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RESEARCH ON BIG DATA VISUALIZATION TECHNOLOGY BASED ON MULTI-SOURCE VIBRATIONAL DATA ACQUISITION

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Abstract. In order to scientifically and reasonably monitor the soil environment of green spaces in urban residential areas, the layout and sampling methods of soil monitoring points for green spaces in residential areas were studied, including the selection of representative residential areas, determination of monitoring point sampling positions, and determination of the number of points. The author proposed a research on the layout and sampling of soil monitoring points for green spaces in urban residential areas based on multi-source data collection and big data visualization. By using multi-source big data visualization methods, representative residential areas of a certain city were selected to monitor heavy metals (cadmium, mercury, arsenic, lead, copper, chromium, zinc, and nickel) in the green soil of their residential areas. The study reveals variations in heavy metal concentrations in the soil across residential areas of differing building ages. To ensure thorough monitoring of soil environmental conditions in residential areas, it's recommended to include neighborhoods of varying building ages as monitoring sites. Our findings indicate that the choice of sampling locations within these areas does not substantially affect the heavy metal content in soil samples. Therefore, it's preferable to prioritize sampling from residential areas rather than focusing solely on large green spaces within them, There are differences in samples from different monitoring points within the same residential area, and at least 3-4 monitoring points should be set up in each residential area to represent the soil environmental conditions of that residential area. The application of multi-source big data has a positive effect and advantage on the distribution of urban soil monitoring points.

Key words: Multi-source data collection, Urban residential areas, Soil monitoring, Big data, Layout points

1. Introduction. With the rapid development of IT technology worldwide, various industries and industries have generated their own information data, and corresponding data centers have also been established. From the current situation, the direction of information technology development in various industries is shifting from discrete to centralized. The amount of information that needs to be managed in data centers has sharply increased, and the information in small data centers cannot reflect comprehensiveness in a timely manner and is difficult to control. Therefore, it is necessary to centrally manage distributed data centers to further promote the development of data centers.

As an important IT infrastructure, enterprises and institutions are highly concerned about its importance. Furthermore, data centers are currently evolving towards a wider range of shared resources. Contemporary data centers are no longer simply using management commands or tools, but also adopting security technology, standardization technology, virtualization technology, and automation management technology. The current data center is constantly advancing, step by step towards a more complete data center. In the view of more mature data centers, standardization and automation are their basic characteristics, visualization and virtualization are their essential attributes, and security is an important consideration direction [1]. Among them, standardization and automation refer to the ability of data centers to have unified standards and fully automated network maintenance and operation management, standardized scripts and software configurations, visualization and virtualization refer to the use of computer 3D technology and virtual storage technology to change the appearance of data centers, express the large amount of digital information generated during their monitoring process in a simpler and more reliable way, and reduce labor costs.

In the data center industry, finance and telecommunications were the earliest to invest in construction, with large investments and a high market share. The importance of data centers in this industry is at the core. After entering the mobile Internet, the financial and telecommunications industries have developed rapidly, which

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has led to the management and construction of the data center. After more than 20 years of development, the construction of data centers has shown exponential growth [2].

Driven by the mobile Internet and the rapid development of wearable technology, a large amount of information data has been generated. With the help of these, the demand for bandwidth has been growing, which has refreshed enterprises' understanding of data centers. In recent years, the development of domestic data centers has shown a trend of large-scale. Data centers have developed from small scale to large scale. Under the influence of "Internet Plus", two operators have strengthened the construction of big data centers and the support of cloud services.

In the past, the focus of data centers was on information stability, mainly to be able to recover data in a timely manner when problems occurred. Therefore, data in one place would be backed up in multiple locations according to different geographical locations, and data standardization processing would also be carried out at certain intervals. This way, in case of accidents, data could be recovered within a certain period of time, ensuring the normal operation of services.

Today, the focus of data centers is no longer on data recovery. With the rise of big data, data analysis, real-time processing, and real-time transmission have become key research directions in contemporary data centers [3].

In particular, the network interconnection of mobile Internet and wearable devices has put forward unprecedented requirements for the network delay of contemporary data centers. Netizens hope to access cloud data in real-time as quickly as accessing local data, which requires a wider and more uniform distribution of data centers. According to this development trend, data centers will become more efficient, achieve higher density, and at the same time, obtain higher computing processing capabilities. The entire network will have new computing concepts, content distribution will become more important, and data information will be redundant and scattered throughout the network to reduce the difficulty for users to obtain data and reduce latency [4].

2. Literature Review. Eldahshan, K. A. et al. tackled the issue of visualizing large datasets by employing feature selection techniques to reduce data volume and minimize model training time (Tt) while preserving data integrity. They utilized the Random Forest Importance Algorithm (RFI) and the Embedding Method based Selection from Model (SFM) method to identify the most crucial features, comparing them with the Chi2 tool based on Selection Percentile (SP) method. Subsequently, logistic regression (LR) and k-nearest neighbor (KNN) algorithms were applied for classification. The study concludes that by eliminating redundant and irrelevant data, feature selection methods significantly enhance data analysis and visualization capabilities [5].

Barik, R. K., and others introduced GeoTCloud, a cloud-based geospatial big data infrastructure model tailored for visualizing geospatial data within the tourism sector. This model facilitates the storage, analysis, and presentation of large-scale geospatial data, offering valuable support for the advancement of smart city initiatives and the enhancement of tourism-related services [6].

Yang, H. P. et al. introduced a novel approach for efficiently transmitting and visualizing meteorological big data using WebGIS technology. Leveraging open-source tools like HTML5 and Mapbox GL, their solution optimizes data compression and transmission on the server side, as well as distributed requests and rendering on the browser side. They developed a high-low 8-bit compression method capable of compressing 100MB files to megabyte-level files with 90% compression rate, maintaining data accuracy to two decimal places. Additionally, their approach integrates pyramid tile cutting, concurrent domain name request processing, and texture rendering. Experimental results demonstrate rapid transmission and display of up to 100MB grid files within milliseconds, supporting multi-terminal service applications. This grid data visualization model offers insights for big data and technology centers, with potential applicability across various industries [7].

The author's research is based on multi-source big data visualization technology to select representative residential areas from tens of thousands of residential areas in the city, and investigate the soil of different types of representative residential green spaces in the central urban area of a northern city; Quantify the concentrations of heavy metals, including cadmium (Cd), mercury (Hg), arsenic (As), lead (Pb), chromium (Cr), copper (Cu), zinc (Zn), and nickel (Ni); Using methods such as non parametric testing and principal component analysis, this paper analyzes the selection of representative residential areas, establishing the spatial distribution and number of monitoring sites for soil analysis in urban residential areas is crucial. This framework serves as a foundation for monitoring heavy metal levels in urban soil and offers technical assistance in accurately assessing

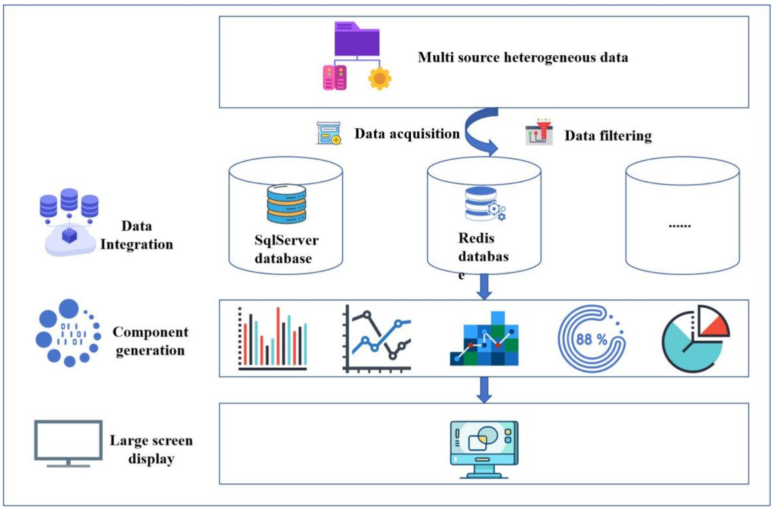

Fig. 3.1: Basic ideas for data visualization

and evaluating the environmental quality of urban residential areas.

3. Research Methods.

3.1. Overview of Data Visualization Content. With the continuous progress of information technology, traditional manual statistics, calculations, lists, and graphs can no longer be effective interpretation methods for massive heterogeneous data from multiple sources. Scientists have also exclaimed, "What we do is only collect data." In order to solve such problems, a new technological field - data visualization has emerged [8]. The basic idea of data visualization is shown in Figure 3.1.

Data visualization refers to organizing information points based on a proposed framework, dividing them into business modules, selecting and matching appropriate charts according to different data types, and depicting information from multiple perspectives and levels. It can also provide a fast human-computer interaction experience. Due to the fact that people perceive graphics more quickly and deeply than text or numbers, data visualization technology utilizes computer graphics to replace large, dense, and complex data with vivid graphic forms, mining valuable information from the vast ocean of data and presenting it intuitively.

Data visualization not only saves people time receiving information, but also provides rich visual impact, which is more conducive to gaining insight into the essence of data, so as to better serve the next step of work decision-making and play a certain role in the survival and development of the enterprise.

3.2. Data Visualization Design Steps. Data visualization is the last step in the data analysis process and an important step in presenting the analysis results. An excellent data visualization work needs to comprehensively consider three factors: indicator content, aesthetic design, and user interaction experience. It closely combines and flexibly applies statistics, computer technology, and art design. The specific design steps are shown in Figure 3.2.

1. Clearly define design objectives. When facing visualization requirements, it is necessary to conduct research on product requirements and indicator content, and determine the two main directions of "what to display" and "how to display". At the beginning of data visualization design, only by fully understanding the business content can we grasp the design goals. Taking the visualization design of shipbuilding accuracy data as an example, it is necessary to have a deep understanding of the entire shipbuilding process and the focus of precision control work in the early stage. Only in this way can data and graphics be better combined, playing a crucial role in how to explore the value of data in the future.
2. Reasonably divide the sectors. After the goal is determined, it is necessary to preliminarily divide the

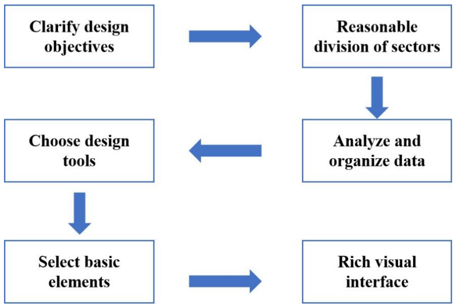

Fig. 3.2: Data Visualization Design Steps

business modules and develop a page layout based on the work content. Place important information in the middle and above, and lower priority information on both sides and below, highlighting the hierarchical structure. Then organize the information points according to the divided sections, and start organizing and mining the data accordingly [9].

3. Analyze and organize data. After preliminary preprocessing of the obtained multi-source heterogeneous data, data indicators are analyzed and mined from multiple dimensions to determine the perspectives and contents that need to be expressed for each indicator. A multi-level system and correlation are established for the data, and the calculation methods for each indicator are summarized. These data are then integrated into multiple data tables according to different classifications, which serve as the data source for visual components and lay the foundation for component generation.
4. Choose a design tool. In the context of big data, data visualization technology is becoming increasingly mature and can now integrate various emerging technologies such as user interaction technology and data interaction technology. The available tools also have richer presentation forms, simpler operation methods, and support more data sources. Choosing the appropriate data visualization based on functional requirements and the programming ability of designers can help reduce the difficulty of design work and improve the ideal level of final presentation. Data visualization tools can generally be divided into chart libraries, business intelligence analysis, visualization screens, and professional categories, which can meet various functional requirements in various industries. Give examples to illustrate the main differences in the characteristics of three widely used data visualization tools.
5. Select basic elements. The common basic elements of data visualization include column charts, tables, maps, etc. Select specific elements under each element based on data relationships, render the organized data into visual graphics, and complete data mapping and component generation. At the same time, make good use of extended functions such as chart linkage and highlight dynamic analysis to enrich the visual hierarchy and enhance the user experience. There are various types of data visualization charts, including bar charts, line charts, pie charts, scatter charts, radar charts, and their variations. Each chart has its own applicable situation, and only by comprehensively considering factors such as data relationships, project requirements, and audience orientation can we make the most of everything and truly play the role of the chart [10]. When the types of information are different, the requirements for data relationships will vary, and the chart forms presented will also be different. List six main data relationships and their corresponding chart types.
6. Rich visual interface. The final step is to handle the overall details, and the rational design of the visual aspect can also provide assistance in the optimal presentation of data results. Attention should be paid to the reasonable arrangement of layout, uniformity and coordination of fonts, color matching, and other visual expressions of the visual interface, in order to complement the content and complete the overall construction of the visual interface. A reasonable spatial layout can make the content of the data visualization interface more hierarchical, highlight key data information, and thus improve the efficiency of user interpretation of information. The layout design of data visualization interfaces should generally follow three principles: Ensure that critical information is centrally located and readily

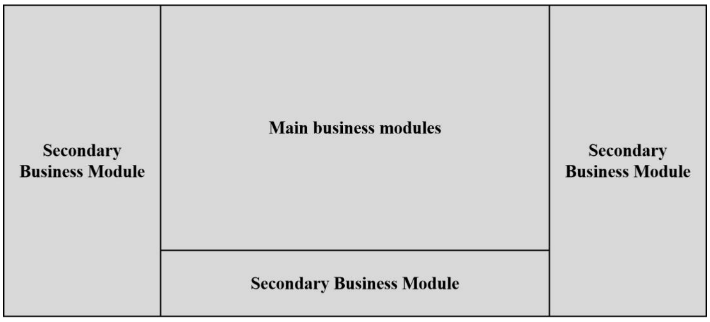

Fig. 3.3: Data Visualization Layout Scheme

discernible, facilitating the capture of key points. Maintain a balanced spatial arrangement of various page elements to enhance design aesthetics. Emphasize data presentation in the layout while avoiding unnecessary complexities or elements that hinder the effectiveness of conveying information. Based on the above principles, multiple layout design schemes can be developed, and the scheme shown in Figure 3.3 can cover most application scenarios. The central position of the page is the main module used to display the main indicators, while the left, right, and bottom of the page are secondary modules that can display a large number of secondary indicators. It has the characteristics of clear content hierarchy and simple and beautiful design.

3.3. Materials and Methods.

3.3.1. Overview of the research area. The research area is a residential area in the central urban area of a northern city. As an important urban area, this area has a long history of construction and development, high population density, and mature socio-economic development.

3.3.2. Multi source big data visualization. In order to monitor the soil environmental quality of green spaces in urban residential areas and scientifically reflect their impact on the health of residents, priority is given to selecting residential areas with high population density and frequent population activities as monitoring objects. Visualize multi-source big data and select representative residential areas. Visualize the city's POI points, weibo posts, and dianping website evaluation information through spatial processing using geostatistical software. Using web scraping technology to obtain urban residential area information on Baidu Maps and Lianjia.com, vectorizing and mapping it to obtain a spatial distribution map of residential areas. According to the results of the sixth national population census in 2010, the population density spatial distribution map was obtained by vectorizing the population of each street [11].

3.3.3. Soil Sample Collection. Using the method of judging and distributing points uniformly in space, set up sampling points in green spaces within residential areas, with 5 sampling points set up in each residential area. The sampling points are set up in large concentrated green spaces to ensure that samples are collected from the lawns, shrubs, and trees in each residential area. Each sample is composed of 5 surface samples with a depth of 0-20 cm and evenly mixed in equal quantities using the diagonal method, with a sampling amount of 2 kg. Sampling is carried out using the Global Positioning System (GPS) to locate and record geographic coordinates. The sample is stored in a cloth bag and labeled with a sample label. Based on the monitoring results of this study, the pH range of soil samples is 7.85-8.58, with an average of 8.19. The soil samples in residential areas of the urban center are alkaline.

3.3.4. Sample pretreatment and analysis. Soil cadmium was determined by solid direct injection and graphite furnace atomic absorption spectroscopy. The mercury content is determined by solid direct injection and cold atomic absorption method. The total amount of arsenic, lead, chromium, copper, zinc, and nickel was determined by powder pressing method and X-ray fluorescence spectroscopy. During the analysis process, no less than 10% of soil standard samples are inserted into each batch and analyzed in parallel in the laboratory.

The analysis results of all standard samples are within the uncertainty range, and the relative deviation of parallel sample determination is 0% to 7%, which meets the technical specification requirements [12].

3.3.5. Data statistical analysis methods. Discriminate outliers based on data. Use independent sample K-W test to test for differences in soil samples from different types of residential areas. Use Principal Component Analysis (PCA) to analyze soil samples within residential areas. The Kruskal Wallis test is a non parametric method aimed at testing whether the median of multiple samples is equal. Kruskal Wallis ranks high, so it remains invariant to any monotonic transformation of the measurement range. Known names: Kruskal Wallis H-test, one-way analysis of variance.

Calculate the average rank of each group of samples as shown in equation 3.1:

$$\overline{R_j} = \frac{R_j}{n_j} = \frac{\sum_{i=1}^{n_j} R_{ij}}{n_j} \tag{3.1}$$

Among them, R_{ij} is the sorting number, and n_j is the number of samples in the jth group.

Calculate the Kruskal Wallis statistic, as shown in equation 3.2:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} n_i(\overline{R_i} - \overline{R})^2 \tag{3.2}$$

Among them, N is the sum of the number of samples in each group, ni is the number of samples in the i-th group, and k is the number of sample groups.

3.3.6. Data statistics. ArcGis 10.1 software was used for spatial data processing, and SPSS 18.0 was used for statistical and analytical analysis of soil heavy metal content, correlation, and differences; Canoco 5.0 conducts principal component analysis and plotting of heavy metal content in soil samples.

4. Result analysis.

4.1. Selection of Residential Areas. Perform geographic information processing on urban residential area information to obtain a distribution map of residential areas. Perform geographic information processing on the 2010 census results to obtain a population density distribution map. The above results are spatially overlaid with urban POI point data spatial distribution, Sina Weibo sending volume data distribution, and Dianping evaluation information distribution data [13,14]. From the distribution map of residential areas and population density, it can be seen that the residential areas and population of the city are concentrated in the central area. Among them, the density of residential areas in the urban center is higher than that in the suburban areas, and its density gradually decreases from the urban core to the outer periphery; The highest population density in the urban core area exceeds 2 × 104 people/km^2. It can be seen that the distribution of residential areas and population density is most concentrated in the urban center. For example, selecting residential areas for soil sample collection in concentrated areas can have a larger radiation population and better reflect the impact of soil on the population, making it more representative.

The distribution map of urban POI, Weibo sending volume, and Dianping network evaluation reflects the laws and spatial distribution characteristics of human social activities. The POI, Weibo posts, and Dianping comments of the city are all concentrated in the central area of the city, which is basically consistent with the distribution of residential areas and population density. It can be seen that crowd activities are most concentrated in the central area of the city. After data space integration and visualization, the distribution of residential areas with high population density, dense POI points, and frequent crowd activities was obtained. These residential areas were selected as alternative residential areas, and priority was given to selecting residential areas in the central urban area. In addition to considering the population density and frequency of activities in the area, residential area screening is conducted based on factors such as the distance of construction, distribution of administrative jurisdiction, and green space area within the residential area [15]. In order to consider that the selected residential areas can represent different situations of urban residential areas, the selection principle takes into account residential areas of different building ages and administrative jurisdictions. At the same time, the concentrated green space area in residential areas should not be less than 10% of the

Table 4.1: Residential Area and Monitoring Point Information

Residential area name	Architectural Era	Monitoring points
A community	1986	A1 A5
B community	2008	B1 B5
C community	1980	C1 C5
D community	2003	D1 D5
E community	2000	E1 E5
F community	1982	F1 F5
G community	2001	G1 G5

Table 4.2: Significance of K-W test for heavy metals in soil samples from different sampling locations

Heavy metal	Cd	Hg	As	Pb	Cr	Cu	Zn	Ni
Progressive significance/P	0 365	0 201	0 210	0 301	0 763	0 962	0 614	0 880

total area of residential areas, facilitating the collection of soil samples. Based on the above considerations, 7 residential areas were selected. The construction period of residential areas varies from 1980, 1990, 2000, and 2010. Research on these residential areas can represent the soil environmental characteristics of the main residential areas in the city. The selected residential areas are shown in Table 4.1.

The selected residential areas have different building ages and are distributed in various administrative districts in the central area of the city. The area of concentrated green space in residential areas shall not be less than 10% of the land area occupied by residential areas.

4.2. Abnormal value discrimination. The Grubbs method was used to identify outliers in soil heavy metal content, and the G values of all samples did not exceed the critical values given in the Grubbs Table, with no outliers. All monitoring data in this study were used for subsequent analysis and calculation [16].

4.3. Differences in Soil Heavy Metals in Residential Areas of Different Building Ages. Designate neighborhoods built before 2000 as "old neighborhoods" (A, C, F neighborhoods), and neighborhoods built after 2000 as "new neighborhoods" (B, D, E, G neighborhoods). Perform principal component analysis on the heavy metal content of soil samples from two groups of residential areas to determine the differences in heavy metal content among soil samples from different types of residential areas. Principal component analysis is obtained through Euclidean distance projection. The distance between the sample points in the figure represents the similarity in the composition of heavy metal content between them. The closer the sample points are, the more similar they are. From the results, it can be seen that there is a difference in the heavy metal content of soil samples between the "old community" and the "new community". The soil samples from "old communities" such as A and C are relatively concentrated in the first and fourth quadrants of the map [17]. The soil samples of new communities such as B, D, E, and G are mainly concentrated in the second and third quadrants. The dominant elements in the soil samples of community A are Pb and Cu; The dominant elements in the soil samples of community C are Cu, Cr, Ni, and Zn. F community belongs to the "old community", but the soil samples in F community are more similar to the "new community", which may be due to the location of F community on the edge of the urban center and the slow development of facilities around the residential area. Considering the comprehensiveness and representativeness of soil environment monitoring in residential areas, it is advisable to consider different building ages when selecting residential areas.

4.4. Differences in Soil Heavy Metal Content at Different Sampling Positions. Differential analysis was conducted on the heavy metal content of samples at three different sampling locations: lawn, under trees, and shrubs. The analysis results are shown in Table 4.2. The progressive significance of the K-W test for heavy metal content in three soil samples was greater than the given test level by 0.05, indicating that there was no significant difference in heavy metal content among the samples obtained from the three sampling positions [18]. It can be seen that the sampling location has no significant impact on the monitoring results

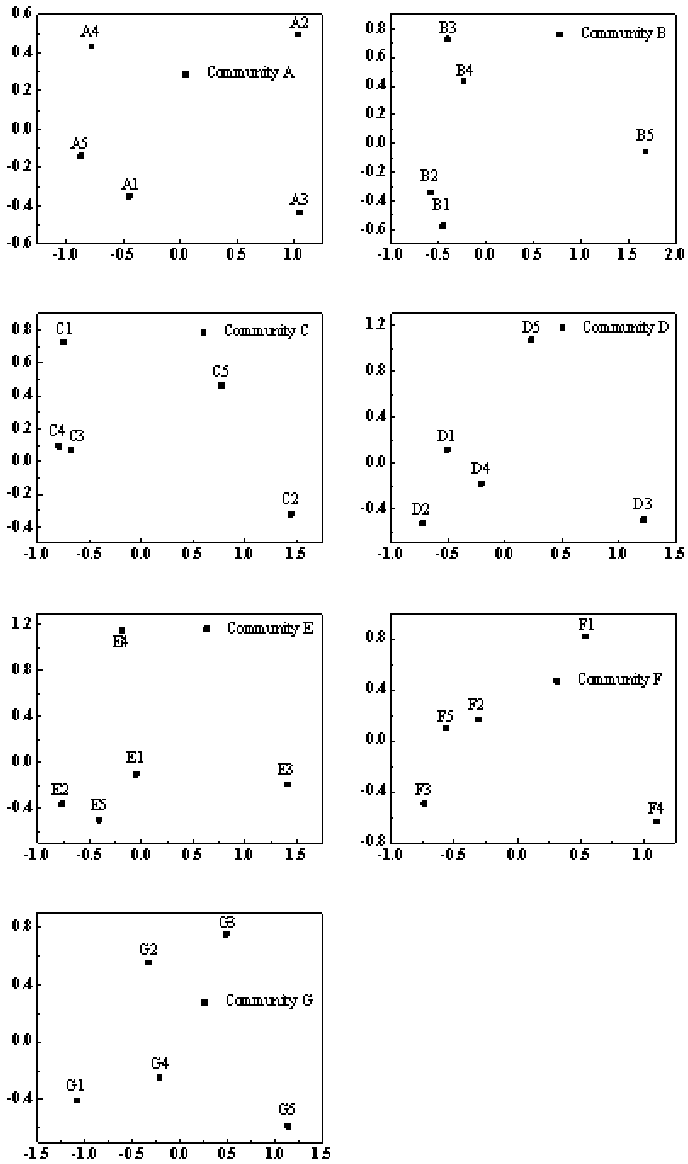

Fig. 4.1: Principal component analysis of soil samples from various residential areas

of soil samples in residential areas. Considering the convenience and representativeness of on-site sampling for soil monitoring in residential areas, priority should be given to sampling from green spaces with a relatively large area in residential areas.

4.5. Sampling quantity. In order to determine the differences in different locations within each residential area, principal component analysis was performed on the heavy metal content of soil samples from each residential area, as shown in Figure 4.1. There are certain differences in the heavy metal content among different soil sampling points in different residential areas. Except for B and E communities, the sampling points in other residential areas are scattered in four quadrants, indicating that at least four sampling points need to be set up in these residential areas to represent the heavy metal content characteristics of the soil environment in that residential area. B1 and B2 points in community B are relatively similar, while B3 and B4 points are relatively similar, indicating that retaining only one point per pair of these two points in community B can represent the soil heavy metal content characteristics of each pair of sample points. E1, E2, and E5 in E community have high similarity, meaning that one of these three sampling points can represent the heavy metal content of these three sampling points. For B and E communities, three soil monitoring points can represent the heavy metal content in the soil within that community. Based on the analysis results of all residential areas, at least 3-4 soil sampling points should be set up in residential areas. In special circumstances such as complex green space types or pollution accidents, the number of points can be appropriately increased.

5. Conclusions.

1. Multi source big data visualization technology can be applied to the monitoring of green soil environment in urban residential areas. It can quickly and accurately determine regional boundaries and urban structure related to crowd activity and population density. It has the advantages of fast, comprehensive, and representative selection for residential areas with frequent crowd activity and high radiation population.
2. The heavy metal content in soil samples from residential areas of different building ages varies to a certain extent. If in the actual monitoring process, considering the comprehensiveness and representativeness of soil environment monitoring in urban residential areas, accurately and objectively reflecting the soil environment status of the entire city's residential areas, residential areas of different building ages should be selected as monitoring objects.
3. Different sampling positions have no significant impact on the heavy metal content of soil samples. In actual monitoring work, while ensuring the accuracy and representativeness of monitoring, the convenience and timeliness of on-site sampling should be considered. Priority should be given to collecting soil samples from green areas with a dominant area in residential areas.
4. There are differences in the content of heavy metals in the soil within the same community. At least 3-4 soil sampling points should be set up in a residential area. In special circumstances such as complex types of green spaces or pollution accidents, the number of points can be appropriately increased.

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