=Transmitted; S=Scattered; R=Reflected. [5]

3. Remote sensing data sources

Remote sensing data sources are rich in variety and classified in many ways. In water quality remote sensing, most of the studies are based on satellite and UAV remote sensing data, and some examples of these two data sources and corresponding studies will be introduced in detail below.

3.1. Satellite remote sensing data

Satellite remote sensing data is the most commonly used source in water quality remote sensing because of its wide coverage, ease of obtaining and other advantages. Typical satellite remote sensing data include Landsat program satellite data, NOAA satellite data, Sentinel satellite data, and MODIS data. All these data have various applications in water quality remote sensing.

3.1.1 The Landsat program

There are nine satellites in the Landsat program, each having difference in their remote sensors.

Landsat MSS (Multispectral Scanner) is a sensor carried by Landsat 1-5 and Landsat 7 with 4 bands, each with a spatial resolution of 70 meters. Yasuoka et al. performed linear regression analysis using MSS data and radiation data measured on the water surface to evaluate path radiation, path radiance, and transmittance and used these metrics to make water quality measurements [6]. The MSS sensor was launched earlier, and its lower image spatial resolution and wider image band are no longer suitable for high precision and high-resolution monitoring requirements.

Landsat TM (Thematic Mapper) is carried by Landsat 4 and Landsat 5, and it produces images with 7 bands and a spatial resolution of 30 meters for bands 1-5 and 7, and 120 meters for band 6 (thermal infrared band). Dewidar et al. used TM data to obtain the results compared with in situ measurements of water samples, proving that some water quality parameters have an obvious correlation with TM radiation data [7]. Chen et al. established the inverse model of water quality parameters by combining TM band data with actual measurement data, and proved that it can obtain the distribution of water quality in the study area efficiently and in a large area [8].

Landsat ETM+ (Enhanced Thematic Mapper Plus) is equipped by Landsat 7, which adds one new band to the TM sensor, and the spatial resolution of band 6 becomes 60 meters and that of band 8 is 15 meters. Yang et al. used ETM+ data and multiple linear regression to establish a high accuracy TN and NH3-N concentration inversion model, which proved its high accuracy[9]. Gao used linear mixed image element decomposition model, NDVI model and lake surface water temperature inversion model to quickly obtain the eutrophication distribution map of water bodies, which proved its high practical value [10].

Landsat OLI (Operational Land Imager) is the sensor on Landsat 8, which also has a TIRS (Thermal Infrared Sensor) to capture thermal infrared images. Compared to Landsat ETM+, OLI provides a dark blue visible band (band 1) specifically for water quality monitoring operations, and a new infrared band (band 9) for detecting cirrus clouds. Using OLI data, Wang used the MCR-LALS algorithm to invert the Chl-a concentration in water bodies and demonstrated that it can be used for quantitative inversion of Chl-a [11].

3.1.2 NOAA satellite data

The sensors carried on NOAA satellites are mainly AVHRR and TOVS. AVHRR is a remote sensor that observes clouds' distribution, temperature distribution on the surface (mainly in the sea), and the vertical and air temperature distribution in the atmosphere are measured using the multi-channel spectrometer TOVS. AVHRR sensor covers an extremely wide range and is usually used for general trend analysis at large spatial scales (e.g., national, continental to global), while it has fewer applications at small and medium scales. He et al. used AVHRR data to determine the macroscopic distribution of water quality in major water bodies in the Yangtze River Delta region, demonstrating the advantages of wide coverage and continuous time phase of meteorological satellites incomparable to many remote sensing techniques [12].

3.1.3 MODIS data

In strict terms, MODIS(Moderate Resolution Imaging Spectroradiometer) is an imaging spectrometer carried by Terra and Aqua satellites. MODIS data has many advantages, its global free, high update frequency, and its relatively simple data reception ensures that users only need to have a small antenna to get a quality signal. At the same time, its data resolution compared to AHVRR carried by NOAA satellite has a significant increase. Many studies on water quality remote sensing are centered on MODIS data with these advantages. Hae-Cheol et al. used MODIS data to analyze the water quality of ten areas near the western coast of the Korean Peninsula, proving that MODIS data are highly suitable for large spatio-temporal scale changes [13].

3.1.4 Sentinel satellite series data

In the Sentinel satellite series, Sentinel-2 and Sentinel-3 satellite data are widely used in water quality remote sensing.

Sentinel-2 is equipped with MSI (Multispectral Imager) for land monitoring, providing images of vegetation and waters. In addition, it is usually used for emergency relief efforts. The two satellites that make up Sentinel-2 are 2A and 2B, which have 13 spectral bands with a width of 290 kilometers. With detailed image data from the VIS and NIR to SWIR, among the optical data, Sentinel-2 data are the only ones to contain 3 bands in the red-edge spectrum, making them especially useful for spotting phytoplankton.

Sentinel-3 carries OLCI and SLSTR to provide global, multi-spectral, medium-resolution ocean-land observation capability. OLCI provides data continuity for ENVISAT MERIS with 21 bands at a resolution of 300 meters. For the oceans, SST, sea color, sea level height and sea ice thickness can be measured, and the measured data can be used to monitor ocean pollution and biological productivity. Roberto et al. used combined data from both Sentinel-2 and Sentinel-3, proposing a continuous monitoring solution to detect pollution on Acapulco coasts, which are sometimes polluted by indiscriminate wastewater discharge [14].

3.2. UAV remote sensing data

UAV remote sensing is an emerging technology. Compared with traditional satellite remote sensing, UAV has higher spatio-temporal resolution, lower altitude flight under clouds and higher mobility, which can solve the problems of traditional water quality monitoring work. UAV is powered, controllable, can carry a variety of mission equipment, perform various tasks, and can be reused unmanned aerial vehicle. Even if the operation in complex weather conditions (such as cloudy, hazy weather), UAV can also avoid the problem of weather because it can work at a certain height (< 1 km) and ignore the impact of the atmosphere and cloud cover.

The emergence of UAV remote sensing allows real-time and rapid monitoring of water pollution and other situations, rapid aerial photography of monitoring targets, inspections, through an extensive, comprehensive collection of information, and real-time delivery of on-site information, monitoring the development of dangerous situations. It could thus provide data for water resources survey and a timely grasp of the hydrological situation to provide new opportunities and ways of monitoring and evaluating water quality.

With the gradual maturity of UAV, the data acquired by it largely solves the problem of insufficient spatial resolution and temporal resolution of satellite remote sensing data. It provides a new solution for more precise remote monitoring of water quality. For example, Liu inverted the water quality parameters of micro waters using UAV multi-spectral images, and the results showed that the accuracy of the UAV inversion model was high, and the spatial distribution of water quality remote sensing indicators such as TP, SS and TUB of water bodies could be measured more accurately, proving that UAV remote sensing data remove the resolution limitation of satellite remote sensing images [15]. Enzo et al. make a comparison between satellite data and UAV data in monitoring CyanoHABs thrive in On-Farm Reservoirs (OFRs) and prove that UAV data are reliable complements to satellites due to their superior spatio-temporal resolution [16].

4. Typical indicators of water quality remote sensing

The monitoring scope of water quality remote sensing is extensive. It needs to monitor the types of various pollutants in the water body and the change of concentration trends, so the use of water quality remote sensing indicators is also extensive, such as water colour index, water transparency, dissolved organic matter, suspended solids, nutrient status index. Some indicators show strong spectral characteristics, such as Chl-a with two prominent absorption bands of 640nm-660nm and 430nm-450nm. In contrast, others are difficult to find independent spectral characteristics, such as ammonia nitrogen (NH3-N), which requires a combination of different remote sensing bands (such as summation, difference, multiplication) to extract sensitive inversion indicators. Some commonly used and widely studied water quality remote sensing indices are described in detail below.

4.1. Forel-Ule index

The quantitative representation of watercolour is an important reference indicator for comprehensive water quality assessment, and Forel-Ule index (FUI) is an effective indicator for monitoring the color of water bodies. FUI is based on Forel colourimetric table to divide the color of natural water bodies from dark blue to red-brown into 21 color classes (Figure 2), and generally speaking, the larger the FUI, indicating that the more impurities in the water body, and its water body

is also more turbid. FUI has a strong potential and advantage for regional and global long-term water quality monitoring. Wang et al. used multi-source satellite remote sensing data to extract the FUI of Guantan Reservoir and corrected it by using the chromaticity angle α. The results showed that the FUI strongly correlates with the optical parameters of the water body and proved its potential to evaluate the nutrient status of the water body [17].

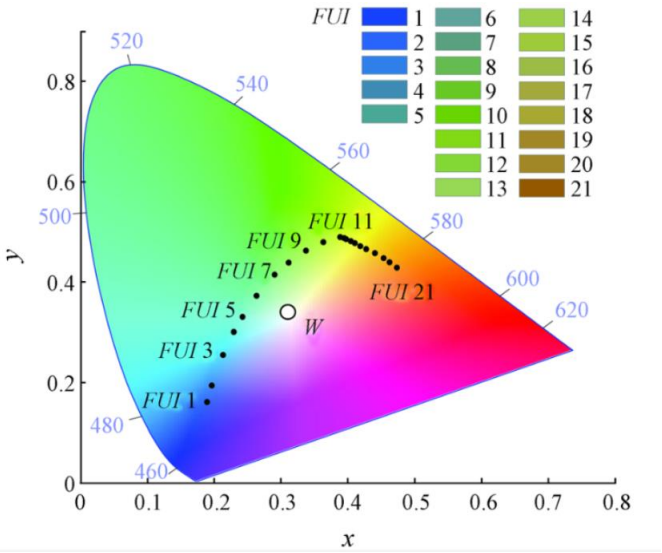


Figure 2. Different FUI values in CIE Chroma Space

4.2. Suspended solids

Suspended soilds in water is an indicator to measure water pollution level, and they are the main cause of water turbidity. They include insoluble substances of both organism and inorganism, sand, clay, etc. They are particles with a particle diameter of about 0.1μm-100μm. Different waters have different compositions, particle size distribution and concentration of suspended soilds, and their corresponding reflectance spectral characteristics also differ.

Suspended soilds itself has a strong instability, such as precipitation, river flow rate, flux and other environmental factors that can largely affect the distribution of suspended matter concentration in the water body. Hence, its monitoring index is strongly time-sensitive, requiring remote sensing data with a high temporal resolution.

4.3. Colored Dissolved Organic Matter

Colored Dissolved Organic Matter (CDOM) has important implications for biological activity, material cycling and remote sensing in the aquatic environment. CDOM is a mixture of soluble organic matter consisting of humic acid, fulvic acid and aromatic polymers, which reduces the amount of daylight transmitted through the water, affects photosynthesis, inhibits the growth of plankton and influences the biological activity of the water body.

The study of CDOM by remote sensing of water quality started late, and the scope of the study is mainly in lakes and near-shore waters. However, the research on the absorption characteristics of CDOM is becoming more and more mature. The researchers could select suitable bands according to the water quality characteristics of different water bodies. The combination of spectral absorption information and mathematical models has achieved a better separation effect, which has contributed significantly to the progress of CDOM research [18].

4.4. Chlorophyll-a

Chlorophyll-a (Chl-a) is one of the important components of plankton, so it can well reflect the nutrient level of the water body. The concentration of Chl-a in the water body shows a positive correlation with the degree of trophication.

Many researchers have established many remote sensing inversion models of Chl-a for different studies, but since Chl-a is highly related to plankton, it has apparent seasonal variation characteristics. What's more, many factors have a significant influence in observing the density of Chl-a. For example, the presence of suspended solids and CDOM would mask the spectral absorption characteristics of Chl-a. Therefore, a specific type of algorithm can only guarantee its accuracy in a certain region degree, and there are few Chl-a inversion methods for large areas. Generalized inversion algorithms need further research.

4.5. Total Nitrogen

Total Nitrogen (TN) , defined as the total amount of nitrogen in various forms in water, is a common indicator of water quality. Its measurement evaluates the polluted and self-purifying status of waters. When the nitrogen substances exceed the standard, microorganisms and plankton thrive, resulting in the eutrophication of water bodies.

As an indicator without strong spectral characteristics, the inversion algorithm of TN is more complicated than other indicators, but TN reflects water quality in a more stable way over time.

5. Monitoring methods of water quality remote sensing

The monitoring method of water quality remote sensing has changed dramatically with the progress of the times. In the 1980s-1990s, the method was mainly empirical method, after 1990s the semi-empirical method and analytical method are mainly, and in the 21st century, the rise of computer science makes the water quality remote sensing method towards the direction of automation and machine learning. Its development process is closely integrated with remote sensing. Research with universal applicability of analytical methods will be the future trend of water quality remote sensing quantitative inversion. Each method has its own advantages and disadvantages, and in the process of practical research, researchers usually combine multiple methods to test the inverse model's robustness and accuracy. Several methods are described below.

5.1. Empirical methods

The empirical method is to invert the water quality parameter values by establishing a statistical relationship between data and water quality indicators. The method selects the band or combination of bands with the highest correlation coefficient for statistical regression analysis to obtain the best inversion model of water quality indicators.

Generally speaking, the empirical method to obtain the inverse model requires fewer parameters. Its model construction is relatively simple, but the inverse model does not have a strict physical meaning. Its model and the actual water quality between the inevitable causal link, so its credibility is low. Furthermore, the inverse model has a strong specificity, so it can not be used as a general model to promote.

5.2. Semi-empirical methods

Unlike the empirical method, the semi-empirical method uses known more accurate statistical analysis models (such as linear regression models and Bayesian analysis models) combined with the spectral characteristics of water quality parameters and remote sensing data, which has a certain physical significance and higher credibility than the empirical method.

The semi-empirical method is a more common method of remote sensing of water quality, but this method also has the limitations of time and space, for different times and waters have to re-select the statistical model and calculate the relevant parameters.

5.3. Analytical methods

The analytical method rigorously establishes the relationship between the reflectance spectra of water bodies and the composition of substances in the water bodies by simulating the propagation of

electromagnetic waves by studying the radiative transfer model, and then inverse the content of each component of waters from remote sensing data.

The analysis method has a strict physical meaning and is not limited by time and space, but the modeling requires an extremely large number of parameters, which requires high accuracy of both the measurement equipment and the remote sensing data. In the last century, the development of the analytical method was stagnant due to technical reasons such as the insufficient resolution of data sources. However, with the update of remote sensing instruments and the improvement of the computing power of computers, the analytical method has been well developed.

5.4. Methods of automation and machine learning

These methods emerged with computer technology, and they typically use generic algorithms to input data directly and build out the algorithm's logic on top of the data on which to refine and predict the inverse model. Machine learning is inherently adaptive and fault-tolerant, and it can improve the accuracy of the inverse model by providing error feedback based on the amount of new data received, a capability that is well suited for analyzing the complex spectral characteristics of water bodies.

Jiang et al. used BP neural network to predict Chl-a content in water bodies. They introduced the evolutionary thinking algorithm to significantly improve the network training stability and accuracy, which provides a reference for optimising the input factors of Chl-a prediction model based on the BP neural network [19]. Leonardo used methods such as naive Bayes and support vector machine to classify the Paraopeba River water turbidity with Sentinel-2 satellite data, proving that all these methods got an accuracy of over 0.87 [20].

6. Conclusions

This article introduces the current research status and development problems of water quality remote sensing monitoring neighborhood from water quality remote sensing principle, data source, indicators and monitoring methods.

The principle is to model the relationship between the reflectance of the water body and the water quality parameters measured at the surface.

The remote sensing data source mainly contains satellite data and UAV data. The former roughly includes Landsat, NOAA, MODIS, and Sentinel data. Landsat data are derived from multiple sensors, from Landsat MSS to Landsat OLI, and are widely used by researchers in water quality remote sensing. NOAA data show features of the wide range of sensor coverage. Therefore, its data are typically used for general trend analysis at large spatial scales. MODIS data are widely used in various water quality remote sensing monitoring operations because of their global free and general availability. Sentinel data have become one of the most popular multi-spectral remote sensing inversion data sources in recent years due to their high resolution and multiple spectral bands. UAV data has the advantages of high spatial and temporal resolution, low altitude flight under clouds, high mobility, which can solve the problems existing in traditional water quality monitoring work.

The remote sensing indicators typically have FUI, suspended solids, CDOM, Chl-a and TN. FUI is an effective indicator in revealing the color changes of waters over time. Suspended solids are one of the essential indicators for water environment monitoring and evaluation, and it is the first indicator of remote sensing to estimate water quality. CDOM is an important bio-optical parameter that determines the watercolour of natural water bodies. Chl-a is an important component of planktonic organisms, so it is used to visualize the distribution and concentration of plankton in waters. TN is an indicator without strong spectral characteristics and can reflect the water quality more stably.

The remote sensing monitoring methods include empirical, semi-empirical, analytical and machine learning with automation. Empirical and semi-empirical methods are based on statistical analysis models, and their physical foundation is not strong. The analytical method strictly simulates the process of electromagnetic wave transmission, so it has the highest reliability of results. Methods of

machine learning and automation are born with the development of computer science. It uses generic algorithms to analyze data, such as BP neural network, random forest and support vector machine.

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