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A Novel Spatiotemporal Data Model for River Water Quality Visualization and Analysis

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ABSTRACT River water quality (RWQ) data has obvious characteristics of spatial and temporal distribution, and tables are conventionally exploited for storage of multi-period monitoring data of RWQ; however, neither effective visualization nor accurate analysis of the obtained data can be realized due to its dispersion character. In this paper, a novel spatiotemporal data model is proposed for RWQ data to realize conveniently data representation and spatiotemporal analysis. In this model, a spatial point, containing both location and dynamic water quality information, is considered as the basic element of river spaces, and methods of expanding a point to a line segment, a flat surface and a cube are designed respectively so as to make this model be applicable to different generalizations of river spaces. Moreover, a temporal data storage structure is designed so that efficient inquiry and advanced analysis of RWQ data can be guaranteed and the occupied memory space can be reduced. Finally, case studies are conducted by performing 3D visualization, trend analysis and anomaly identification on RWQ data, the result of which showing that tridimensional representation of RWQ data can be realized efficiently, the computational complexity is reduced significantly and the occupied memory space of monitoring data is effectively economized. Accordingly, the proposed spatiotemporal data model can contribute to the efficient visualization and advanced analysis of RWQ data.

INDEX TERMS River space, spatiotemporal data model, water quality prediction.

I. INTRODUCTION

With the continuous growth of population and the rapid development of industry and agriculture, rivers are suffering various degrees of pollution, presenting a serious threat to drinking water safety, social and economic development, etc. [1]–[3] In recent years, river pollution incidents, e.g., the one occurred in Animas River, America in 2015 [4] and another one occurred in Jialing River, China in 2017 [5], have caused serious impacts on regional economic development and the safety of the peoples life and property. It has been an urgent demand to gain timely both existing situation and abnormal information of RWQ [6]–[8]. Under this background, rapid acquisition and efficient analysis of RWQ data have aroused great attention of government departments at all levels and researchers at home and abroad [9]–[11].

Considerable attention has been paid to the research and development of hardware devices to improve the efficiency of in-field RWQ monitoring. Limited by the hardware configuration of mobile equipment, only several simple water quality parameters (e.g., pH, temperature, etc.) can be obtained in the earlier researches [12]. Along with the development of basic hardware, e.g., sensors, digital cameras, etc., more water quality parameters, e.g., COD, NH3-N, Chl-a, etc., can be obtained conveniently [13], [14]. To describe efficiently the spatial distribution characteristics of RWQ, the design and optimization schemes of monitoring networks have been investigated by many researchers. Both the numbers and locations of monitoring sites are commonly determined according to basic characters of watershed basin [15], e.g., point and diffuse pollution sources [16]. And the spatial distribution of monitoring sites is usually further optimized from the global perspective so that RWQ state can be grasped with less sampling sites [17]. After the acquisition of monitoring data, efficient means for data transmission are also essential and have been concerned by some researchers. To realize efficient and reliable transmission of monitoring data of RWQ, several monitoring systems [18]–[20] have been designed

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and implemented based on wireless sensor network, realizing continuous and remote data monitoring based on wireless communication protocols.

Great progress has been made by the above-mentioned approaches in terms of RWQ data monitoring & transmission. Efficient organization and analysis of obtained RWQ data, nevertheless, is ignored. As a result, it is difficult to grasp global distribution, changing trend and abnormal information of RWQ, which may result in property damage, personal injury, etc. To the best of our knowledge, there is only a limited number of works that are focused on the topic of RWQ data organization and analysis; for instance, a knowledge discovery algorithm of hydrological data was put forward for quantitative information extraction of RWQ, extracting sequential patterns based on stations located along several rivers and then filter and group theses patterns to generate spatialized indicators for decision support [21]. Another approach based on ontology modeling was proposed to evaluate RWQ and the relevant processing knowledge, in which the built ontology model is specially designed for RWQ monitoring so that RWQ data with semantic properties can be represented and the semantic relevance among the different concepts involved in RWQ monitoring domain can be built [22]. A GIS-based scheme of RWQ assessment was designed and applied in Klang River, Malaysia, in which a risk hazard map is constructed according to data sets of BOD, COD, TSS and NH3, and the hazard level for each parameter of each station is assessed by the Risk Matrix Approach [23]. To achieve the goal of abnormal RWQ prediction, different landscape effects on RWQ were commonly assessed by geographic analysis methods, e.g., principal component analysis [24], fuzzy c-means and subtractive clustering [25], artificial neural networks [26], etc.

In summary, the main emphases of traditional researches in terms of RWQ monitoring include three major aspects, i.e., design & development of monitoring devices, construction & optimization of monitoring networks and efficient & reliable transmission of monitoring data. Organization, management and analysis of obtained RWQ data, however, have captured relatively little attention, especially from the aspect of data model construction. To fill this gap, a spatiotemporal data model is designed and implemented in this paper, the innovations of which can be summarized as follows:

- ❖ A data structure is designed to improve the efficiency of RWQ visualization and analysis.
- ❖ A method is put forward for memory space reduction of RWQ data without affecting normal uses.
- ❖ A spatiotemporal data model is implemented which is applicable to various generalizations of river spaces.

II. THE MAIN IDEA OF THE PROPOSED SPATIOTEMPORAL DATA MODEL

It is well known that RWQ data has strong spatial and temporal distribution characteristics. Although it cannot be visualized directly by human eyes, it fills up river spaces in its own way. At present, it is still a problem that how to represent and analyze the invisible RWQ data. The main idea of the spatiotemporal data model in this paper is put forward based on the following assumption. Similar to water quality indicators, imagine that there are abundant spatial points that can detect water quality parameters (e.g., TN, TP, COD, NH3-N, Chl-a, etc.) around their locations and each river space is full of such innumerable points. It can be inferred from the above assumption that RWQ data and its distribution characteristics can be described by gathering these points and analyzing their inherent attribute information. In this study, the idea of designing the spatiotemporal data model is proposed as follows: each spatial point has its own coordinate (x, y, z), as well as the water quality data in the exact location at various times. A spatial point in river spaces could be expressed by

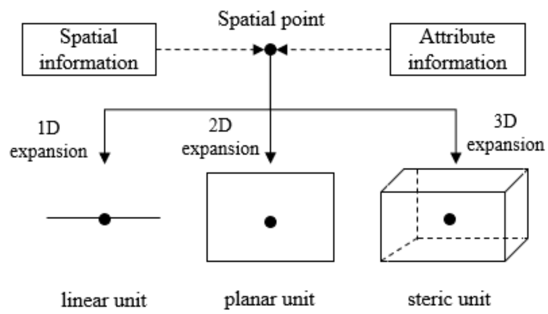

FIGURE 1. Idea of a spatial point to form linear, planar and steric units.

$$Pt = F\ \{(x,y,z)\ ,Seq\langle tuple_i[time_i,\ value_i(v_1, v_2, \ldots, v_n)]\rangle\} \quad (1)$$

where Pt represents the spatial point, (x, y, z) denotes the 3D coordinate of Pt, $tuple_i$ $[\cdot]$ means a tuple which is exploited to record RWQ parameters of Pt at various times, $time_i$ is the time mark, $value_i$ stands for the corresponding RWQ data of $time_i$ and $v_i (i \in [1, n])$ represents the $i\text{-}th$ parameter of RWQ.

In practical applications, river spaces can be abstracted into three types, i.e., linear space, planar space and steric space. The basic units of the three types of river spaces are linear unit, planar unit and steric unit, respectively. In the proposed spatiotemporal data model, a spatial point, containing both spatial (coordinates) and attribute (water quality) information, is the fundamental unit of river spaces. And each spatial point can be multi-dimensionally expanded to construct linear, planar and steric units (Fig. 1).

Obviously, in the proposed spatiotemporal data model, river spaces in each dimension can be filled up by setting reasonable radii of point expansion. Accordingly, RWQ data can be expressed efficiently by the designed data model in theory.

III. ABSTRACTION OF THE PROPOSED SPATIOTEMPORAL DATA MODEL

In this study, for practical uses, river spaces are logically classified into three types of spaces, namely linear space, planar space and steric space (Fig. 2). The steric space is the

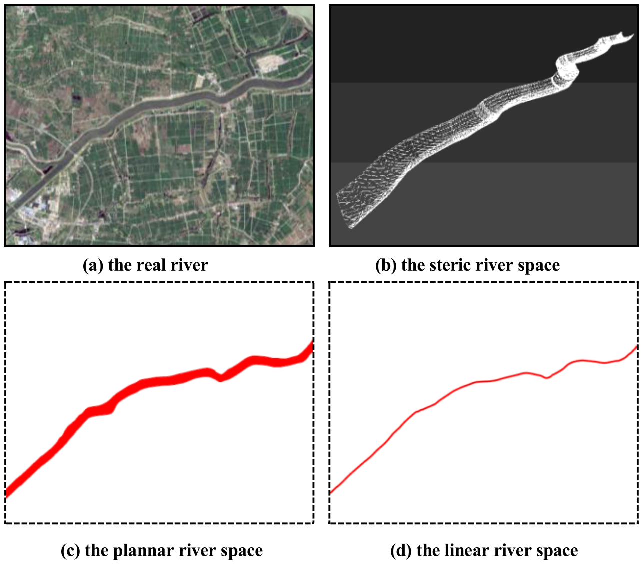

FIGURE 2. Diagram for the logical abstraction of river space.

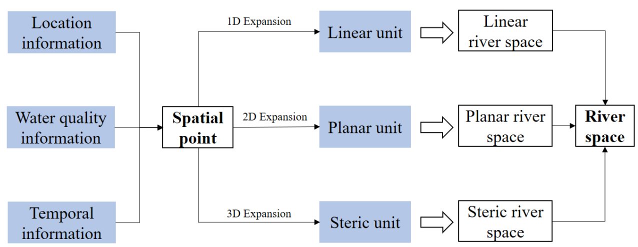

FIGURE 3. Design of the proposed spatiotemporal data model.

closest to reality, while the linear space and the planar space are two frequently applied forms of river spaces.

A steric river space (Fig. 2(b)) can be regarded as a very similar counterpart of the river existing in the real world. In this kind of river spaces, the visualization of RWQ data can be very realistic and the convenient analysis and prediction of water quality can be guaranteed. In this case, a river space is made up of numerous cuboids and water quality data has characteristics of both horizontal and vertical distribution.

Although a steric river space is the optimal expression of the corresponding real river space, it is sometimes not exploited for the visualization and analysis of RWQ data, for the limitation of both data source and computer hardware. Accordingly, a planar river space (Fig. 2(c)) is commonly applied to represent approximatively the real river space. In this case, a river space is composed of a number of planar polygons.

A linear river space (Fig. 2(d)) is usually employed to make generalization of the corresponding real river space when the geographical scope of the study area is very wide or only the summary distribute information of water quality is required. In this case, a river space is composed of a number of line segments.

Based on the above-mentioned abstractions, the proposed spatiotemporal data model can be designed as shown in Fig. 3.

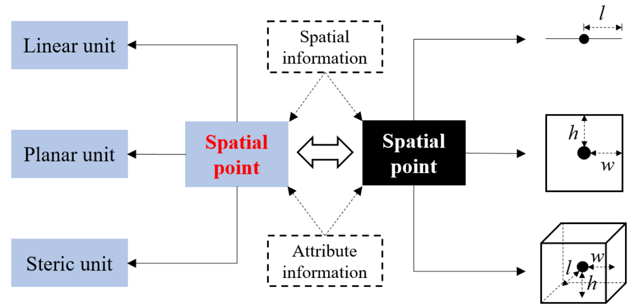

FIGURE 4. Data structure framework for the realization of the spatial data model.

IV. REALIZATION OF THE PROPOSED SPATIOTEMPORAL DATA MODEL

A. REALIZATION OF DATA STRUCTURE

According to the logical analysis above, linear, planar and steric units can be constructed by the basic elements, i.e., spatial points, using multidimensional expansion mode. To implement the spatiotemporal data model, the data structure should be designed accordingly (Figure 4).

For those linear units, planar units and steric units organized by expanding spatial points, the corresponding structures can be designed as

(i) Linear unit:

$$\{(x, y, z)\,, half\ \ length, Seq\,\langle tuple_i\,[time_i, value_i]\rangle\}$$

(ii) Planar unit:

$$\{(x, y, z)\,, half\ width, half\ \ height\,, Seq\,\langle tuple_i\,[time_i, value_i]\rangle\}$$

(iii) Steric unit:

$$\{(x, y, z)\,, half\ width, half\ height\,, half\ length,\\ Seq\,\langle tuple_i\,[time_i, value_i]\rangle\}$$

where a spatial point is located at the center of each unit and (x, y, z) is the coordinate of the point, half length, half width and half height indicate the half-length of the sides of units, Seq$\langle\cdot\rangle$ denotes the sequence of time series RWQ data which is realized by a list structure in this paper.

B. DISCRETIZATION OF RIVER SPACE

The key task of this study is to divide river spaces into independent parts and characterize them by spatial points. It can be obviously seen from the description in Part A of Section IV that each spatial point occupies an individual part within a river space, and thus spatial points will not be recorded redundantly when constructing different units. Moreover, adjacent parts in a river space must be consecutive with no intersection to guarantee (i) the whole river space can be filled up completely and (ii) there are no parts that have ambiguity attribute information. Accordingly, the following condition must be satisfied:

$$\begin{cases} S\,(Pt_0) \cup S\,(Pt_1) \cup \ldots \cup S\,(Pt_{m-1}) = R \\ S\,(Pt_i) \cap S\left(Pt_j\right) = \emptyset\,(i \neq j) \end{cases}$$

where R represents the whole river space, m is the total number of spatial points that fill up the river space, $S(Pt_i)$ means the part of river space occupied by Pt_i.

C. OPTIMIZATION OF DATA STORAGE

RWQ data is composed of several parameters which are commonly represented by float numbers. It is well known that float numbers occupy more memory space than integer ones. An optimization method of RWQ data storage is designed in this section to reduce the occupied memory space during data processing phase, which can be summarized as the following three steps:

Step 1: Unify the fraction length of values of RWQ parameters using the rounding method. Assume that the unified length is l.

Step 2: Magnify the values of water quality parameters 10^l times, and it can be inferred that all the values of RWQ parameters will be converted into integers which can be then stored as unsigned short integer values.

Step 3: Store these converted values which will be reconverted into floating numbers, i.e., divided by 10^l, before data representing and analysis.

For example, the TN parameter of a spatial point at one time is 1.38 (unit: mg/L), then 4 bytes (the basic storage unit of a float number) are needed to store the value. Exploiting the designed method (assume that $l = 2$), 1.38 is firstly magnified 10^2 times and 138 can be generated, which can be stored by 1 byte (the range of unsigned short integer numbers stored by 1 byte is from 0 to 255). It can be concluded that the occupied memory space of RWQ data can be economized greatly by the designed method.

V. CASE STUDIES

A. VISUALIZATION OF RWQ DATA

Long-term RWQ data of a river in Chaohu Basin, China, was employed to test and verify the proposed spatiotemporal data model. The key parameters are set as follows: $l = 2$, spatial points are arranged using equally distant method and $half\ width = half\ height = half\ length = 0.1m$. Moreover, functions of RWQ data visualization and analysis are implemented employing Unity3d platform and C# programming language.

It is well known that river spaces are continuous while the distribution of monitoring stations is discrete. Accordingly, it is necessary to make RWQ data spatial interpolated so that each spatial point can be assigned water quality information. In this paper, based on long time series monitoring data, the spatial and temporal distribution characteristics of RWQ can be expressed visually and intuitively by exploiting spatial interpolation methods (Fig. 5). Applying the same method, RWQ can be easily represented in a linear river space.

Within traditional methods (using tables to store RWQ data), it is difficult to achieve ''stereo-vision'' representation or advanced analysis of RWQ. In this study, a stereo river space can be represented conveniently by visualizing

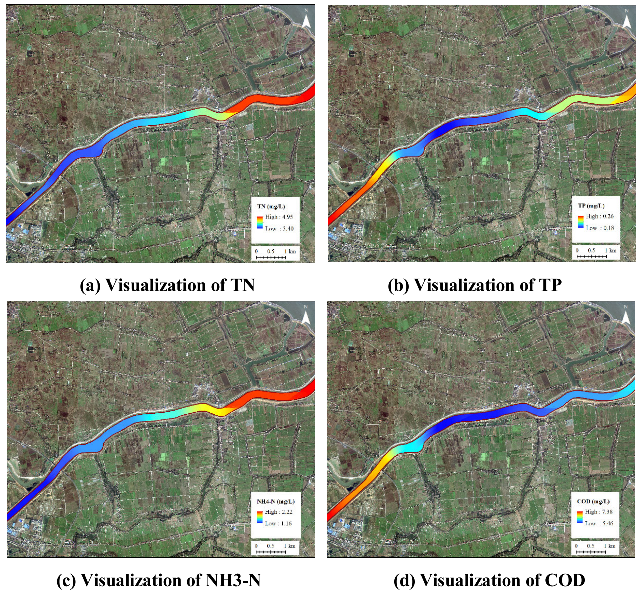

FIGURE 5. Visualization of water quality data in a planar river space.

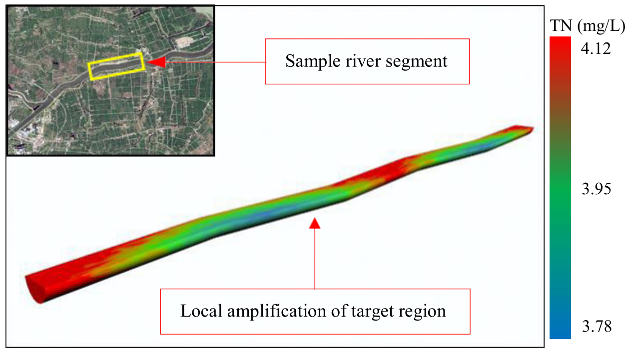

FIGURE 6. Visualization of TN in stereoscopic view.

the attribute information of spatial points, i.e., water quality parameters. Fig. 6 shows the stereo-visualization result of RWQ data, taking the TN parameter of a target river segment as example.

In addition, RWQ data is projected onto a 2D planar plane in conventional methods for data visualization, and it is extremely difficult to grasp the vertical distribution characteristics of water quality. In this paper, by gathering spatial points at a horizontal or an upright plane and acquiring information from their inherent properties, the vertical distribution of RWQ can be described. Fig. 7 shows the distribution of TP at three different depths in a chosen river segment (depth means the distance from the surface of the water to the specified layer), and the visualized result of RWQ in the view of profile is given in Fig. 8 (taking the value of Chl-a concentration as example).

B. ADVANCED ANALYSIS OF RWQ DATA

Effective expressing methods could make invisible RWQ data visualized, which can contribute to grasp the spatial-temporal distribution of water quality. On this basis, it is

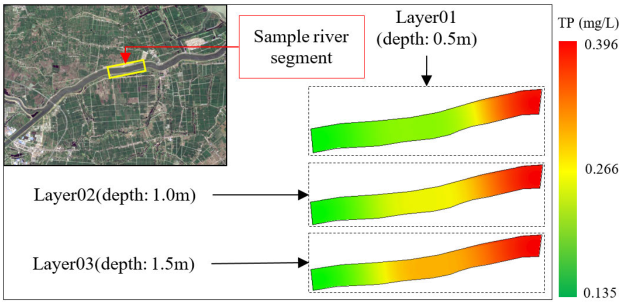

FIGURE 7. Visualization of TP in the view of layered-graph.

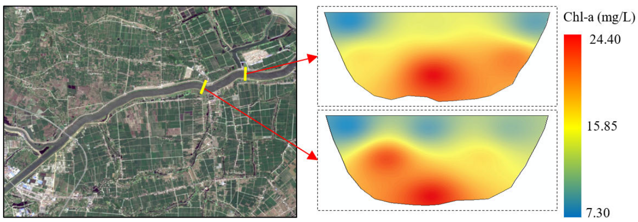

FIGURE 8. Visualization of RWQ in the view of profile.

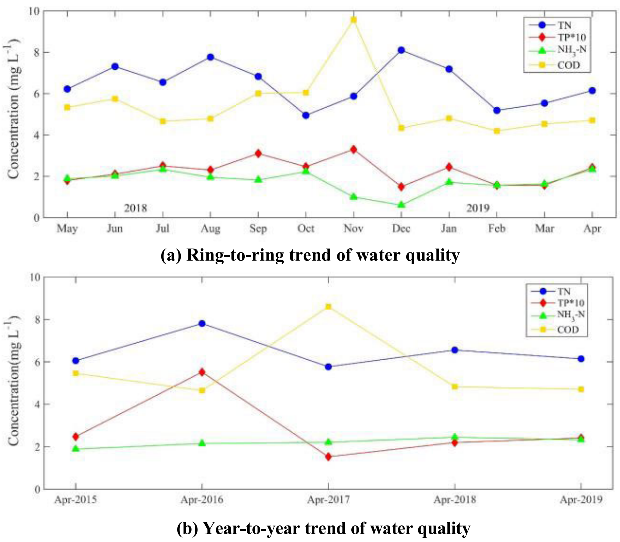

FIGURE 9. The result of time trend analysis of water quality.

more significant to conduct advanced analysis on the acquired RWQ data to grasp rapidly both changing trend and abnormal information of RWQ data.

1) TREND ANALYSIS

Trend analysis of RWQ data refers to the trend calculation of water quality parameters over time at fixed positions in river spaces. In traditional methods, this kind of work is mainly completed by analyzing large amounts of monitoring data manually, the efficiency of which is quite low. Based on the proposed spatiotemporal data model, the time trend analysis of RWQ at a certain position can be realized conveniently by fitting the time series attribute data of the corresponding spatial point in chronological order (Fig. 9).

Here, let k and l be the numbers of monitoring sites and data periods respectively. It is obvious that each period of RWQ data of each sampling site will be calculated one time to represent RWQ data, and the computation times of trend analysis is $k \times l$. In traditional methods, different periods of monitoring data are stored in various tables, and it can be inferred that the computation times of trend analysis is $l \times k \times l = k \times l^2$.

2) ABNORMAL INFORMATION IDENTIFICATION OF RWQ

Compared with normal water quality data in river spaces, abnormal information about RWQ (e.g., location, area, concentration of parameters, etc.) has captured more attention of managers of water environment. In this paper, river spaces are actually discretized into abundant solid, planar or linear spaces, each of which is formed by expanding a spatial point. And long time series RWQ data is considered as attribute information of discrete units in river spaces. Accordingly, the abnormal water quality information can be identified automatically and rapidly by analyzing the attribute information of spatial points.

In this research, abnormal information of RWQ can be classified into two categories, i.e., temporal anomaly and spatial anomaly. While temporal anomaly can be recognized by conducting comparisons among current water quality data and the historical counterparts, spatial anomaly can be discriminated by extremum judgment of water quality parameters within a certain region.

For temporal anomaly identification, target data (RWQ parameters within a specific time range) will be firstly chosen and organized in chronological order. Let L_i $(0 \leq i \leq n-1)$ be the sequence of the target data (L_{n-1} means the latest water quality parameter). Then, L_{n-1} will be regarded as an anomaly if Eq. (2) is true. Here, n denotes the total number of target data periods and δ stands for the given threshold.

$$\left| \frac{1}{n} \sum_{i=0}^{n-2} L_i - L_{n-1} \right| \geq \delta \tag{2}$$

Here, let k' and l' be the numbers of monitoring sites and the number of target data periods respectively. Each period of monitoring data of each sampling site must be calculated one time for anomaly judgment, as well as subtraction (one time) and threshold comparison (one time). The total computation times is thus $k' \times l' + 2$. In conventional schemes, it can be inferred that the required computation times for temporal anomaly identification is $k' \times (l')^2 + 2$.

For spatial anomaly recognition, the key task is to judge whether the specified RWQ parameter is the maximum one within a given region. The corresponding spatial points in the region will be chosen firstly according to spatial distance, which can be calculated exploiting Eq. (3). Here, (x_1, y_1, z_1) and (x_2, y_2, z_2) represent the coordinates of two spatial points.

$$s = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2} \tag{3}$$

The target data can be obtained then by extracting attribute information of the chosen spatial points, and the specified water quality parameter will be considered as a spatial anomaly if Eq. (4) is true. Here, N means the number of chosen spatial points, P_i denotes the target water quality parameter of the *i-th* spatial point, and ε is the given threshold.

$$\left| \frac{1}{N} \sum_{i=0}^{N-1} P_i - P^* \right| \geq \varepsilon \tag{4}$$

Here, let k'' and l'' be the numbers of monitoring sites and total data periods respectively. Similar to the process of temporal anomaly identification, it can be inferred from Eq. (4) that the essential computation times of the proposed scheme and conventional schemes are $k'' \times l''+2$ and $k''\times(l'')^2+2$, respectively.

C. PERFORMANCE ASSESSMENT OF DATA STORAGE OPTIMIZATION

An optimization method is presented in this paper to economize memory space of RWQ data. And a set of simulation experiments have been done to test and verify the performance of the presented method. Ten periods of monitoring data of RWQ are taken as experimental data, which are stored by conventional form (float values) and the optimized method (unsigned short integer values) respectively and the occupied memory spaces are separately calculated and compared. The experimental results are shown in Table 1, indicating that the proposed method has a satisfying ability in terms of memory space economization.

TABLE 1. Experimental results of data storage optimization.

Data period	Stored by conventional method (unit: MB)	Stored by the optimized method (unit: MB)
#0	14.04	4.51
#1	25.48	8.37
#2	19.53	5.88
Average of ten periods	21.32	6.33

VI. DISCUSSION

Experimental results show that the efficiency of RWQ data visualization and analysis is improved significantly and the occupied memory space is reduced drastically, exploiting the designed spatiotemporal data model. Firstly, the tasks of multi-period RWQ data visualization and analysis are boiled down to the dealing with time series attribute data of spatial points, and the efficiency can be thus improved. Moreover, RWQ data are stored by integer values, instead of float ones, and the storage space can be reduced accordingly (the larger the volume of RWQ data, the more obvious the effect is).

VII. CONCLUSION

This study mainly contributes on three aspects. Firstly, a spatial point with both spatial and attribute information is exploited as the basic unit of river spaces to efficiently visualize the spatial-temporal distribution of RWQ data. Then, methods of expanding a point to a line segment, a flat surface and a cube are designed respectively to make the proposed data model available for common generalizations of river spaces. Finally, an optimization method of data storage is designed and the occupied memory space of RWQ data can be economized.

There are still some limitations to be solved in our future research. Spatial points are arranged at equal intervals in the proposed data model so that the whole river space can be filled up conveniently and entirely. However, the variation of water quality is uneven in real river spaces and this method has some shortcomings. In those regions where water quality varies greatly, the intervals among spatial points need to be as small as possible so that detailed water quality information can be represented. In contrast, to reduce maximally the occupied memory space of RWQ data, the corresponding intervals should be as large as possible in those regions with little difference of water quality. In our future research, we will pay more attention to the self-adaption adjustment of intervals among spatial points so that both details representation of RWQ and memory space reduction of long-term monitoring data can be realized.

AUTHOR CONTRIBUTIONS

Data curation, Hui Xie; Formal analysis, Hui Xie and Jiuyun Sun; Investigation, Yinguo Qiu; Methodology, Yinguo Qiu; Validation, Jiuyun Sun; Writing – original draft, Yinguo Qiu; Writing – review & editing, Hongtao Duan.

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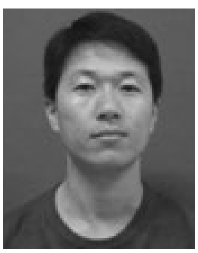

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