LE GOUVERNEMENT
DU GRAND-DUCHÉ DE LUXEMBOURG
Ministère de l'Économie

Le Ministre de l'Économie,

Vu la loi du 20 juillet 1992 portant modification du régime des brevets d'invention, telle que modifiée ;

Vu le règlement grand-ducal du 17 novembre 1997 concernant la procédure et les formalités administratives en matière de brevets d'invention ;

Vu le dépôt de la demande de brevet luxembourgeois daté du : **27/09/2021 ;**

Arrête :

Art. 1er.- Il est délivré à la (aux) personne(s) mentionnée(s) sur le tableau des données bibliographiques attaché au présent arrêté, sous le numéro de code 73, un

BREVET D'INVENTION N° LU500691

pour : Non-touching Real-time In-situ Water Quality Detection Method
tel que décrit dans les duplicata des pièces techniques joints en annexe.

Art. 2.- Le brevet est délivré sans examen préalable de la brevetabilité de l'invention, sans garantie de l'exactitude de la description et aux risques et périls des demandeurs.

Art. 3.- Le présent arrêté, qui constitue le titre de protection, est expédié au(x) mandataire(s) agréé(s), mentionné(s) sur le tableau des données bibliographiques attaché au présent arrêté, sous le numéro de code 74 ou, à défaut, à la (aux) personne(s) visées(s) à l'article 1er, pour servir de document probant à celle(s)-ci.

Luxembourg, le **28/03/2022**

Pour le Ministre de l'Économie,

Corinne Müller
Inspecteur
Office de la propriété intellectuelle

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DU GRAND-DUCHÉ DE LUXEMBOURG
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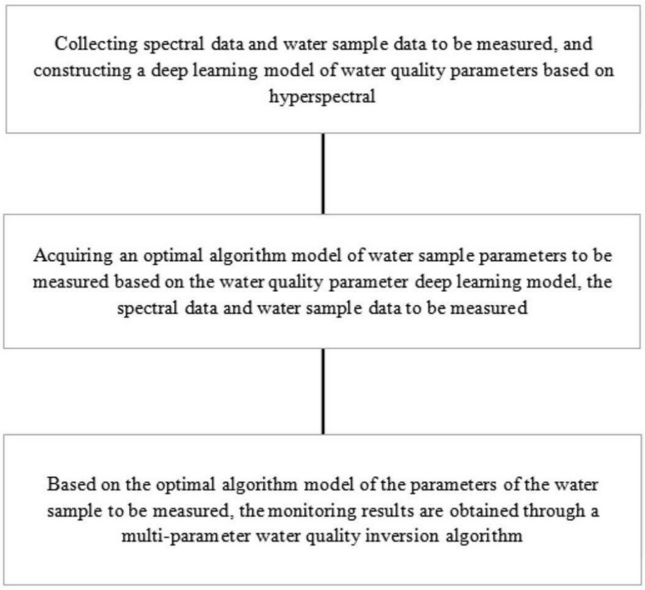
(73) Titulaire(s):
NANJING INSTITUTE OF GEOGRAPHY AND LIMNOLOGY, CHINESE ACADEMY OF SCIENCES – Nanjing City, Jiangsu (Chine)

(72) Inventeur(s):
ZHANG Yunlin – Chine, ZHANG Yibo – Chine, SHI Kun – Chine, SUN Xiao – Chine, LI Na – Chine, WANG Weijia – Chine, QIN Boqiang – Chine

(74) Mandataire(s):
Patent42 SA – 4081 Esch-sur-Alzette (Luxembourg)

(54) Non-touching Real-time In-situ Water Quality Detection Method.

(57) The invention discloses a non-touching real-time in-situ water quality monitoring method, which comprises the following steps: collecting spectral data and water sample data to be measured, and constructing a deep learning model of water quality parameters based on hyperspectral; Based on the deep learning model of water quality parameters, spectral data and water sample data to be measured, the optimal algorithm model of water quality parameters is obtained; Based on the optimal algorithm model of water quality parameters, the monitoring results are obtained by multi-parameter water quality inversion algorithm. The monitoring method of the invention does not need to be in direct contact with the water body to be measured, and compared with the traditional underwater probe contact monitoring, the monitoring method has the advantages of low energy consumption, small loss, simple and convenient maintenance.



DESCRIPTION

Non-touching Real-time In-situ Water Quality Detection Method

TECHNICAL FIELD

The invention belongs to the field of water quality monitoring, and particularly relates to a non-touching real-time in-situ water quality monitoring method.

BACKGROUND

With the rapid development of China's economy, the problem of water pollution is becoming increasingly serious. In order to monitor the change of water quality, there are many monitoring sections and monitoring points in China. Until June of 2019, there are 2,050 national surface water assessment sections in China, and provincial and local control sections are dotted. It will cost a lot of manpower, material resources and financial resources to supervise these important sections by relying on the traditional methods of ground investigation and water quality measurement. In addition, in situ sensors monitoring methods are based on the immersion of sensors in the water to be measured, which are usually limited by conditions and cannot be conveniently measured. More importantly, because the sensor is easy to be corroded in water or because of the existence of attached organisms, it is necessary to carry out regular maintenance at high frequency. Real-time high-frequency and large-scale observation of water quality has always been an important shortcoming in scientific research and environmental management.

Remote sensing technology has the advantages of rapidity, macrocosm, low cost and periodicity. It can detect the changes of water quality parameters in time and space, and can also find some pollution sources and migration characteristics of pollutants that are difficult to reveal by conventional methods. At present, however, the spatial resolutions of satellite sensors such as SeaWiFS, MODIS, HY-1A/1B CCD, MERIS, GOCI, VIIRS and OLCI range from 30m to 1000m, which is acceptable for large lakes to estimate water quality parameters. However, for small lakes, reservoirs, rivers and important sections, the low spatial resolution of these satellites will make them lose their monitoring ability, and they can only be observed by Landsat, Sentinel, Gaofen and other land-based medium and high-resolution satellites (10~30m). However, the shortcomings such as long revisiting period, wide band, low signal-to-noise ratio and non-color band setting will limit their application in remote sensing of water environment in small lakes, reservoirs, rivers and important sections. Therefore, it is urgent to make a breakthrough in developing water quality remote sensing monitoring equipment with high time resolution and high spatial resolution.

Because of the different optical components and their contents in water, the absorption and scattering changes in water, and the remote sensing reflectivity in a specific wavelength range changes accordingly, which is the basis for estimating water quality parameters by remote sensing. The existing optical parameters that can be retrieved by remote sensing include chlorophyll a, phycocyanin, suspended matter and CDOM.

At present, the data used for remote sensing estimation of the above parameters mainly include water color satellite data (CZCS, SeaWiFS, MERIS, MODIS, GOCI, etc.) and land satellite data (Landsat, Sentinel, Gaofen, etc.). These satellites are mainly designed for marine water and land resources, and some problems will be encountered when facing small lakes, reservoirs, rivers and important sections, which are summarized as follows:

(1) Insufficient spatial-temporal resolution: more than two-thirds of lakes in China are less than $10km^2$, and for rivers, their width is basically less than 1km. At present, the spatial resolution of water color sensors is usually above 250m, which can only meet the monitoring requirements of large lakes. At present, small water bodies can only be observed by Landsat, Sentinel, Gaofen and other land-based medium and high-resolution satellites (10~30m). However, due to the long revisit period of land-based satellites, it is difficult to capture the short-term changes of water environment, which limits the application of remote sensing of water environment in lakes, reservoirs, rivers and important sections.

(2) The radiation dynamic range is narrow, and the signal is easily saturated: the marine water body is relatively clean, and the water body signal is weak. The water color sensor receives the water body signal well, so the radiation dynamic range is set low. However, in inland turbid water bodies such as lakes and rivers, the radiation signal is much higher than that in marine water bodies, and often exceeds the threshold range of

sensors, which leads to saturation of the wave band signal reflecting water quality changes, thus reducing the accuracy of remote sensing estimation.

(3) The band setting does not meet the requirements of inland water: the concentration of chlorophyll a in inland water is high and affected by suspended solids and CDOM, and the water signal is complex, so it is often necessary to have bands around 665nm and 705nm at the same time for accurate inversion, and the sensitive band of phycocyanin is around 620nm. However, none of the water color sensors currently in operation have these sensitive bands.

In addition, 90% of the signals received by satellites come from the contribution of the atmosphere, while the signals of water bodies are less than 10%. Therefore, removing the influence of the atmosphere and accurately obtaining the remote sensing reflectance of water from remote sensing images is the key to water quality remote sensing. For ocean clean water, the contribution of water in near infrared band is approximately 0, and the atmospheric correction algorithm based on two near infrared bands can obtain better accuracy. However, for optically complex water bodies such as lakes and rivers, the "zero hypothesis" in the near infrared band is invalid, and the ocean standard algorithm is no longer applicable. Although a large number of scientists have made different attempts, they have proposed different inland water atmospheric correction algorithms, such as MUMM and SWIR algorithms. However, the empirical factors in MUMM algorithm change due to the influence of water conditions, so its universality is not good. While SWIR algorithm requires two short-wave infrared bands, except MODIS, VIIRS and Landsat, most sensors do not have this condition. The method of ground-based (shore-based) monitoring can effectively avoid the influence of atmosphere on the extraction accuracy of water remote sensing signals. Although ground-based monitoring technology has been widely used at present, such as traffic camera and video surveillance, these monitoring devices can only provide very limited spectral bands, and these bands are not designed for water bodies, so it is impossible to extract water quality parameters by remote sensing.

Therefore, it is urgent to develop a remote sensing monitor with high spatial and temporal resolution for inland lakes, rivers and other water bodies in China, which is free from atmospheric interference and time limit, and can better respond to multiple water quality parameters. Through data transmission and cloud sharing technology, the remote sensing inversion results with high spatial and temporal resolution can be transmitted to the terminal in time to monitor the changes of multiple water quality parameters of important rivers, lakes and reservoirs in real time, which is of great significance for water pollution prevention and water environment management.

SUMMARY

The purpose of the invention is to construct a water quality monitoring method under complex scenes based on a non-touching high spectrometer, which can realize rapid and real-time monitoring of multi-parameter water quality under complex weather conditions, improve the automation and intelligence level of ecological environment monitoring, and is suitable for different types of water bodies such as rivers, lakes and reservoirs, wetlands, offshore and offshore waters, etc. Meanwhile, the operation method is simple and convenient, easy to maintain, convenient to popularize and apply.

To achieve the above purpose, the present invention provides the following scheme: a non-touching real-time in-situ water quality monitoring method, which is characterized by comprising:

collecting spectral data and water sample data to be measured, and constructing a deep learning model of water quality parameters based on high spectrometer;

acquiring an optimal algorithm model of water quality parameters deep learning model, the spectral data and water sample data to be measured;

based on the optimal algorithm model of the parameters of the water sample to be measured, the monitoring results are obtained through a multi-parameter water quality inversion algorithm.

Preferably, the spectral data is collected by real-time in-situ water quality monitor or artificial light source irradiation;

the real-time in-situ water quality monitor comprises an auxiliary installation device, a solar power supply device and a hyperspectral imager.

Preferably, in the process of collecting the spectral data by the real-time in-situ water quality monitor, hyperspectral imaging is performed by the hyperspectral imager to obtain the spectral data.

Preferably, after collecting the spectral data and the water sample data to be measured, the method further comprises preprocessing the spectral data and the water sample data to be measured;

preprocessing the spectral data comprises the following steps: performing spectral data cleaning, spectral data abnormal value elimination and spectral data threshold elimination on the spectral data to obtain a spectral data set;

pretreatment of the water sample data to be tested comprises data division of the water sample data to be tested to obtain training set data and verification set data.

Preferably, the water quality parameter learning model is constructed by measuring upward and downward irradiance to obtain irradiance ratio, and the water quality parameter learning model is constructed according to the coupling relationship between the irradiance ratio and water sample parameters;

the water quality parameter learning model integrates neural network algorithm, Gaussian process regression algorithm, random forest algorithm and support vector machine algorithm.

Preferably, obtaining the optimal algorithm model of the water sample parameters to be measured comprises inputting the training set data to train the water quality parameter learning model based on the water quality parameter learning model, and inputting the verification set data to verify the water quality parameter learning model to obtain the optimal algorithm model of the water sample parameters to be measured.

Preferably, inputting the verification set data to verify the water quality parameter learning model comprises obtaining the algorithm precision of different training algorithms according to the decision coefficient and the average relative error;

according to different water sample parameters, optimization is carried out based on the accuracy of the algorithm, and the optimal training algorithm for each water sample parameter is obtained.

Preferably, the monitoring results include water quality parameters and environmental condition parameters;

the water quality index parameters include total nitrogen, total phosphorus, chlorophyll, transparency, suspended matter, permanganate index, turbidity, extinction coefficient, ammonia nitrogen, phycocyanin, algae density, absorption coefficient of colored soluble organic matter, soluble organic carbon, particulate organic carbon and eutrophication index.

The environmental condition parameters include observation point position information, air temperature and observation time.

Preferably, the monitoring method further comprises uploading the monitoring results to a server and displaying; When the water quality index exceeds a specific threshold, alarm will be given by alarm bell and short message.

The invention has the following technical effects:

(1) Compared with the traditional aerospace and unmanned aerial vehicle remote sensing, the non-touching monitoring method provided by the invention does not need atmospheric correction, and is also suitable for rainy, cloudy conditions, and can work normally at night through lighting equipment, thereby expanding the spectrum imaging time range, and having high spectral resolution and very high water environment parameter inversion accuracy.

(2) Compared with the existing ground object spectrometer or hyperspectral imager, the hyperspectral imager of the present invention can automatically monitor at high frequency in all weather and in real time, and is unattended.

(3) The method can realize continuous high-frequency monitoring of total nitrogen, total phosphorus, chlorophyll a, chemical oxygen demand and transparency in various complex scenes such as different weather conditions and water conditions, and can be widely applied to remote sensing inversion, eutrophication and surface water environmental quality evaluation research of different types of water bodies, and deepen the basic theory and prevention and control technology research of water environment formation.

(4) The hyperspectral imager supported by the invention is not in direct contact with the water body to be measured, and belongs to non-touching observation. Compared with the traditional underwater probe contact monitoring, the hyperspectral imager has low energy consumption, small loss, simple maintenance, and limited influence by external environment such as wind and waves, so the accuracy of observation and algorithm can be guaranteed.

BRIEF DESCRIPTION OF THE FIGURES

In order to more clearly explain the embodiments of the invention or the technical solutions in the prior art, the following will briefly introduce the drawings to be used in the embodiments. It is obvious that the drawings described below are only some embodiments of the invention. For those skilled in the art, without paying creative labor, Other drawings can also be obtained from these drawings.

Fig. 1 is a method flowchart of an embodiment of the present invention;

Fig. 2 is a comparison diagram of chlorophyll a optimization algorithm model according to the embodiment of the present invention;

Fig. 3 is a comparison diagram of the total nitrogen optimization algorithm model of the embodiment of the present invention.

DESCRIPTION OF THE INVENTION

The following will clearly and completely describe the technical scheme in the embodiments of the present invention with reference to the drawings in the embodiments of the present invention. Obviously, the described embodiments are only part of the embodiments of the present invention, not all of them. Based on the embodiments of the present invention, all other embodiments obtained by ordinary technicians in the field without creative labor belong to the scope of protection of the present invention.

In order to make the above objects, features and advantages of the present invention more obvious and easy to understand, the present invention will be further explained in detail with reference to the drawings and specific embodiments.

As shown in Fig. 1, the present invention provides a non-touching real-time in-situ water quality monitoring method.

1) By constructing a hyperspectral imager, hyperspectral imaging is carried out within a certain range from a water body to be measured; In case that natural light cannot be satisfied (for example, at night), illuminate with artificial light source;

2) The height from the water surface of the water body to be measured is preferably 4-10m, which is determined according to the observation requirements and on-site installation conditions and considering the actual situation in the field;

3) By measuring hyperspectral and synchronous water quality parameters of different water bodies in different weather conditions in the field, a machine learning

algorithm for typical water quality parameters based on multispectral is constructed, and the parameters involved include total nitrogen, total phosphorus, chlorophyll, transparency, suspended matter, permanganate index, absorption coefficient of colored soluble organic matter, soluble organic carbon, particulate organic carbon and eutrophication index;

Further optimization scheme, step 3) also includes:

(1) The spectral imager collects spectral data and records the collection time; Cleaning the spectral data, eliminating abnormal spectra, and forming a spectral data set, the data set range is 400-1000nm, and the spectral resolution is 1nm.

(2) Collecting water samples at the same time of spectral measurement, and measuring the concentration of water quality parameters such as total nitrogen, total phosphorus, chlorophyll, transparency, suspended solids, permanganate index, absorption coefficient of colored soluble organic matter, soluble organic carbon, particulate organic carbon and eutrophication index in the laboratory to form a data parameter data set corresponding to the spectral data set.

(3) Selecting two thirds of samples in the data set for algorithm training to form a training data set; One-third of the samples are used for algorithm verification to form a verification data set.

(4) Selecting the spectral reflectance of 400-900nm band in the training data set, take the average value of spectral reflectance every 5nm as the algorithm input parameter, and select neural network (BP), Gaussian process regression (GPR), random forest (RFR) and support vector machine (SVR) models for training, and construct the trained algorithm.

(5) Select the spectral reflectance of 400-900nm band in the test data set, take the average spectral reflectance every 5nm as the algorithm input parameter, and there are 100 input bands in 400-900nm, and verify the trained neural network (BP), Gaussian process regression (GPR), random forest (RFR) and support vector machine (SVR) models, and use R2 (determination coefficient). Taking the total phosphorus parameters as an example, the results were verified by neural network (BP), Gaussian process regression (GPR), random forest (RFR) and support vector machine (SVR) respectively. After comparison, it was found that the GPR results were the best, and the instrument

selected the GPR algorithm. Similar calculations and comparisons are made for other parameters, and the optimal algorithm is selected. Different parameter optimization algorithms may be different. Some parameters may be BP, some parameters may be GPR, some parameters may be RFR and some parameters may be SVR. As shown in Fig. 2 and Fig. 3, the optimal model of chlorophyll a is GPR, and the optimal model of total nitrogen is SVR.

4) After the instrument receives the spectral reflectance of the water body to be measured, various water quality index parameters and environmental condition parameters at that time are output in real time through the implanted multi-parameter water quality inversion algorithm, including total nitrogen, total phosphorus, chlorophyll, transparency, suspended matter, permanganate index, turbidity, extinction coefficient, ammonia nitrogen, phycocyanin, algae density, absorption coefficient of colored soluble organic matter, soluble organic carbon, particulate organic carbon, eutrophication index, etc.

5) Transmitting data to the server through wireless signals to form an interface end for display; When the water quality index exceeds the specific threshold, the relevant personnel can be informed by means of alarm and short message, which can do a good job in disaster early warning and forecast of sudden change of water quality.

The above embodiments only describe the preferred mode of the invention, but do not limit the scope of the invention. On the premise of not departing from the design spirit of the invention, various modifications and improvements made by ordinary technicians in the field to the technical scheme of the invention shall fall within the protection scope determined by the claims of the invention.

CLAIMS

1. A non-touching real-time in-situ water quality monitoring method is characterized by comprising the following steps:

collecting spectral data and water sample data to be measured, and constructing a deep learning model of water quality parameters based on hyperspectral;

acquiring an optimal algorithm model of water sample parameters to be measured based on the water quality parameter deep learning model, the spectral data and water sample data to be measured;

based on the optimal algorithm model of the parameters of the water sample to be measured, the monitoring results are obtained through a multi-parameter water quality inversion algorithm.

2. The non-touching real-time in-situ water quality monitoring method according to claim 1 is characterized in that,

the spectral data is collected by a real-time in-situ water quality monitor or illuminated by an artificial light source;

the real-time in-situ water quality monitor comprises an auxiliary installation device, a solar power supply device and a hyperspectral imager.

3. The non-touching real-time in-situ water quality monitoring method according to claim 2 is characterized in that,

in the process of collecting the spectral data by the real-time in-situ water quality monitor, hyperspectral imaging is performed by the hyperspectral imager to obtain the spectral data.

4. The non-touching real-time in-situ water quality monitoring method according to claim 1 is characterized in that,

collecting the spectral data and the water sample data to be measured further comprises preprocessing the spectral data and the water sample data to be measured;

preprocessing the spectral data comprises the following steps of: cleaning the spectral data and removing abnormal values of the spectral data to obtain a spectral data set;

pretreatment of the water sample data to be tested comprises data division of the water sample data to be tested to obtain training set data and verification set data.

5. The non-touching real-time in-situ water quality monitoring method according to claim 1 is characterized in that,

the water quality parameter learning model is constructed by measuring upward and downward irradiance to obtain irradiance ratio, and the water quality parameter learning model is constructed according to the coupling relationship between the irradiance ratio and water sample parameters;

the water quality parameter learning model integrates neural network algorithm, Gaussian process regression algorithm, random forest algorithm and support vector machine algorithm.

6. The non-touching real-time in-situ water quality monitoring method according to claim 4 is characterized in that,

obtaining the optimal algorithm model of water sample parameters to be tested includes inputting the training set data to train the water quality parameter learning model based on the water quality parameter learning model, and inputting the verification set data to verify the water quality parameter learning model to obtain the optimal algorithm model of water sample parameters to be tested.

7. The non-touching real-time in-situ water quality monitoring method according to claim 6 is characterized in that,

entering the verification set data to verify the water quality parameter learning model includes obtaining the algorithm precision of different training algorithms according to the decision coefficient and the average relative error;

according to different water sample parameters, optimization is carried out based on the accuracy of the algorithm, and the optimal training algorithm for each water sample parameter is obtained.

8. The non-touching real-time in-situ water quality monitoring method according to claim 1 is characterized in that:

the monitoring results include water quality parameters and environmental condition parameters;

the water quality index parameters include total nitrogen, total phosphorus, chlorophyll, transparency, suspended matter, permanganate index, turbidity, extinction coefficient, ammonia nitrogen, phycocyanin, algae density, absorption coefficient of colored soluble organic matter, soluble organic carbon, particulate organic carbon and eutrophication index;

the environmental condition parameters include observation point position information, air temperature and observation time.

9. The non-touching real-time in-situ water quality monitoring method according to claim 1 is characterized in that:

the monitoring method also comprises uploading the monitoring results to a server and displaying; when the water quality index exceeds a specific threshold, alarm is given by alarm bell and short message.

PATENTANSPRÜCHE

1. Ein berührungsloses Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit ist dadurch gekennzeichnet, dass es die folgenden Schritte umfasst:

Sammlung von Spektraldaten und zu messenden Wasserprobendaten und Erstellung eines Deep-Learning-Modells der Wasserqualitätsparameter auf der Grundlage von Hyperspektren;

Erhaltung eines optimalen Algorithmusmodells der zu messenden Wasserprobenparameter auf der Grundlage des Deep-Learning-Modells für Wasserqualitätsparameter, der Spektraldaten und der zu messenden Wasserprobendaten;

Erhaltung der Überwachungsergebnisse durch einen Algorithmus zur Inversion der Wasserqualität mit mehreren Parametern auf der Grundlage des optimalen Algorithmusmodells für die Parameter der zu messenden Wasserprobe.

2. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 1 ist durch die Folgenden gekennzeichnet:

Erfassung der Spektraldaten durch einen In-situ-Wasserqualitätsmonitor in Echtzeit oder durch eine Beleuchtung der künstlichen Lichtquelle;

der Echtzeit-In-situ-Wasserqualitätsmonitor umfasst eine zusätzliche Installationsvorrichtung, eine solare Stromversorgung und einen Hyperspektralbildgeber.

3. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 2 ist durch die Folgenden gekennzeichnet:

bei der Erfassung der Spektraldaten durch den Echtzeit-Insitu-Wasserqualitätsmonitor wird die hyperspektrale Bildgebung durch den Hyperspectral Imager durchgeführt, um die Spektraldaten zu erhalten.

4. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 1 ist die Folgenden gekennzeichnet:

nach dem Sammeln der Spektraldaten und der zu messenden Wasserprobendaten ist es außerdem erforderlich, die Spektraldaten und die zu messenden Wasserprobendaten vorzuverarbeiten;

die Vorverarbeitung der Spektraldaten umfasst die folgenden Schritte: Bereinigung der Spektraldaten und Entfernung anormaler Werte aus den Spektraldaten, um einen Spektraldatensatz zu erhalten;

die Vorbehandlung der zu prüfenden Wasserprobendaten umfasst die folgenden Schritte: Datenteilung der zu prüfenden Wasserprobendaten, um Daten des Trainingssatzes und des Verifikationssatzes zu erhalten.

5. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 1 ist die Folgenden gekennzeichnet:

das Lernmodell für die Wasserqualitätsparameter wird durch Messung der aufwärts und abwärts gerichteten Bestrahlungsstärke konstruiert, um das Bestrahlungsstärkeverhältnis zu erhalten, das Lernmodell für die Wasserqualitätsparameter wird entsprechend der Kopplungsbeziehung zwischen dem Bestrahlungsstärkeverhältnis und den Wasserprobenparametern konstruiert;

das Lernmodell für die Wasserqualitätsparameter umfasst einen neuronalen Netzalgorithmus, einen Gaußschen Regressionsalgorithmus, einen Random-Forest-Algorithmus und einen Support-Vector-Machine-Algorithmus.

6. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 4 ist die Folgenden gekennzeichnet:

das Erhalten des optimalen Algorithmusmodells der zu prüfenden Wasserprobenparameter, wobei die Daten des Trainingssatzes eingegeben werden, um das Lernmodell für die Wasserqualitätsparameter auf der Grundlage des Lernmodells für die Wasserqualitätsparameter zu trainieren,

und die Verifizierungsdaten zur Überprüfung des Lernmodells für die Wasserqualitätsparameter eingegeben werden, um das optimale Algorithmusmodell der zu prüfenden Wasserprobenparameter zu erhalten.

7. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 6 ist die Folgenden gekennzeichnet:

die Eingabe der Daten des Verifizierungssatzes zur Überprüfung des Lernmodells für die Wasserqualitätsparameter, wobei die Algorithmuspräzision der verschiedenen

Trainingsalgorithmen auf der Grundlage des Entscheidungskoeffizienten und des durchschnittlichen relativen Fehlers ermittelt wird;
entsprechend den verschiedenen Wasserprobenparametern wird eine Optimierung auf der Grundlage der Genauigkeit des Algorithmus durchgeführt, der optimale Trainingsalgorithmus für jeden Wasserprobenparameter wird ermittelt.
8. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 1 ist die Folgenden gekennzeichnet:
die Überwachungsergebnisse umfassen Parameter der Wasserqualität und des Umweltzustands;
die Indexparameter für die Wasserqualität umfassen Gesamtstickstoff, Gesamtphosphor, Chlorophyll, Transparenz, Schwebstoffe, Permanganat-Index, Trübung, Extinktionskoeffizient, Ammoniumstickstoff, Phycocyanin, Algendichte, Absorptionskoeffizient von gefärbten löslichen organischen Stoffen, löslicher organischer Kohlenstoff, partikulärer organischer Kohlenstoff und Eutrophierungsindex;
zu den Parametern für die Umgebungsbedingungen gehören Informationen über die Position des Beobachtungspunkts, die Lufttemperatur und die Beobachtungszeit.
9. Das berührungslose Verfahren über Überwachung der In-situ-Wasserqualität in Echtzeit nach Anspruch 1 ist die Folgenden gekennzeichnet:
das Überwachungsverfahren umfasst auch das Hochladen der Überwachungsergebnisse auf einen Server und die Anzeige; wenn der Wasserqualitätsindex einen bestimmten Schwellenwert überschreitet, wird durch eine Alarmglocke und eine Kurznachricht Alarm gegeben.

FIGURES

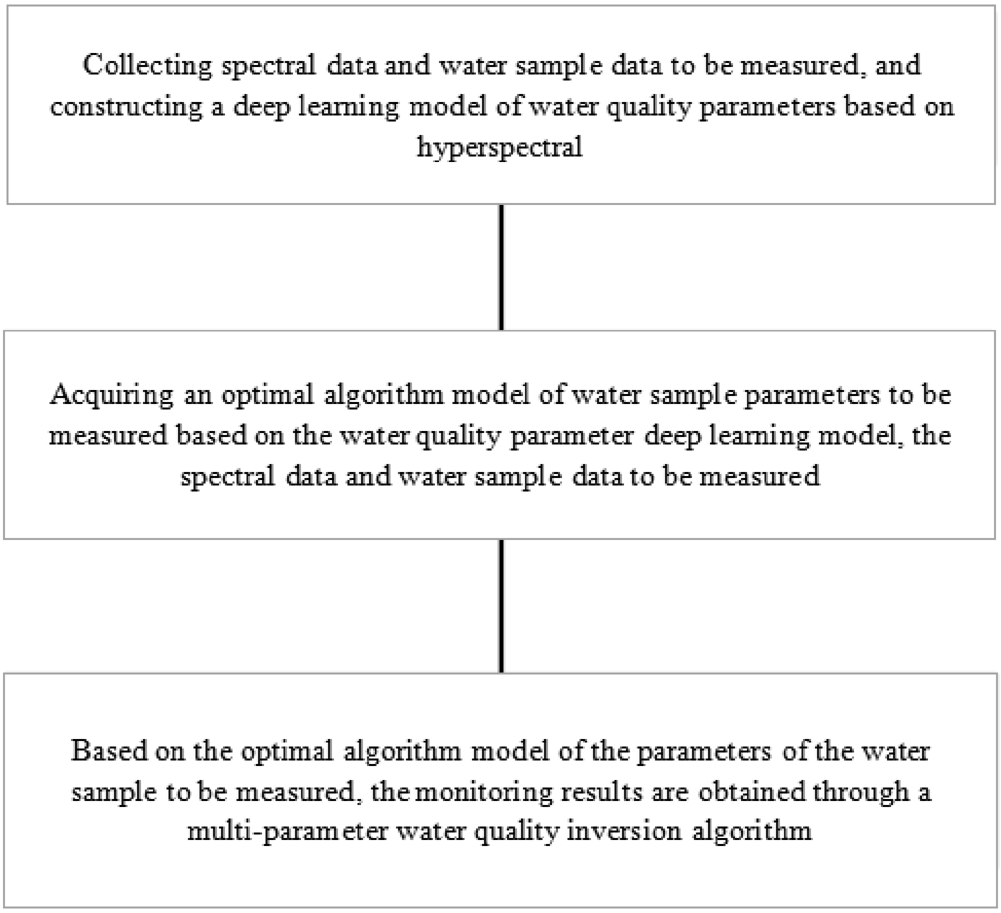


Fig. 1

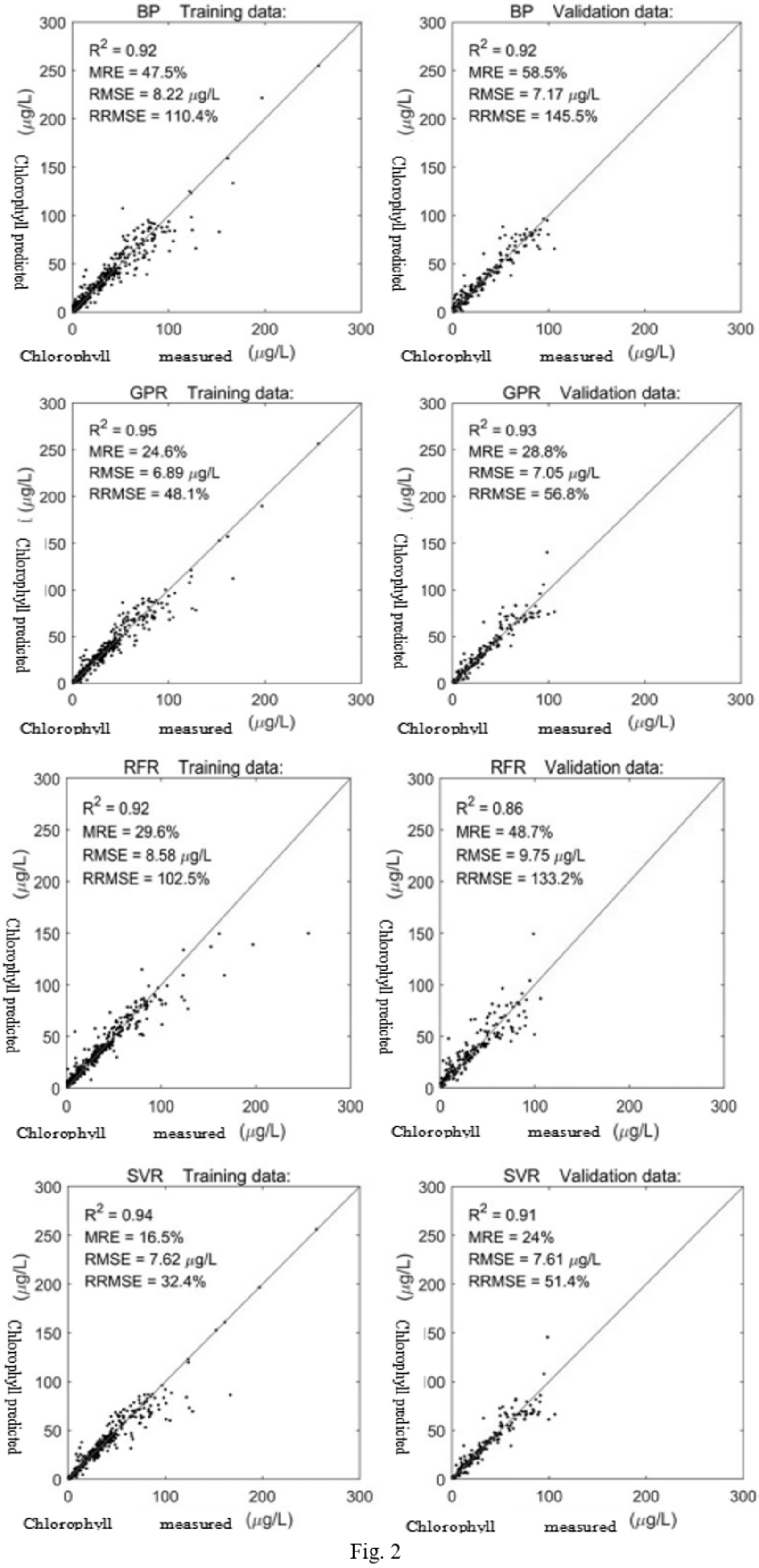

BP Training data:
R^2 = 0.92
MRE = 47.5%
RMSE = 8.22 μg/L
RRMSE = 110.4%
BP Validation data:
R^2 = 0.92
MRE = 58.5%
RMSE = 7.17 μg/L
RRMSE = 145.5%
GPR Training data:
R^2 = 0.95
MRE = 24.6%
RMSE = 6.89 μg/L
RRMSE = 48.1%
GPR Validation data:
R^2 = 0.93
MRE = 28.8%
RMSE = 7.05 μg/L
RRMSE = 56.8%
RFR Training data:
R^2 = 0.92
MRE = 29.6%
RMSE = 8.58 μg/L
RRMSE = 102.5%
RFR Validation data:
R^2 = 0.86
MRE = 48.7%
RMSE = 9.75 μg/L
RRMSE = 133.2%
SVR Training data:
R^2 = 0.94
MRE = 16.5%
RMSE = 7.62 μg/L
RRMSE = 32.4%
SVR Validation data:
R^2 = 0.91
MRE = 24%
RMSE = 7.61 μg/L
RRMSE = 51.4%
Chlorophyll predicted (μg/L)
Chlorophyll measured (μg/L)

Fig. 2

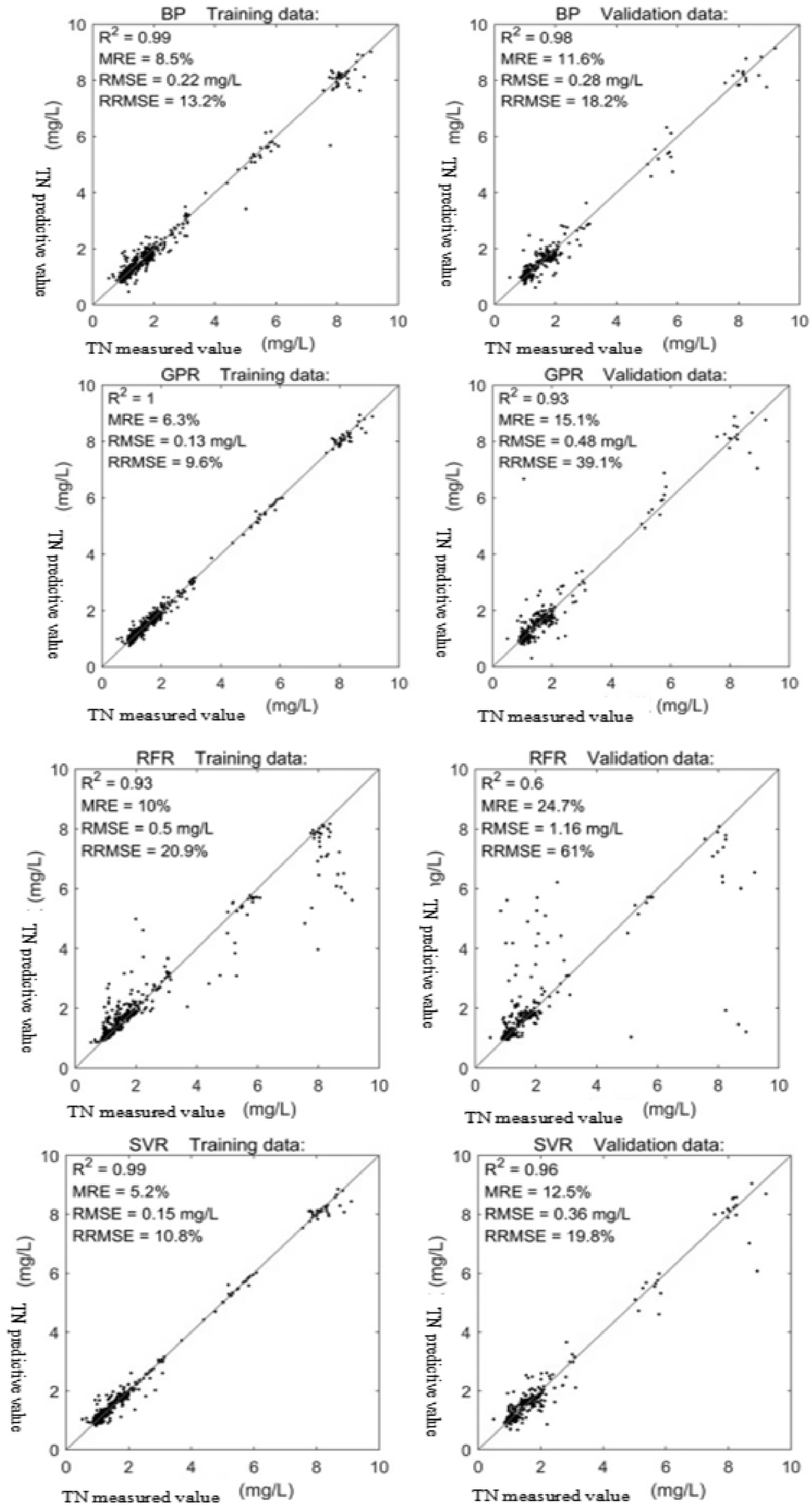

BP Training data:
R^2 = 0.99
MRE = 8.5%
RMSE = 0.22 mg/L
RRMSE = 13.2%
BP Validation data:
R^2 = 0.98
MRE = 11.6%
RMSE = 0.28 mg/L
RRMSE = 18.2%
GPR Training data:
R^2 = 1
MRE = 6.3%
RMSE = 0.13 mg/L
RRMSE = 9.6%
GPR Validation data:
R^2 = 0.93
MRE = 15.1%
RMSE = 0.48 mg/L
RRMSE = 39.1%
RFR Training data:
R^2 = 0.93
MRE = 10%
RMSE = 0.5 mg/L
RRMSE = 20.9%
RFR Validation data:
R^2 = 0.6
MRE = 24.7%
RMSE = 1.16 mg/L
RRMSE = 61%
SVR Training data:
R^2 = 0.99
MRE = 5.2%
RMSE = 0.15 mg/L
RRMSE = 10.8%
SVR Validation data:
R^2 = 0.96
MRE = 12.5%
RMSE = 0.36 mg/L
RRMSE = 19.8%
TN predictive value (mg/L)
TN measured value (mg/L)

Fig.3