

Retraction

Retracted: Big Data Storage Index Mechanism Based on Spatiotemporal Information Cloud Platform

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] J. Xu, B. Chen, and L. Sun, "Big Data Storage Index Mechanism Based on Spatiotemporal Information Cloud Platform," *Security and Communication Networks*, vol. 2022, Article ID 6774821, 8 pages, 2022.

Research Article

Big Data Storage Index Mechanism Based on Spatiotemporal Information Cloud Platform

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In order to study the storage and management mechanism of raster data and vector data for different purposes in data services, a research method of big data storage and indexing mechanism based on spatiotemporal information cloud platform is proposed. This paper discusses the application of big data storage index in virtualization platform, cloud management software, and storage management, so that Hadoop cluster can use the dynamic expansion ability of cloud platform to obtain better expansion ability. High performance statistical applications for geographical conditions are constructed. A high performance geostatistical analysis system Hadoop-Geostatistics is designed and implemented. A variety of spatial statistics index calculation, flow, and MapReduce algorithm was realized. The experimental results show that in the cluster environment, the time consumption is basically the same as that of the single index calculation, while in the single computer environment, when the comprehensive index is calculated in parallel for 10,000 statistical objects, the system performance drops rapidly and reaches an early inflection point. In the comprehensive statistical concurrent calculation, when the time consumption reaches 5×10^7 , the amount of calculation data is as high as 7000, which increases linearly. The experimental data show that the designed spatiotemporal information cloud platform model can store spatial big data, and the storage method is very accurate. By establishing a spatiotemporal information cloud platform, cloud computing technology can provide higher spatial information services.

1. Introduction

Influenced by the development of space science and information science, the computer technology used in the past has also been upgraded and innovated [1]. Under the new development background, the application scope of computer technology is becoming more and more extensive, which requires a more advanced information cloud platform for big data management and high-performance computing, so as to improve the application level of big data in cloud computing [2]. At this stage, China's big data technology has made great achievements in the application of geological management. The Geological Survey Bureau has developed and applied the geological survey information network platform, which includes the application of cutting-edge technologies, such as grid GIS, information technology, distributed computing, and so on. The platform uses Internet technology to complete the acquisition, storage, and

processing of distributed data. In addition, geological cloud 1.0 and geological cloud 2.0 platforms make full use of big data technology and cloud technology to realize efficient management and unified scheduling of infrastructure, data, business applications, and services in traditional geological work. Relevant departments of the ministry of land and resources have built the geoscience big data technology research experimental platform GeoBAD, which is based on Oracle and Hadoop, respectively, providing a good reference for solving the problems of geological big data storage and organization [3, 4].

In a sense, cloud computing and big data complement each other. Cloud computing appeared earlier. It is a computing method based on high-speed network with shared attributes. In essence, it is the virtualization of hardware resources. Big data emerged late. It is a massive data processing technology with three-tier architecture. In essence, it is the efficient storage of massive data [5]. Cloud computing

pays more attention to resource allocation, while big data focuses on resource processing. In short, cloud computing provides data support for big data and a processing platform for big data [6]. At present, big data technology has been able to complete the complete data processing life cycle from data acquisition to data release and has realized the flow operation of the complete chain. However, the following is the highlight of the safety problems in all links of the whole chain. The safety problems are very important, which directly affect the prospect and practicability of the development of big data technology [7]. Chen and others proposed a dynamic coherent quality measure, focusing on the possibility of key errors in achieving the desired performance by characterizing the information effectively transmitted in an integrated system (i.e., the system's system) that can be used to evaluate whether large data interact. Here, we believe that two new measures to calculate the higher than expected error, that is, the conditional expectation of tail error and excessive error (conditional tail error), are used as the quality measurement of a big data system. We illustrate the proposed dynamic coherent quality measurement of several properties (i.e., sufficient random time invariance) of the big data system. In our empirical study, three big data systems based on wavelet transform monitor and predict power demand and carry out reliability and quality management to minimize decision-making errors. The performance of our method in the evaluation shows its superiority and confirms the efficiency and robustness of this method [8].

Based on this research, this paper focuses on data management and high performance in the cloud. The concept of big data and critical technology has been studied in detail, and the DAAS layer of big data has been developed based on the information in the weather platform. According to DAAS, the use of big data and the distribution of census area maps have been developed. It offers procedures to optimize the average-length measurement for control and access to spatial mass data stored on the spatial-temporal cloud platform. DAAS has developed a large data distribution platform for counting public maps, which enables DAAS's ability on a space-time data cloud platform to provide spatial services.

The calculation, processing, and MapReduce algorithms for various spatial statistical indicators are implemented. The experimental results show that the energy consumption is basically the same as that in a single index in the cluster environment, while in the single machine environment, when 10,000 statistics are calculated in parallel, the system performance drops rapidly and reaches an early inflection point. In comprehensive statistical concurrent calculations, when time consumption reaches 510^7 , the computational data volume increases early up to 7,000. Experimental data show that the designed spatiotemporal information cloud platform model can store spatial large data, and the storage method is very accurate.

2. Research Methods

2.1. Spatial Big Data Management Based on Spatiotemporal Information Cloud Platform. Spatiotemporal information

cloud platform is the key support in the construction of smart city. It requires the integration of various digital information in urban management and urban operation, combined with spatial cloud computing technology, to provide solutions for geographical science research and application. At present, most spatiotemporal information cloud platforms focus on providing services using one of the H levels of IaaS, PAAS, and SaaS of cloud computing. For example, the original GIS application system will be directly migrated to the SaaS layer by using the resource services of the IaaS layer to obtain the resource expansion support of the cloud. Moreover, because many geographic information data belong to classified data, they cannot run on the public cloud [9]. The spatio-temporal information cloud platform constructed in this way does not fully utilize the advantages of spatio-temporal information cloud computing. In addition, the platform is difficult to meet the further development needs of geographic science research and application in terms of autonomy, control and security (see Figure 1 for details).

2.1.1. Spatial Data Model

(1) *Topographic Data.* The content of topographic and geomorphic data includes multi-scale DEM data, slope and aspect data derived from DEM, and high-rise zone and slope zone zoning data [10]. The size of its framing grid is 2 m. Slope, aspect, elevation, and slope zoning are derived from DEM. Figure 2 describes the conceptual model of DEM data in topographic data, which is divided into 10 m grid and 2 m grid data according to the grid size, with 1:50000 grid of 10 m and 1:10000 grid.

(2) *Remote Sensing Image Data.* Remote sensing image data are divided into orthophoto image data, original image data, and control point data [11]. The orthophoto image includes divided orthophoto image and whole scene orthophoto image data. The original image data are composed of the original image itself and image thumbnail. The image control point data include control point image and control point information file. The framing orthophoto and image control point data are organized in 1:50000 map frames and are associated with relevant image data through map frame index. Only the satellite image has the whole scene orthophoto image. There is a corresponding relationship between the whole scene orthophoto image and the original satellite image data. The original aerial image is directly associated with the framing orthophoto image data [12]. Figure 3 shows the data model of remote sensing image.

(3) *3D Data.* By overlaying aerial photos, satellite images, digital elevation models, and various vector geographic data, massive 3D terrain datasets are quickly and conveniently created [13]. It supports a variety of data formats and can realize the fusion, projection transformation, and data clipping of data with different resolutions and sizes, so as to produce real texture 3D scenes with any resolution and build the final massive terrain dataset. Through the artificial modeling of ground buildings and road data, the three-

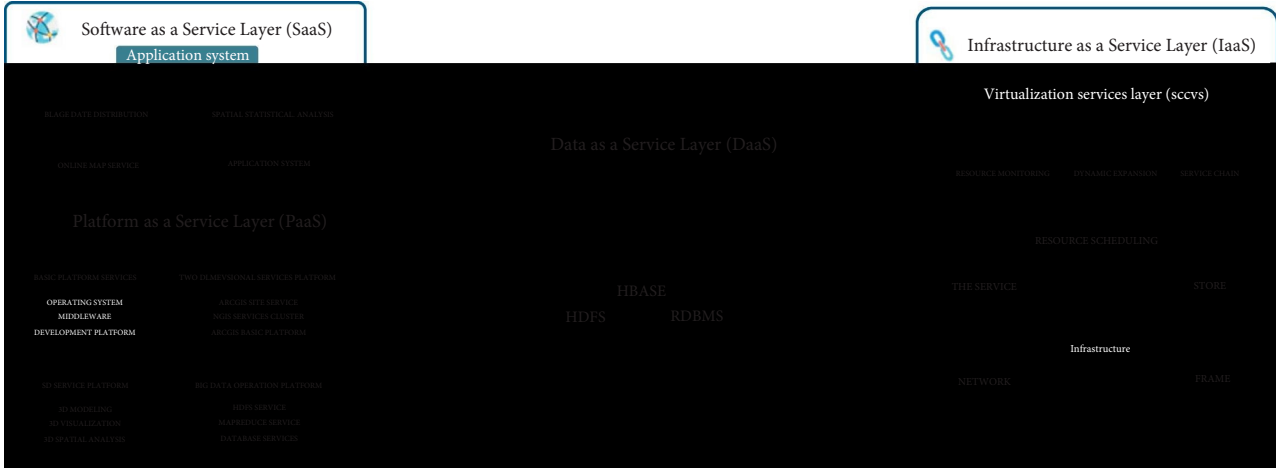


FIGURE 1: Framework of spatiotemporal information cloud platform.

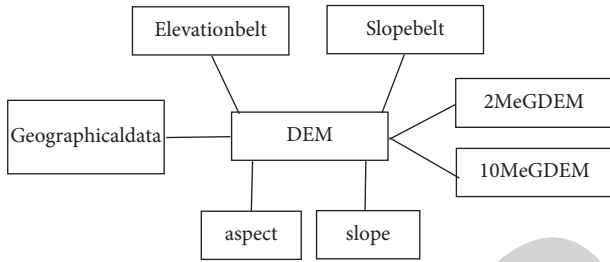


FIGURE 2: Topographic data model.

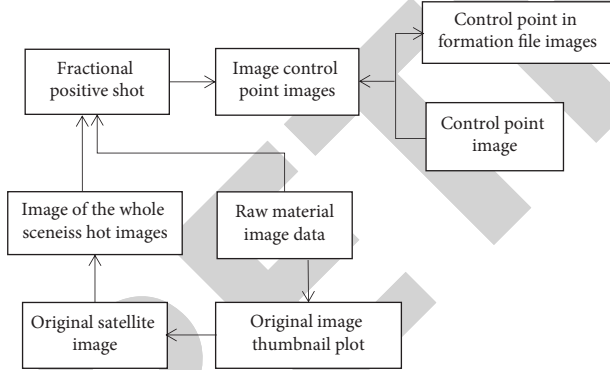


FIGURE 3: Remote sensing image data model.

dimensional result data are finally formed. Figure 4 describes the organization of the three-dimensional data model.

2.1.2. Division of Spatial Data. Because the spatial data may have data skew in distribution, the whole data space needs to be divided. If the ratio of the amount of sampled data to the size of the dataset is relatively small, the required data blocks can be obtained randomly. If the amount of data to be sampled and the actual amount of data are relatively large, it will be cheaper to obtain all data blocks in sequence for sampling. The estimation of the number of disk blocks required for random acquisition has been proposed. It is a function of the amount of sampling data, which can be estimated by formula (1), where M represents the number of disk blocks occupied by the dataset

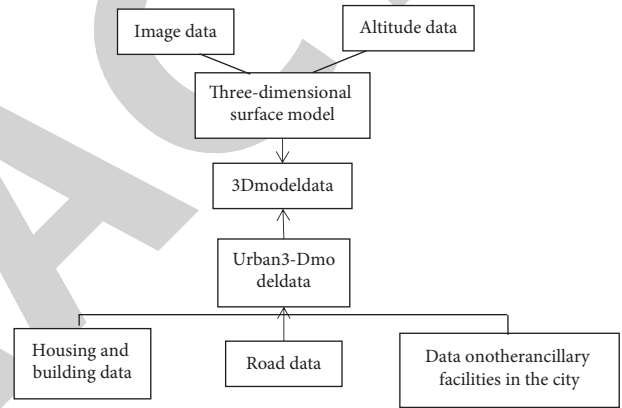


FIGURE 4: Conceptual model of 3D data.

file, n is the number of entries of all data, and K is the size of the amount of sampling data:

$$X_D = m \cdot \left[\prod_{i=1}^k \frac{n \cdot d - i + 1}{n - i + 1} \right] \text{ where} \quad (1)$$

$$d = \frac{1 - 1}{m}$$

A simpler expression can be used to estimate its lower bound, as shown in the following formula:

$$X_D = m \left(1 - \left(\frac{1 - 1}{m} \right)^k \right). \quad (2)$$

Suppose P is the ratio of the cost of sequential read sampling and random read sampling to the disk block. If $X_D > m \cdot p$, the total cost of sequential reading will be smaller. The critical value p can be shown in the following formula:

$$k > \frac{\ln(1 - p)}{\ln(1 - 1/m)}. \quad (3)$$

Therefore, the sampling method to be used can be determined by calculating the values on both sides of the

TABLE 1: Comparison of mainstream virtualization platforms.

Virtualization platform	Full virtualization	Semi-virtualization	Framework	Support libvirt	Support InfiniBand	Support GPU
KVM	Yes	Yes	X86-64, IA64, PPC	Yes	Yes	Yes
Xen	Yes	Yes	X86-64, IA64, PPC	Yes	Yes	Yes
VMware	Yes	No	i686, X86-64	Yes	Yes	Yes
VirtualBox	Yes	No	i686, X86-64	No	No	Yes

formula. If the partition K is greater than the value on the right side of formula (3), sequential reading sampling can be used. Otherwise, random reading should be used to reduce the cost of sampling.

After waiting for the completion of sampling, it is necessary to find the $P-1$ value from the sample as the cutting point of the data partition. After the cutting point is formed, the data partition can be carried out by using the spatial partition function shown in the following formula:

$$f(o) = \begin{cases} 1, H(o) \leq H'[1], \\ j, H'[j-1] < H(o) \leq H'[j], & j = 2, \dots, p-1, \\ p, H(o) > H'[p-1]. \end{cases} \quad (4)$$

2.2. High-Performance Computing of Spatiotemporal Information Cloud Platform

2.2.1. High-Performance Computing Platform in Spatiotemporal Information Cloud Platform. For high-performance computing cloud platform, Linux operating system is easy to expand and customize in application due to its open-source characteristics. Good support for the latest hardware (such as the latest processors, network devices, and so on) is the primary choice of high-performance computing platform. In the world's top 500 high-performance computing, almost all computing platforms adopt Linux operating system. After selecting the operating system, the second key choice of the high-performance computing platform is the virtualization platform, which is the key technology for the spatiotemporal information cloud platform to abstract various resources into a unified and manageable resource pool [14]. At present, the widely used virtualization platforms include Xen, KVM, VMware, VirtualBox, and so on. Different virtualization platforms are suitable for different cloud computing applications. In the spatiotemporal information cloud platform, we pay more attention to the support of high-performance CPU and high-speed network. Table 1 lists the characteristics of the main virtualization platforms.

Libvirt is a set of API to realize the virtualization function under Linux operating system. It can manage the client operating systems established under different virtualization platforms. In the high-performance computing of building spatiotemporal information cloud platform, there are many customer opportunities of operating systems to build in the cloud platform. Therefore, supporting libvirt is a

function that must be selected when building spatiotemporal information cloud platform.

2.2.2. High-Performance Computing Cloud Management Software of Spatiotemporal Information Cloud Platform.

After the cloud platform virtualizes the infrastructure into a resource pool, the management of the resource pool is completed through cloud management software, which is usually called "cloud platform." In the construction of high-performance computing of spatiotemporal information cloud platform, factors such as user management, security, communication, and ease of use need to be considered [15]. With the wide application of cloud computing technology in various industries and fields, many cloud platform software programs with different characteristics and advantages have been produced. In the construction of spatiotemporal information cloud platform and private cloud high-performance computing, the use of open-source cloud platform software is an important consideration for the safe and effective management of spatiotemporal information cloud platform. Typical open-source cloud platform software includes Eucalyptus, OpenStack, XCP (Xen Cloud Platform), Nimbus, and so on. Table 2 compares the characteristics of the main open-source cloud platforms.

Amazon EC2 is currently the world's largest public cloud service, which mainly provides infrastructure (IaaS) layer services. Among the mature cloud platform management software in the industry, the compatibility of EC2 has become an important consideration. Eucalyptus is an open-source cloud platform software. Due to its good user management, KVM support, and multiple sets of high-speed network support, Eucalyptus4.0 is used as the spatiotemporal information cloud platform management software in this paper.

3. Result Analysis

3.1. Experimental Data. The experiment is based on the first geographical national survey database of a province. Its contents mainly include digital orthophoto data results, multi-scale digital elevation model data results, surface coverage classification data results, geographical national condition element data results, geographical national condition survey data production metadata results, remote sensing image interpretation sample data results and geographical national condition survey result analysis series reports, and so on [16].

TABLE 2: Comparison of main cloud platform software.

Cloud platform software	User interface	Other cloud platform compatibility	Support virtualization platforms
Eucalyptus	EC2WS, CLI	Amazon EC2	Xen, KVM
OpenStack	EC2WS, CLI	Amazon EC2	Xen, KVM
XCP	EC2WS, CLI, WSRF	Amazon EC2	Xen, KVM, UML
Nimbus	CLI	No	Xen

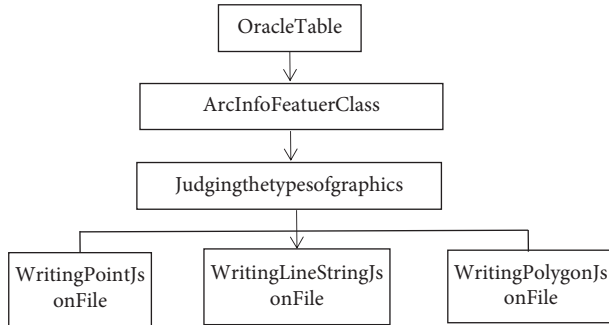


FIGURE 5: Experimental data extraction.

3.1.1. Experimental Data Extraction. Because the geographic census database used in the experiment is based on Oracle12c and ArcGISSE10.1 software, the data in the database include a table in ArcGeoDatabase format, and the data in the database cannot be directly assigned to Hadoop distributed computing nodes. The data format used in the experiment is GeoJSON, so the data in the database should be extracted, preprocessed, and converted. The data to be converted include vector data, raster data, and non-spatial data. The data conversion process is shown in Figure 5.

For vector data, first use the ArcObjects interface to read the table in Oracle to get the Arc info Feature Class, then judge the spatial graphics type of the layer, and generate different GeoJSON data files for points, lines, and faces [17]. For grid data, according to the needs of statistical calculation, firstly generate grid statistical maps such as slope map and elevation zone distribution map and then vectorize them to generate GeoJSON data file.

3.2. Setting of Experimental Environment. In this paper, we test the computing performance of the high-performance computing platform. The comparative experiment includes two kinds of comparisons in the single machine environment and the high-performance statistical platform environment: (1) the computing performance of different data amounts of single index and (2) comparison of calculation performance of large amount of comprehensive index data. The configuration of stand-alone environment is shown in Table 3, and the high-performance computing cluster of spatiotemporal information cloud platform is shown in Table 4.

3.3. Experimental Process. Two kinds of comparative experiments are carried out: single index, calculation performance experiment with different amount of data;

TABLE 3: Single machine environment of comparative experiment.

System	CPU	Disk	RAM (GB)	GIS
Windows 8.1 Enterprise x64	Intel Core CPU @2.40GHz4core	SSD 250 GB	8.0	ArcGis10.1 Python2.6

comprehensive index, calculation performance experiment with different amount of data.

- (1) Single index, different data volume, and comparative experimental process.

Under the same single calculation index, single machine environment calculation and Hadoop-based distributed calculation are carried out for different amounts of data, and the calculation time is compared. In order to compare the performance of different amounts of data, the original data are increased by the order of magnitude after preprocessing, which is 10 times, 100 times, 1000 times, and 10000 times of the original data, and then the data of different orders of magnitude are statistically calculated for the same index in the single machine environment, 5-node Hadoop cluster, and 10-node Hadoop cluster, and the calculation time is recorded, respectively.

- (2) Comprehensive statistical experiment process.

In the stand-alone environment, different statistical units, different statistical contents, and multiple indicators are calculated concurrently. In the Hadoop cluster, the set Oozie Workflow is used to drive the comprehensive statistical calculation of multiple indicators. The comprehensive calculation of recording original data, 10 times data volume, and 100 times data volume takes time.

3.4. Real Face Results and Output

3.4.1. Statistical Result Report. The statistical results calculated by Hadoop cluster are output to HDF5. The system generates statistical reports according to the statistical requirements of geographical conditions. Table 5 shows the classified statistical results of surface coverage within different slope zones.

3.4.2. Visualization of Statistical Results. In the application, the results of system classification statistics can be downloaded from HDFS to Client through the system, which can be visualized according to the statistical distribution

TABLE 4: High-performance computing cluster environment of spatiotemporal information cloud platform.

The server	Quantity	Collocation	Colony	ArcGIS	Hadoop role
Physical server	1	GPU32 RAM128 GB DISK1.2 TB	CDH5.3 Hadoop2.5	10.1	Resource manager/node manager/data node
Physical server	1	GPU32 RAM128 GB DISK1.2 TB	CDH5.3 Hadoop2.5	10.1	Secondary node manager/node manager/data node
Physical server	8	GPU32 RAM128 GB DISK1.2 TB	CDH5.3 Hadoop2.5	10.1	Node manager/data node

TABLE 5: Classified statistics of surface coverage area in different slope zones.

High range band	Surface coverage area (km ²)	Proportion (%)
0-<500	0	0
500-<800	200.3	20.35
800-<1000	281.29	30.68
1000-<1200	210.83	22.34
1200-<1500	181.39	20.18
1500-<2000	46.51	4.04
2000-<	0.01	0.00

requirements of geographical conditions, including the distribution of statistical objects in the administrative region and the distribution of statistical objects in the elevation zone.

3.5. Performance Analysis

3.5.1. Comparative Analysis of Performance of PC, 5-Node Cluster, and 10-Node Cluster under Different Datasets for Single Index. Through the experiment, the performance of point, line and surface in different indexes, 5-node cluster and 10-node cluster in single machine environment were compared in Figures 6–10. The following conclusions are drawn from the performance comparison. (a) In the case of small amount of data, Hadoop cluster needs to start job-container and initialization calculation, which takes a long time and takes 30–50 seconds, while the efficiency of single machine environment is high, which can be completed in 10 seconds. With the increase of the amount of data, when it reaches a certain range and about 100000 statistical objects, the single machine computing time increases sharply and the layer index increases, while the cluster computing time increases linearly and gently [17]. (b) Taking the statistical efficiency of residential areas and facilities in the statistical unit as an example, it can be seen that the more complex the polygon surface of the statistical unit is, the more time-consuming the spatial query is. (c) In the cluster computing environment, when calculating a single index, when the amount of data is small, the computing performance of 5 nodes is better than 10 nodes, and when the amount of data increases by more than 10000, the performance of 10 nodes is better than 5 nodes. It can be seen that in the case of large amount of data, the more the number of cluster nodes, the higher the computing performance.

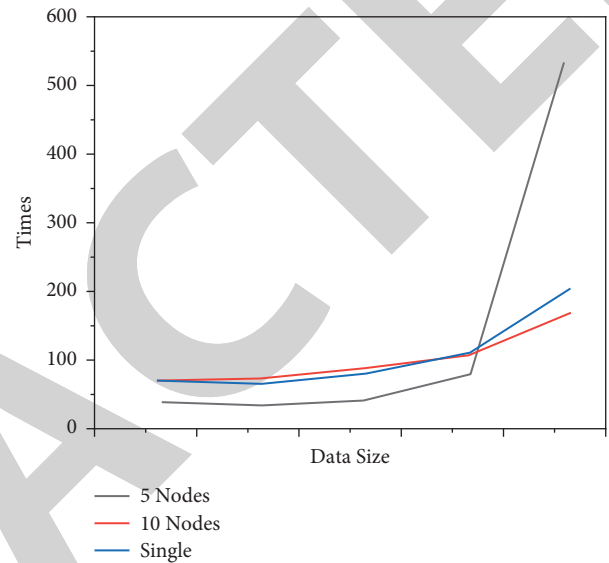


FIGURE 6: Residential areas and facilities in the administrative region.

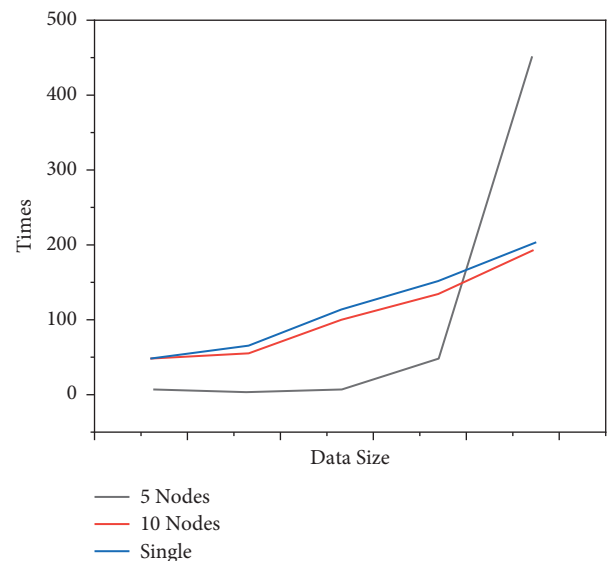


FIGURE 7: Residential areas and facilities in elevation zone.

For multi-index comprehensive statistical calculation, the time consumption comparison is shown in Figure 11. The analysis shows that in a cluster environment, the startup time of OOOZIE MapreduceContainer is basically the same as that of single indicator calculation, and concurrent

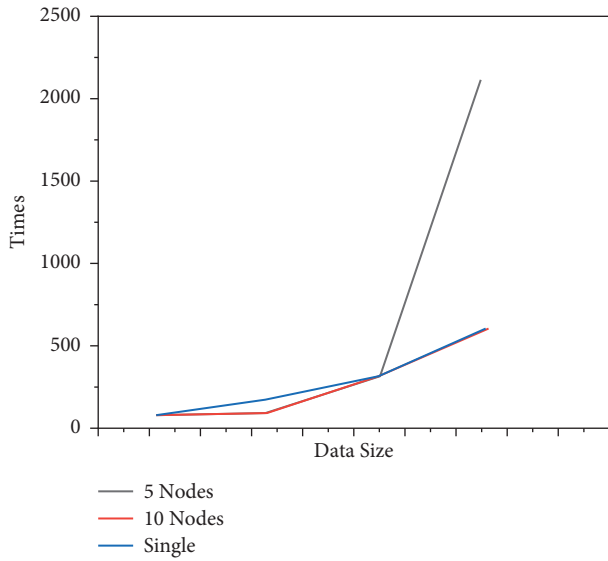


FIGURE 8: Table coverage and accumulation in the administrative region.

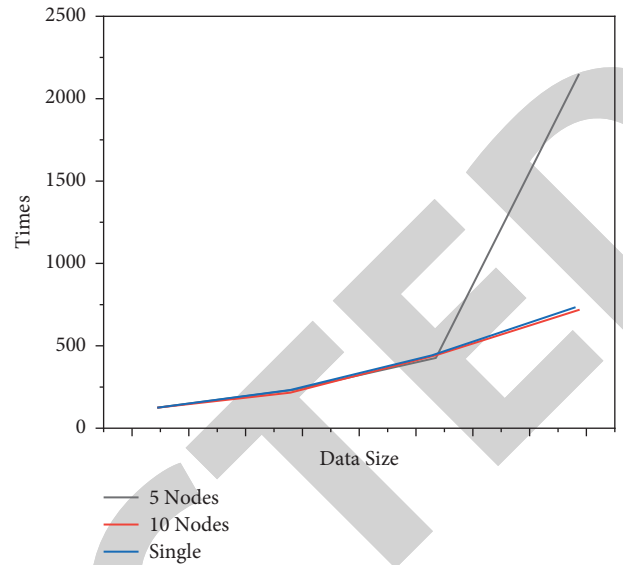


FIGURE 10: Surface coverage and accumulation of elevation zone.

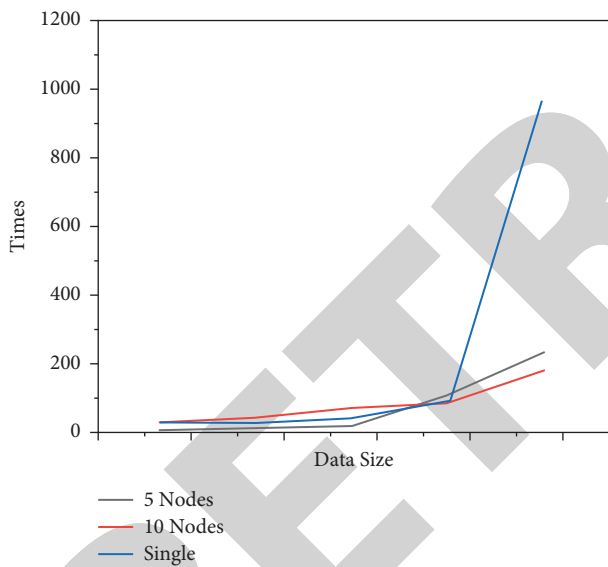


FIGURE 9: Surface coverage and accumulation of slope zone.

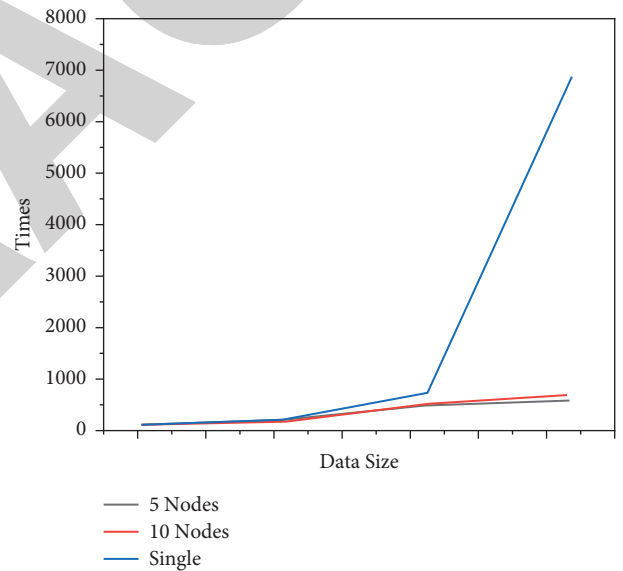


FIGURE 11: Time consumption comparison of comprehensive index calculation in PC, 5-node, and 10-node cluster environments.

calculation can obtain better calculation performance. In the stand-alone environment, when the comprehensive index is calculated in parallel with 10000 statistical objects, the system performance drops rapidly and reaches the inflection point in advance, and the performance curve shows exponential growth. In comprehensive statistical concurrent computing, the performance of cluster computing is only related to the number of cluster nodes and the amount of statistical computing data. When the time consumption reaches 5×10^7 , the amount of computing data is as high as 7000, which increases linearly.

4. Conclusion

In the era of cloud computing and big data, the specific implementation of high-performance computing cloud in spatiotemporal information cloud platform includes virtualization platform, cloud management software, storage, and Hadoop cluster. The research on spatial big data management and high-performance computing based on cloud environment is proposed to support geological spatial analysis and high-performance computing. A high-performance computing platform for supporting the

comprehensive statistics of geographical national survey is constructed. The experiments show that in the high-performance spatial computing of spatiotemporal information cloud platform, compared with the traditional single server and single process computing mode, it has obvious advantages and can be expanded horizontally. The development of spatial big data management and high-performance computing of information cloud platform provides advanced technical support for relevant work. By establishing spatiotemporal information cloud platform, cloud computing technology can provide higher spatial information services. Big data technology has already completed the complete data processing life cycle from data collection to data release and has realized the flow and operation of the whole chain. However, in the future, great attention needs to be paid to the security issues, which directly affect the development prospect and practicability of big data technology development, and they need to be studied in one step.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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