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Water Pollution Source Management Resources Incorporating Microscopy Images and Clustering Algorithms

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Abstract: The main source of water resources in China is agricultural irrigation. With the increase of agricultural scale operation and agricultural mechanization, agricultural irrigation and water resources protection have become one of the main causes of current water environment pollution problems. Traditional water pollution source management methods have serious problems of resource waste and inefficiency. The main purpose of this paper is to integrate microscopic technology images and clustering algorithms to conduct research on the construction of water pollution source management resources. In this paper, we use microscopy technology and clustering algorithm to fuse high-resolution images with GIS data to classify water classes, land and rivers in the images into classes and construct a comprehensive remediation resource construction plan for polluted rivers. The results show that the water pollution source management resource construction scheme based on microscopic technology image and clustering algorithm can significantly improve the efficiency of water resources monitoring; at the same time, it can realize the use of higher resolution land water quality monitoring resources; realize the low investment and operation cost of water pollution source management.

1. Introduction

At present, the number of completed water resources monitoring systems is insufficient, their monitoring means and technology is backward, the level of analysis is low, easy to cause waste of resources and management chaos. Water pollution source monitoring is the key link to achieve water resources monitoring and management, and improve the utilization of water resources. Water environment monitoring mainly uses two means of static monitoring and dynamic monitoring. By establishing a basin water environment monitoring system as well as dynamic monitoring and real-time monitoring of the basin water environment, the efficiency of basin water environment monitoring and the management of water pollution sources can be effectively improved [1-2].

In a related study, Sudipa et al. mentioned that pollution source location is a complex problem because urban water supply networks contain a large number of nodes and is also a computationally expensive problem. Intelligent optimisation algorithms based on alternative models can effectively solve such problems [3]. In addition, various model management strategies were proposed and their effectiveness was verified experimentally.Priyanka et al. concluded that excessive pollutant discharges from multiple sources may lead to increased pollutant concentrations downstream of a river segment. A robust approach to support load (I) reduction and effective water quality management in river reaches was developed by combining a multi-source water quality model (MPSWQM) with Bayesian statistics [4]. The analysis allows decision makers to assess the impact of each load and how best to manage water quality objectives for each period.

In this paper, CCD cameras are used to acquire surface images of water bodies, combined with high-resolution satellite remote sensing images and infrared thermal imaging based on hyperspectral imaging technology for water body surface analysis. By classifying and ranking the analysis results, we obtain information on the characteristics of water pollution sources and water environment quality targets. Finally, the classification results are clustered and processed to derive scientific and reasonable treatment suggestions.

2. Design Research

2.1. Water Environment Monitoring Resources Construction Objectives

In terms of resource construction goals, the construction goals are complementary to the construction goals of water resources monitoring resources, and provide decision support for water resources monitoring resources [5-6]. According to the water environment monitoring resources construction goals, in terms of water resources monitoring resources construction goals, it requires water resources monitoring resources to meet the environmental quality monitoring and evaluation, national environmental emergencies monitoring and national water special monitoring requirements. In terms of the construction objectives of water resources monitoring resources need to achieve: (1) to realize the monitoring indicators of water resources monitoring resources and monitoring resources can be effectively monitored online and the monitoring results can be effectively analyzed [7-8]; (2) to realize online and timely uploading of monitoring indicators; (3) to realize multi-source monitoring data sharing of water resources monitoring resources and monitoring resources; (4) to realize automatic online prediction of monitoring indicators; (5) to realize automatic calculation of water quality indicators and automatic release of intelligent analysis results; (6) to meet the requirements of relevant national laws and regulations on water resources monitoring data sharing and analysis [9-10]. There is also a need to further strengthen and refine the construction goals of water resources monitoring resources. It is clearly stated in the national environmental emergencies monitoring requirements that national environmental emergencies monitoring needs to have the basic performance of technical capabilities, the ability to accurately monitor online in real time, the ability to timely transfer monitoring data to the national monitoring department and other basic performance [11-12]; it is required to be able to accurately and efficiently, quickly and accurately achieve the automatic acquisition and release of monitoring data during the national environmental emergencies emergency [13-14] .

2.2. Characteristics of Water Pollution Sources

At present, nitrogen and phosphorus pollution has been detected in urban environments above a certain concentration, and industrial production has been stopped in some cities' wastewater treatment plants, so it is important to analyze and study nitrogen and phosphorus pollutants in urban wastewater [15-16]. The detection of water pollution sources can also be observed with the help of remote sensing technology in order to obtain a certain percentage of data on the surface properties of water bodies. A lot of detailed information can be found on the surface of water bodies in remote sensing images [17-18]. After acquiring high-resolution remote sensing images by CCD cameras as well as hyperspectral images for water body surface analysis, it is found that (1) there is a significant chromatic aberration phenomenon on the water body surface, (2) there is a lot of gray scale information (gray scale) on the water body surface, and (3) there are some tiny structures, pores and gaps (pore size) on the water body surface [19-20].

2.3. Principle of the Method

The basic principle of systematic cluster analysis is to first consider all the individuals in the sample as different categories, calculate the distance between different categories, cluster the close categories into one category, and then recalculate the distance between categories and cluster them again, and so on, until the whole sample is grouped into one category. In the output result, there is no fixed number of classification results, and the number of classification results should be selected according to the situation. This systematic clustering analysis uses the method of sum of squares of deviations (Ward's method) as the method of clustering, and the principle is as follows.

In a sample with k classes G1,G2,..., Gk, with xit denoting the vector of variables of the ith sample in Gt, nt denoting the number of samples in class Gt, and xt denoting the center of gravity of Gt, the formula for the sum of squares of the deviations of the samples in Gt is shown in 1.

$$S_t = \sum_{i=1}^{n_t} (x_{it} - \bar{x}_t)^t (x_{it} - \bar{x}_t) \tag{1}$$

In calculating the inter-category distance, the squared Euclidean distance (SED) was used this time to calculate the similarity and difference between the two. The calculation formula is shown in Equation 2.

where d2ab is the square of the distance between samples a and b; m is the dimensionality of the sample, i.e., the number of factors; and yaj and ybj are the measurements of the jth factor of samples a and b, respectively.

$$d_{ab}^2 = \sum_{j=1}^{m} (y_{aj} - y_{bj})^2 \tag{2}$$

In the case of standardised data, the correlation coefficient of the variables is the variable covariance, i.e.

$$r_{ij} = S_{ij} = \frac{\sum_{i=1}^{n} (x_{ij} - \bar{x}_i)^t (x_{ij} - \bar{x}_j)}{\sqrt{\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2} \sqrt{\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2}} (i, j = 1,2,..., p) \tag{3}$$

Therefore, for the data matrix, the correlation matrix R and covariance matrix S of the variables are the same, i.e.

$$S = R = \begin{bmatrix} r_{11} & r_{12} & \Lambda & r_{1p} \\ r_{21} & r_{22} & \Lambda & r_{2p} \\ \Lambda & \Lambda & \Lambda & \Lambda \\ r_{n1} & r_{n2} & \Lambda & r_{np} \end{bmatrix} \tag{4}$$

The factors can be derived by finding the eigenvalues and eigenvectors of the R or S matrix.

3. Experimental Research

3.1. Water Pollution Source Management Resources Construction

(1) Sample collection

In this study, an unmanned aerial vehicle (UAV) was used to collect samples from a river reservoir. The UAV was equipped with a CCD camera to obtain data on the surface characteristics of the water body and to image, locate, pixelate and extract the sample texture to obtain data on the concentration of elements in the water body. The sample for this study was a lake approximately 20 m long, 10 m wide and 3 m high, with a sampling area of 0 to 4 m depth and 2 m spatial resolution. The lake was located mainly 40-50 cm below the river surface, with a water depth of approximately 10-30 cm, a length of approximately 30 m and an area of approximately 8 acres.

(2) A combination of microscopic methods, infrared thermography and water surface features.

Microscopy can quickly provide spectral information of the target image, and this information can be used to effectively extract information about the surface features of the water body. Based on this feature, microscopy techniques and infrared thermography analysis methods are used based on the use of CCD image data to analyse the surface characteristics of water. Both techniques analyse the surface characteristics of water bodies in the same spectral band, using infrared thermography and map microscopy to analyse the surface production index of water bodies. In the process of water pollution source management, the combination of infrared analysis and microscopic analysis can improve the ability to analyse the surface characteristics of water bodies, reduce the analysis workload and improve the accuracy of the analysis, therefore, this paper chooses the combination of infrared and microscopic techniques to conduct a comprehensive analysis of water quality in the process of water pollution source management.

(3) Classification of water bodies

As the physical characteristics of the surface are closely related to the changes in the aquatic environment, the use of regional segmentation methods can effectively improve water quality monitoring and management. Regional segmentation can be subdivided into two regional methods and in this work the microscopic method is used for the regional segmentation of water bodies. As water bodies are circular under the microscope, by using microscopic water body data for area segmentation, geometric information about each water body area, such as the location, size and colour of the centre of the water body, can be obtained. The general method used to segment water body regions is as follows. Determining the position of the centre of the water body in the image; selecting the colour of the centre of the water body and using the colour space difference method; selecting an appropriate colour for the centre of the water body and using grey correlation analysis; using fuzzy functions to obtain the grey scale and area of the centre of the water body; using image segmentation techniques to obtain the shape of the water body and using geometric information to delineate the boundaries.

3.2. System Requirement Analysis and Overall Design

(1) System requirement analysis

From the perspective of quantitatively describing the uncertainty of source term parameters in the process of water pollution traceability, we are committed to developing a simple and practical river outbreak water pollution traceability management system, aiming to save its learning of relevant algorithm theories, eliminating its tedious process of constructing models and programming and debugging.

(2) Overall system design

Based on the architecture of the software development process, the overall design of the river outbreak water pollution traceability management system is carried out. The system consists of 4-layer architecture of user layer, business layer, support layer and data layer, and its specific structural framework diagram is shown in Figure 1.

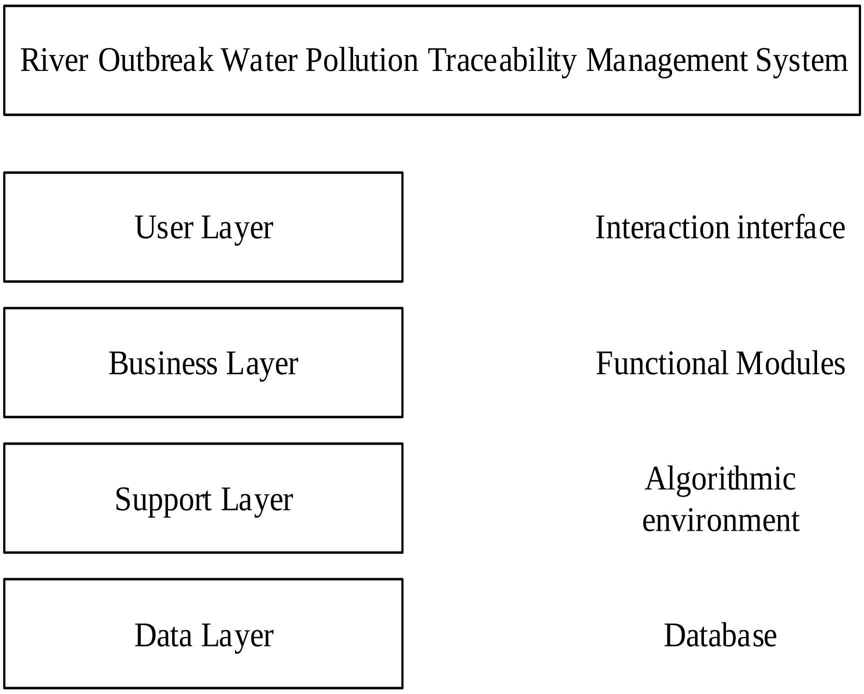

Figure 1. Structural framework of the river outbreak water pollution traceability management system

(3) System development environment

The software and hardware environment for the development of the river outbreak water pollution traceability management system is as follows.

Software environment.

(a) Operating system: Windows 10 Professional 64 bit (10.0, Ver: 17763).

(b) BIOS: BIOS Date: 11/19/2013 17:22:28 Ver: 09.01.

(c) DirectX version: DirectX 12.

(d) Microsoft Windows Server 2008 R2.

(e) MySQL Server.

(f) MATLAB R2019b.

4. Experimental analysis

4.1. Source Analysis of Pollutants in Inland Rivers

Through the investigation of the construction of sewage network in the development zone, the transformation of rural villages, the distribution of agriculture and animal husbandry and the discharge of sewage, the sources of pollutants in the river in the development zone can be summarized into three aspects: 1) point source pollution brought by incomplete interception of domestic sewage and industrial production wastewater in urban areas, direct discharge of domestic sewage in some rural areas, leakage of damaged pipe networks, drainage from livestock farms, etc., the proportion of its pollution volume to the total pollution volume CODCr73.7%, ammonia nitrogen 76.5%, total phosphorus 81.2%; 2) agricultural surface pollution and its rainwater runoff brought about by surface pollution, the proportion of pollution accounted for 6.3% CODCr, ammonia nitrogen 3.5%, total phosphorus 4.0%; 3) the river accumulated over the years the formation of endogenous pollution brought about by the siltation of the substrate, the proportion of pollution accounted for the total amount of pollution were CODCr20.0%, ammonia nitrogen20.0%, total phosphorus14.8%. The discharge of pollutants in the river in the development area is detailed in Table 1 and Figure 2.

Table 1. Summary of pollutant discharges from inland rivers in the Development Zone

Source of pollutants	Pollutants		
	CODcr(t/a)	Ammonia nitrogen (t/a)	Total phosphorus (t/a)
Direct discharge	2286.7	811.9	98.3
Surface Source Influent	197.1	36.6	4.8
Internal source pollution	621	212.1	16.5
Total	3104.8	1060.6	119.5

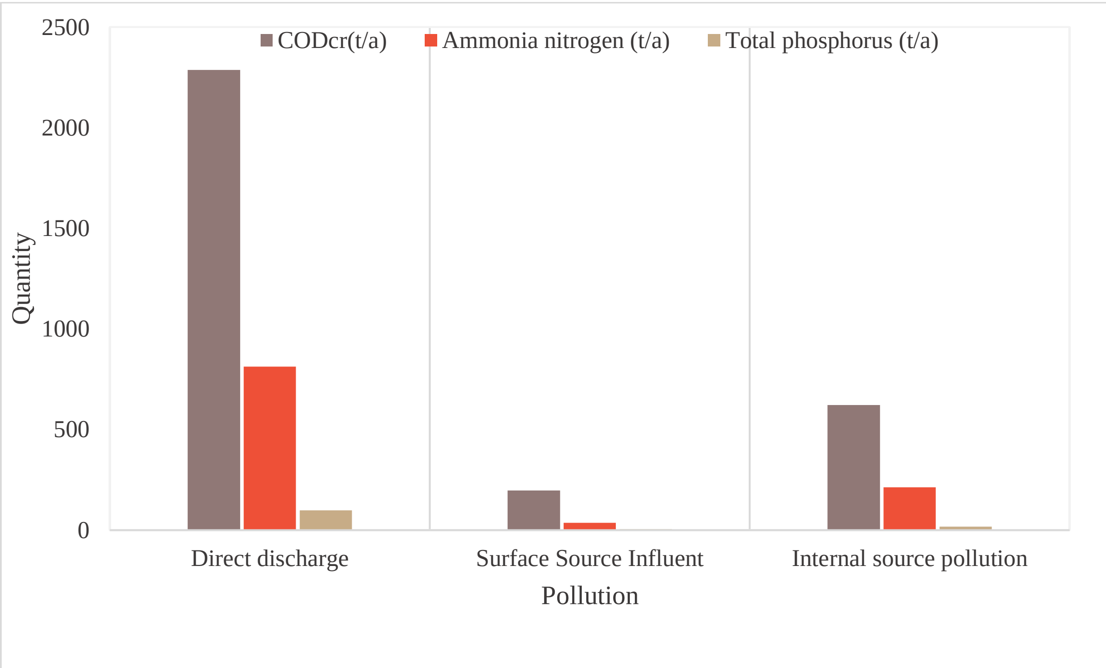

Figure 2. Analysis of pollutant discharges from inland rivers in the development zone

4.2. Selection of River Remote Sensing Inversion Indicators

First of all, the river water quality monitoring data acquired over the years were analyzed to determine the main pollution indicators affecting river water quality. Collect the routine monitoring data of river water quality in the past 4 years, a total of 186 groups. Each group of data includes 21 routine monitoring of water quality indicators. Using surface water Ⅲ water quality standards for data analysis, water quality indicators in CODCr, potassium permanganate index, ammonia nitrogen and total phosphorus there are 85 groups of data do not meet the water quality standards, the remaining 101 groups of monitoring data all meet the requirements of surface Ⅲ water quality. In the 85 groups of data do not meet the water quality indicators, CODCr exceeded 74, potassium permanganate index exceeded 43, ammonia nitrogen exceeded 16, total phosphorus exceeded 24. The number of exceedances accounted for 39.8%, 23.1%, 7% and 12.9% of the total number of monitoring groups, respectively. The main water quality indicators exceeded the number of standards and exceeded the percentage of the total number of monitoring is shown in Table 2.

Table 2. statistics on the number of exceedances of water quality indicators

Index	Number of exceedances	percentage
CODCr	74	39.5%
Potassium permanganate	43	23.3%
Ammonia nitrogen	16	7.3%
Total phosphorus	24	12.7%

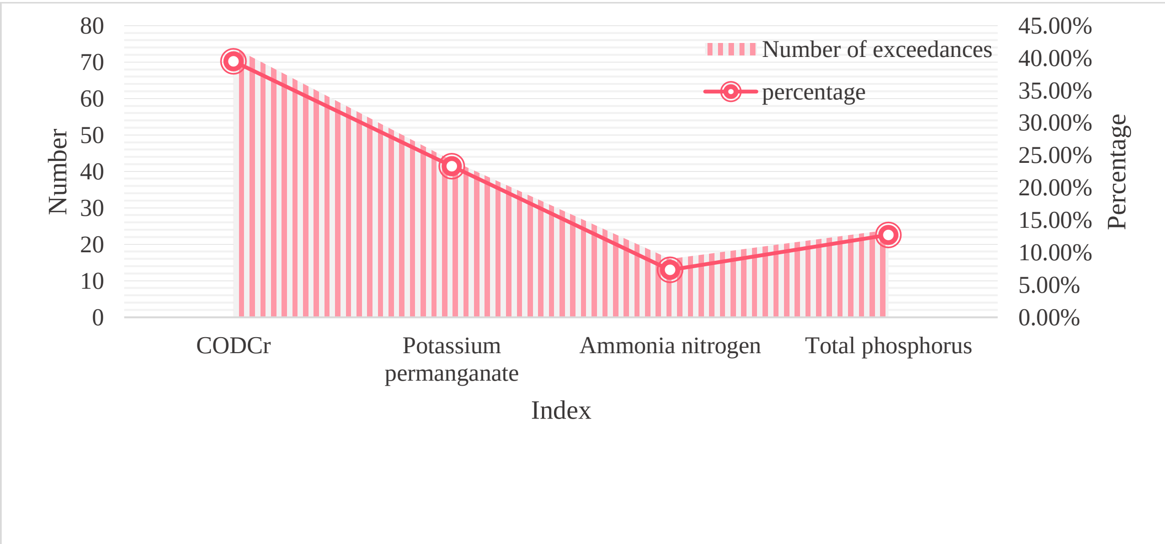

Figure 3. Statistical analysis of the number of water quality indicators exceeding the standard

The analysis results in Figure 3 show that from 186 sets of river water quality routine monitoring data in 4 years, the main indicators affecting river water quality are CODCr, potassium permanganate index, total phosphorus and ammonia nitrogen. According to the aforementioned analysis of remote sensing water quality monitoring principles and monitoring indicators, this study selected ammonia nitrogen, total phosphorus and CWQI values reflecting comprehensive water quality as water quality indicators for remote sensing inversion to understand and grasp the spatial and temporal distribution characteristics of river water environmental quality and water pollution.

4.3. Test Results

Since CWQI is an index reflecting the comprehensive water quality of the water body, which is calculated by the actual measurement data, it has no accurate actual measurement value itself, so the inversion result of CWQI does not need to be verified for accuracy. See Table 3.

Table 3. Inverse model ammonia nitrogen and total phosphorus test results statistics

The River	River 1			River 2		
	Maximum	Min	Mean	Maximum	Min	Mean
Calculated ammonia nitrogen	0.278	0.259	0.268	0.75	0.128	0.439
Measured Ammonia Nitrogen	0.348	0.14	0.211	1.04	0.14	0.59
Ammonia nitrogen error	-	-	26.9%	-	-	25.6%
Calculated total phosphorus	0.021	0.012	0.020	0.052	0.025	0.039
Total phosphorus measured	0.029	0.010	0.016	0.066	0.029	0.048
Total phosphorus error	-	-	21.2%	-	-	18.8%

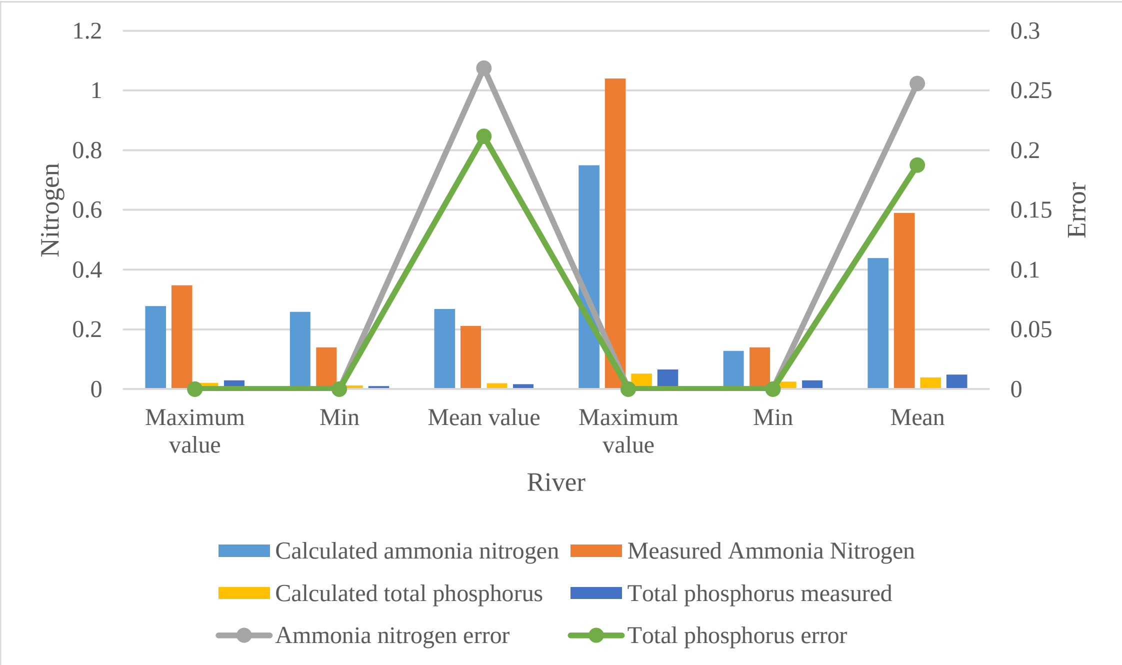

Figure 4. Analysis of ammonia nitrogen and total phosphorus test results of the inverse model

From the validation results Figure 4, the average error of ammonia nitrogen in River 1 is 26.9% and the average error of total phosphorus is 21.2%; the average error of ammonia nitrogen in River 2 is 25.59% and the average error of total phosphorus is 18.75%. The errors are small, and the inverse models established by applying remote sensing technology to the water quality of Yi River and Shushi River have certain accuracy, and this study can apply the inverse models to the study of the spatial and temporal distribution characteristics of river water quality.

5. Conclusion

This paper analyses the current situation of each river through microscopic techniques, and builds and analyses resources for river management based on the water class characteristics, hydrogeology, soil physicochemical, biochemical and water quality characteristics of the river basin. The system analyses the water resources and terrestrial water quality monitoring data, divides the water class, terrestrial and river in the image into classes to establish the resource construction scheme, and gives the optimisation scheme of the corresponding index. Through the establishment of the model in this paper, rivers can be classified in a reasonable way. Through microscopic image recognition, the key indicators that can be used for river water quality class evaluation are screened and the classification of river water resources and terrestrial water quality is carried out in conjunction with relevant literature.

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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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