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Early Warning System for Urban Industrial Wastewater based on Remote Sensing Technology and Image Analysis

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Abstract: With the rapid development of economy, the scale of China's cities is expanding, and the discharge of urban industrial wastewater is also increasing, which has caused some pressure on urban wastewater treatment plants. In this paper, a method of early warning analysis of urban industrial wastewater based on remote sensing technology and image analysis technology is proposed based on the analysis of the current situation of industrial wastewater discharge. The method is used in the sewage early warning system can effectively improve the operational efficiency of sewage treatment plants and water quality monitoring capabilities. It provides a reference basis for enterprises to provide real-time monitoring data and formulate corresponding pollution treatment plans. In view of the industrial sewage pollution, this paper proposes a scheme to build an early warning system for urban industrial sewage based on remote sensing technology and image analysis technology. The system combines remote sensing images and field data to identify industrial wastewater pollution characteristics as the core objective, classify and identify pollutant molecules in images through multi-scale identification and classification algorithms, and use discriminative methods to make a comprehensive evaluation of this water quality model. The results show that the early warning system can accurately identify industrial wastewater pollutants.

1. Introduction

Industrial wastewater also contains a large amount of nitrogen, phosphorus, heavy metals, ammonia nitrogen, sulfide and other pollutants, which contain heavy metals and other pollutants that can cause deterioration of water quality if left unchecked. Also industrial wastewater contains a large amount of organic matter, nitrogen, phosphorus, sulfur and other heavy metals that are harmful to humans, and these pollutants enter the water body through both plant respiration and feces, posing a serious threat to the environment. Therefore, urban wastewater treatment must be subject to early warning [1-2].

In a related study, Saqib et al. proposed a new cloud-based industrial IoT model for real-time wastewater monitoring and control [3]. The proposed system monitors hydrogen power (pH) and temperature parameters at the inlet of wastewater to be treated at a wastewater treatment plant, thus avoiding unacceptable industrial wastewater that the plant cannot treat. The system collects real-time sensor readings via an IIoT Wi-Fi module and uploads them to the cloud. In addition, it reports observed or detected unexpected industrial wastewater inlets via SMS notifications and alarms and controls the gate valves. Experimental work has shown that the proposed system is effective compared to related work.Rejoice et al. proposed three mathematical models to maximise the profitability of a centralised system by considering the separation of wastewater from multiple pollutants [4]. The basic models were tested and case studies were carried out for different quantities of collector pipes used for separation and for different qualities of reclaimed water. The results obtained show that wastewater separation can be highly profitable for centralised systems and provide significant freshwater savings for industry.

In this paper, a scheme to construct an early warning system for urban industrial wastewater based on remote sensing technology and image analysis technology is proposed, which can effectively identify pollutants in the environment by using the characteristics of remote sensing images [5] and applying them to the monitoring of urban environmental pollution, and can judge the degree of pollution by its concentration, flow rate, and other indicators to provide early warning of urban industrial wastewater pollutant discharge indicators [6-7].

2. Design Research

2.1. Basin Water Environment Early Warning System Needs

An ideal and efficient early warning system for the water environment in a watershed [8-9] should meet the following needs; Providing a rapid response to police situations; A sufficiently broad range of pollutant types for early warning; Both sampling and preservation of samples, with the greatest possible automation [10-11]; Moderate cost to purchase, maintain and upgrade the system; Simplicity of operation, avoiding extensive training and excessive skill requirements; Sources of contamination can be identified and basic information on the spread of contaminants downstream can be predicted; Adequate sensitivity for monitoring of contaminants; Minimization of errors; demonstrate sufficient stability and strength for frequent operations [12-13]; Can be operated and adjusted remotely; Capable of continuous operation; Ability to allow third parties to test, evaluate and validate.

However, the currently established early warning system for the water environment in the basin cannot have all the above conditions, although some more central features must be achieved, namely: the monitoring of early warning indicators must be simple to operate, automatable, and capable of continuous operation. While ensuring the sensitivity of monitoring pollutants, early warning indicators are optimally screened to achieve a high level of economy [14-15].

2.2. Screening Principles of Early Warning Indicators

The screening of early warning indicators [16-17] is subject to the following principles.

(1) Watershed representation. Optimization of early warning indicators, should be based on the basin's pollution source discharge characteristics and water quality characteristics analysis results, select a representative water quality indicators to monitor the changes in water quality in the basin.

(2) Operational feasibility. The screened indicators, in monitoring samples need to be easy to fix, and easy to measure the operation, and should meet the needs of online real-time monitoring, in order to protect the timeliness of water quality warning.

(3) Responsiveness. The selected early warning indicators should have the sensitivity to quickly capture the characteristics of water quality changes in the water body, sensitive enough in identifying the process of water pollution.

(4) Economic applicability. The current automatic water quality monitoring instruments are generally high prices, should not affect the early warning results, choose online monitoring of water quality indicators with high cost performance.

On the basis of meeting the above basic principles and without affecting the quality of early warning, the water quality indicators needed for early warning should be optimally reduced as much as possible in order to shorten the process time of early warning and improve the efficiency of early warning [18].

2.3. Algorithm Evaluation

(1) Confusion matrix

As an example, the confusion matrix is the matrix of k tk, and the value of the matrix coordinate is the number of samples that the discriminant model predicts to be category f and the actual category f.

Taking the most common binary classification (category 0, 1) as an example, the structure of the confusion matrix is shown in Table 1.

Table 1. Structure of confusion matrix under binary classification

	Predicted value = 1	Predicted value = 0
True value = 1	True Positive (TP)	False Negative (FN)
True value = 0	False Positive (FP)	True Negative (TN)

This binary classification confusion matrix is commonly used in the algorithm evaluation of water quality anomaly detection, which is mainly from four dimensions of the analysis, including true positive (TP), false positive (FP), true negative (TP) and false negative (FN). If category 1 represents abnormal water quality, category 0 is normal water quality, TP refers to the true state of water quality is abnormal in the case of classification results are also abnormal, FP refers to the true state of water quality is normal in the case of classification results are abnormal, TN refers to the true state of water quality is normal in the case of classification results are also normal, FN refers to the true state of water quality is abnormal in the case of classification results are normal. The larger the value on the diagonal of the confusion matrix matrix and the smaller the value on the non-diagonal, the better the classification effect.

(2) Accuracy, recall, fl score

From the confusion matrix, the number of correctly classified samples is TP+TN, while the total number of samples is TP+FP+TN+FN. Therefore, the accuracy formula is shown in Equation 1.

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Unlike the accuracy rate, the precision rate is for the prediction result result result of the algorithm for the positive class samples, which indicates the proportion of the samples predicted to be positive class that are actually also positive class samples, and the samples predicted to be positive class include TP and FP, while those that are really positive class samples are TP, so the precision rate is shown in Equation 2.

$$precision = \frac{TP}{TP + FP} \tag{2}$$

The recall rate is specific to the category of the sample itself, and it indicates the proportion of positive cases in the sample that are successfully classified as positive samples, and the positive samples in the sample are TP and FN, and the one that is successfully predicted as a positive case is TP, so the formula for the recall rate is shown in Equation 3.

$$recall = \frac{TP}{TP + FN} \tag{3}$$

The accuracy and recall rates evaluate the classification results from the perspectives of accuracy and completeness, respectively. fl score combines the accuracy and recall rates to evaluate the classification results, and its general form is shown in Equation 4.

$$F1 = \frac{(1+\beta^2) * P * R}{\beta^2 * P + R} \tag{4}$$

Where P and R represent the precision and accuracy of classification, respectively, and B is a hyperparameter used to adjust the weights of precision and recall. when B>1, recall has more weight; when B<1, correctness has more weight; when B=1, both have equal weights.

3. Experimental Research

3.1. Pollutant Dynamic Monitoring

(1) Pollutant information inquiry

Water digital earth has multimedia integration, simulation of the real environment and processing of spatial information and other functions, through these functions, according to the actual situation of the body of water modeling, and the constructed model with the digital earth, GIS layer integration, and thus the water pollution information to mark. In the event of a water pollution event, the emergency plan can be taken when the service interface of the data resource center is digitally connected to the digital earth of water resources, thus providing information query services for managers.

(2) Pollutant transport monitoring

For the simulation of water pollution events, the transport of pollutants is the key process. Based on the water resources digital earth, not only can comprehensively display the information of each monitoring section, outfall, etc., the water quality and pollutant concentration at the same point in time will be displayed on different screens in chronological order, the water body and the actual measured data correlation, the construction of water quality model Agent and pollutant multi-intelligence body, combined with the process of time evolution, to achieve the dynamic display of pollutants. By triangulating the river and using color scale to indicate different pollutant concentrations, the river triangulation network and pollutant concentrations can correspond one by one, which is easy for users to query, and the process of pollutant transport can be visualized through the dynamic screen.

(3) Auxiliary information services

The complexity of water pollution events makes it inevitable to encounter problems in the simulation and emergency management process, such as relocation, the protection of historical relics, etc. Therefore, in its emergency response, it is necessary to consider the actual situation in the area where the water pollution event occurred, weighing the pros and cons to minimize the negative impact of water pollution events on the outside world. The creation of auxiliary information services on the water resources digital earth, through text, graphics and other ways to provide some basic information, such as, administrative areas, water quality monitoring information, so that managers can get more comprehensive information about water pollution events, for decision makers to make decisions quickly and easily.

3.2. Business Processes

According to the requirements of data collection and disposal, the business flow chart for water quality data analysis is shown in Figure 1.

The design ideas and principles of wastewater environmental detection and early warning management system should be planned according to the actual situation of the region where the enterprise is located and implemented according to the following basic principles.

(1) Comply with all laws and regulations, and the treated discharge water quality should strictly comply with the discharge standards.

(2) Using advanced methods to integrate artificial intelligence and machines into one.

(3) Reducing the cost of developing systems and ensuring the integrity of data.

(4) The adopted system must be open and scalable.

(5) The data of the system must be open to the national environmental protection regulatory authorities to facilitate their inspection in real time.

(6) Shall not do anything to harm the national interest, treat the data realistically and shall not be falsified.

In accordance with the technical gist of the paper wastewater treatment system, the system uses the detection mode of water quality detection sensor + microcontroller. The information is read through the microcontroller, and also the monitoring signal is input to each control device to realize the data collection, management and monitoring functions.

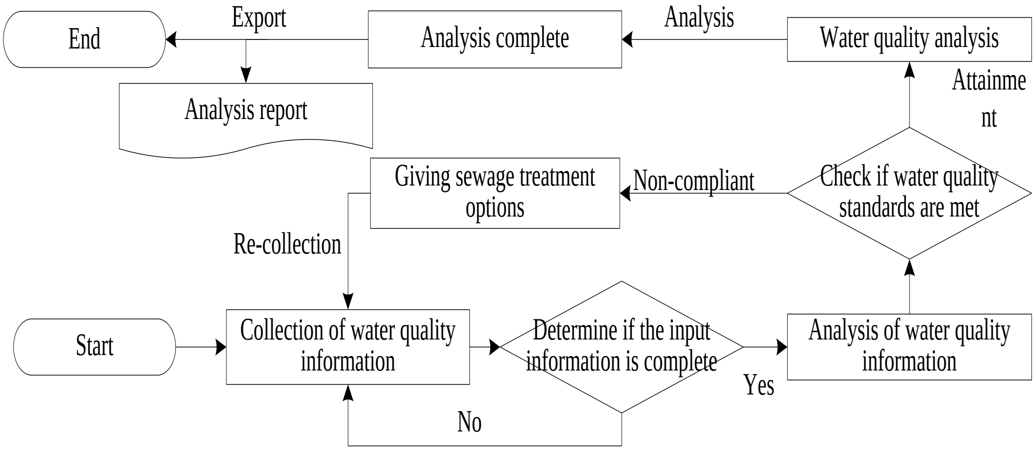

Figure 1. Business flow chart for water quality data analysis

4. Analysis of the watershed distribution of pollution sources

The analysis of the watershed distribution of pollution sources is an analysis of the interannual variation of the number of pollution sources, the distribution of each river and the distribution of wastewater discharge. The study collected data on pollution sources from industrial enterprises and wastewater treatment plants in a river basin for six years to analyze the watershed distribution of pollution sources.

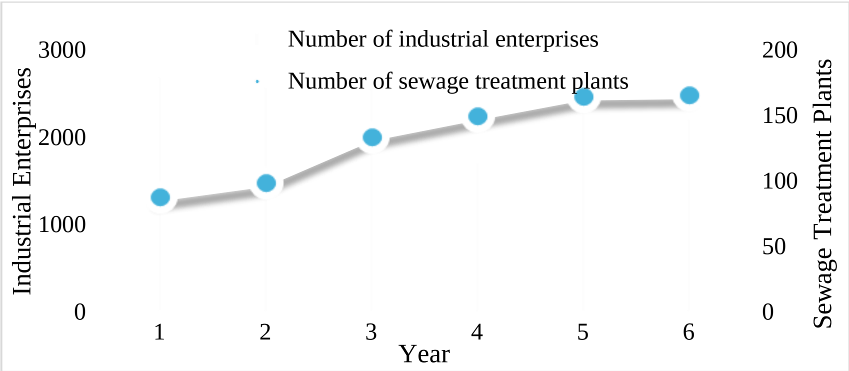

Figure 2. Analysis of the year-on-year variation in the number of industrial enterprises and the number of sewage treatment plants

From Figure 2, it can be analyzed that the number of industrial enterprises has remained basically the same from year to year, with a decrease in the last year, while the number of sewage treatment plants has shown a clear trend of increasing year by year, and has remained basically the same in the last two years. This is because the number of industrial enterprises has been limited and the number of wastewater treatment plants has been increasing to meet the growing need for wastewater treatment.

The distribution of pollution sources and the discharge characteristics of total wastewater are analyzed by taking the data of the last year as the study object, as shown in Table 2.

Table 2. Distribution of enterprise pollution sources and sewage treatment plants

River	River 1	River 2	River 3
Distribution of enterprise pollution sources	26.1%	28.6%	45.3%
Distribution of sewage treatment plants	26.3%	21.4%	52.3%

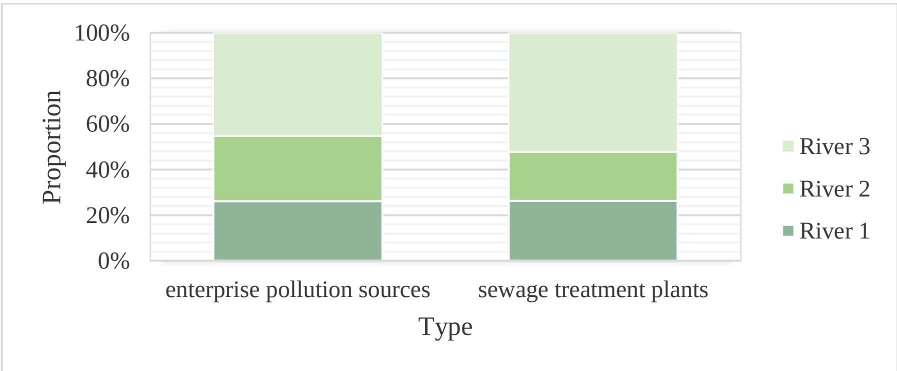

Figure 3. Analysis of the distribution of enterprise pollution sources and sewage treatment plants

From Figure 3, we can see that the distribution of the number of two sources of pollution is relatively similar, in which the percentage distribution of industrial enterprises and sewage treatment plants in the sub-basin is almost the same; the number of sewage treatment plants in the sub-basin of the main stream of a river accounts for more than 50% of the total, slightly higher than the percentage of industrial enterprises; the distribution of the two sources of pollution in the second sub-basin of a river is the opposite of the main stream of a river, the percentage of sewage treatment plants is slightly lower than that of industrial enterprises. The percentage of sewage treatment plants is slightly lower than that of industrial enterprise sources. Further analysis is done by combining the proportion of wastewater discharge from the two types of sources, see Table 3.

Table 3. Distribution of enterprise pollution sources and sewage treatment plants

River	River 1	River 2	River 3
Emission distribution of enterprises	15.6%	33.7%	50.6%
Distribution of treatment plant discharges	11.5%	34.4%	54.1%

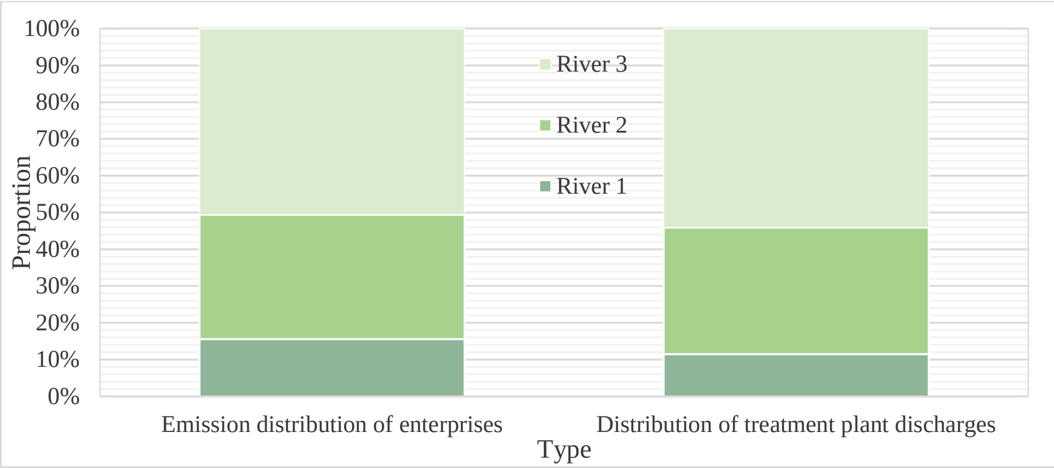

Figure 4. Analysis of the distribution of enterprise pollution sources and sewage treatment plants

Combined with Figure 4, it can be seen that the percentage of wastewater discharge in the second certain river sub-basin has a large increase compared with the percentage of quantity distribution, while the sub-basins are in the opposite state, with a slight increase in the percentage of wastewater discharge in the main stream sub-basin of a river. This indicates that the wastewater discharges from industrial enterprises and wastewater treatment plants in a certain river sub-basin are larger than those in the other two sub-basins, and the discharge characteristics of pollution sources should be considered in the screening of early warning indicators. The percentage of wastewater discharged from sewage treatment plants in the sub-basin is only 11.5%, so the focus of screening indicators should be on water quality characteristics. It can be concluded that when analyzing the watershed distribution of pollution sources, the distribution of both quantity and wastewater discharge should be combined.

5. Conclusion

The construction of urban industrial wastewater early warning system is important to reduce industrial wastewater discharge pollution and improve the operational efficiency and governance of wastewater treatment plants. Using remote sensing and image analysis technology to fuse urban industrial sewage information with sewage data, the industrial sewage detection and early warning system is established. By combining urban geographic environment information to realize industrial sewage information monitoring, industrial water index monitoring and historical database construction, and import the data into the urban industrial sewage early warning system built based on GIS technology. The system can transmit the real-time monitoring data of urban industrial wastewater treatment plants and related data to the enterprise management system through wireless network to realize monitoring and supervision. At the same time, the system can effectively realize the industrial sewage supervision and monitoring informatization capabilities, data sharing and monitoring and early warning functions. And the credit evaluation of the discharge behavior of enterprises. Effectively improve the local government's ability to deal with urban industrial sewage quality control, pollution prevention and effective promotion of urban ecological environmental protection work.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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