RESEARCH ON VISUALIZATION DESIGN OF AIGC EMPOWERING ECOLOGICAL ENVIRONMENT SYSTEM MANAGEMENT AND GREEN SUSTAINABLE DEVELOPMENT

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Abstract

With the accelerating process of urbanization, air quality is gradually deteriorating, and the ecological environment as well as human health are facing severe challenges.This study addresses global ecological environment management and Green Sustainable Development needs by proposing a visualization solution based on Artificial Intelligence Generated Content (AIGC). It presents complex ecological management data in an intuitive and understandable form through visual design, aiming to improve ecological environment management efficiency, provide effective support for Green Sustainable Development decisions, and facilitate the resolution of ecological environmental issues. The research integrates core technologies such as Generative Adversarial Networks (GAN) to build an intelligent analysis framework for multi-source data fusion, enabling visual representation of dynamic ecological environment simulation and decision support. Taking Nanning's air quality environment as an empirical case, the study validates the application performance of optimized AI tools (DeepSeek, Kimi, Doubao) in predicting sulfur dioxide and PM10 concentrations. Results show: 1)Visual design integrated into air quality monitoring data management enhances data readability and comprehensibility; 2)DeepSeek achieves an average absolute percentage error of 0.1128% in ambient air quality prediction, improving accuracy by 31.01% and 43.98% compared to Kimi and Doubao, respectively. The AIGC technology has significantly improved the efficiency of environmental data processing. It has certain promotion value and application prospects both at home and abroad, providing an intelligent and visual innovative path for the systematic management of the ecological environment.

1 Introduction

1.1 Research area

Nanning is located in the central - southern part of Guangxi, with an administrative area of 22,100 square kilometers. As the capital city, it undertakes the important functions of being the political, economic, and cultural center of Guangxi. As a crucial connecting hub in the China - ASEAN economic circle, it occupies a strategic position in China's opening - up initiatives.Overall, Nanning enjoys good air quality. In 2024, the proportion of days with excellent or good air quality in the urban area reached 96.7%. Nevertheless, sulfur dioxide pollution and PM10 remain the key focuses of governance, and efforts are being made to promote coordinated pollution control. With an annual rainfall of 1,453.4 millimeters, the abundant precipitation, combined with the warm climate, has created a lush ecological landscape that remains green throughout the year. The vegetation in Nanning thrives, leading to an extremely high urban green coverage rate. The city stays green in all four seasons and is thus renowned as the "Green City".

By the end of 2024, Nanning's permanent resident population reached 8.9719 million, an increase of 31,100 compared with the previous year. The population has been gradually growing in recent years, as shown in Figure 1. This population growth and structural change reflect the increasing attractiveness of Nanning in urban development, industrial construction, and other aspects.

Table 1. The Permanent Resident Population of Nanning from 2021 to 2024 / ten thousand people

Year	Permanent Resident Population	Change Compared to the Previous Year
2021	883.28	+9.12
2022	889.17	+5.89
2023	894.08	+4.91
2024	897.19	+3.11

Nanning is rich in natural resources, with considerable reserves of energy minerals. Its metallic minerals include cobalt and nickel. The city enjoys good air quality, but still faces pollution issues such as sulfur dioxide. The agricultural areas are widely distributed, and the seven urban districts and five counties form the living areas. The industrial areas are centered around the Guangxi-ASEAN Economic and Technological Development Zone, as detailed in Table 2.

Table 2. Resources and Urban Distribution Characteristics of Nanning

Serial Number	Category	Details
1	Main Natural Resources	Energy minerals include lignite and peat. Non-metallic minerals such as quartz sand and gravel are abundant. The reserves of clay minerals reach 15.41 million cubic meters. The main metallic minerals are cobalt and nickel.
2	Urban Features	In 2024, the urbanization rate reached 71.9%. The air quality is generally good, but pollution problems such as PM10 are prominent. The pollution sources mainly come from industrial production, energy consumption and other fields.
3	Distribution of Industrial Agricultural and Living Areas	The industrial area is centered around the Guangxi - ASEAN Economic and Technological Development Zone. The agricultural areas include Wuming - Long'an, Binyang - Shanglin, Hengzhou, and the main grain - producing areas in the southern part. The living areas cover seven urban districts and the towns of five county - level urban areas.

To present Nanning's geographical location and urban layout more intuitively, Figure 1 clearly shows its coordinates on the maps of Guangxi and the whole country, as well as the distribution of each administrative area and the planning of key regions.

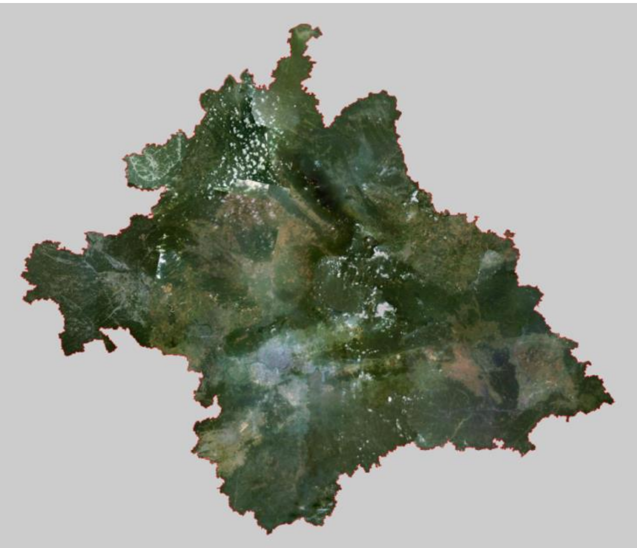

Fig. 1 Map of Nanning

In terms of topography and geomorphology, Nanning is predominantly characterized by flatlands. The Yongjiang River flows through the city, providing extensive space for urban construction and industrial development. The administrative areas of Nanning are closely clustered along both banks of the Yongjiang River. The seven urban districts and five counties radiate outward from the city center. Key industrial areas such as the Guangxi-ASEAN Economic and Technological Development Zone echo with the ecological tourism belts and agricultural demonstration zones, jointly outlining a development blueprint for the city that features the integration of industries and urban areas, as well as a livable ecological environment.

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1.2 Research status at home and abroad

With the acceleration of global industrialization and urbanization, ecological and environmental problems have become increasingly severe. The deterioration of air quality has emerged as a crucial factor affecting human health and ecological balance. As an important city in southern China, Nanning faces challenges of air quality fluctuations while experiencing rapid economic development. Accurately predicting air quality and achieving scientific management of the ecological environment system are inevitable requirements for Nanning's journey towards Green Sustainable Development.The advent of AIGC (Artificial Intelligence Generated Content) technology has brought about a revolutionary transformation in air quality prediction. Compared with traditional methods, AIGC is capable of handling massive, multi-source, and heterogeneous data. It can uncover the underlying patterns in data through deep learning and complex algorithms, and construct more precise prediction models. In the management of ecological environment systems, AIGC technology not only helps improve the accuracy of air quality prediction but also provides comprehensive support for environmental policy formulation, pollution source control, and enhancement of public awareness of environmental protection. This, in turn, promotes the virtuous cycle of the ecological environment system and Green Sustainable Development.

In China, research on the application of AIGC technology in air quality prediction has yielded fruitful results. Many scientific teams and universities have conducted innovative studies targeting China's complex geographical environment and pollution characteristics. For example, some studies integrate convolutional neural networks (CNN) and recurrent neural networks (RNN) to deeply mine air quality data, achieving precise prediction of multiple pollutant concentrations [1]. Meanwhile, certain research applies transfer learning to air quality prediction, leveraging existing data and models from other regions or similar environments to rapidly develop localized prediction models, reducing training time and data requirements [2].

Domestic studies emphasize integrating air quality prediction with ecological environment system management and Green Sustainable Development goals. Through AIGC technology, comprehensive analysis and collaborative management of multiple elements in the ecological environment system—such as air quality, water quality, and soil quality—are realized [3]. For instance, in environmental planning for some cities, AIGC technology simulates air quality trends under different development scenarios to provide scientific support for formulating sustainable urban development strategies. Additionally, research focuses on the impact of air quality improvement on ecosystem service functions and how to promote air quality enhancement through ecological restoration and protection measures to achieve a virtuous cycle of the ecological environment system [4].

China has also innovated in visualization design for air quality prediction, developing various public-facing visualization platforms and applications. These platforms display real-time air quality data, prediction results, and pollution source analysis through user-friendly interfaces, and popularize environmental knowledge via animations, science videos, and other forms to enhance public awareness and participation [5-7]. Some platforms even include public feedback channels to encourage public participation in air quality monitoring and evaluation, fostering a governance pattern with joint participation from governments, enterprises, and the public.

Internationally, numerous studies have focused on using AIGC technology to build high-precision air quality prediction models. For example, some scholars employ deep learning algorithms such as Long Short-Term Memory (LSTM) networks and their variants, integrating extensive historical air quality data, meteorological data, and pollution source emission data to predict pollutant concentrations (e.g., sulfur dioxide, PM10) in the air [8]. These models effectively capture time-series characteristics and complex nonlinear relationships in data, significantly improving prediction accuracy compared to traditional statistical models [9]. Additionally, Generative Adversarial Networks (GANs) have been introduced into the air quality prediction field. Through adversarial training between generators and discriminators, GANs generate air quality data samples closer to real distributions, assisting in the training and optimization of prediction models.

Foreign studies emphasize the importance of multi-source data fusion for enhancing air quality prediction accuracy. In addition to conventional monitoring station data, satellite remote sensing data, mobile monitoring data, and air quality-related text information from social media are widely collected [10]. AIGC technology plays a key role in data fusion by cleaning, integrating, and analyzing data of different formats and sources. For instance, natural language processing technology is used to conduct sentiment analysis and keyword extraction on social media texts, mining public perceptions and feedback on air quality to corroborate with actual monitoring data and provide more comprehensive information for prediction models.

In terms of visual design, advanced platforms and tools have been developed abroad to present air quality prediction results intuitively and understandably to decision-makers and the public. Geographic Information System (GIS) technology is used to display pollutant concentration distributions in map form, combined with dynamic charts and time-series curves to reflect the spatiotemporal changes in air quality in real time [11]. Meanwhile, some studies have introduced Virtual Reality (VR) and Augmented Reality (AR) technologies to enable users to immerse themselves in air quality conditions and enhance their awareness of environmental issues [12]. These visual achievements not only help the public understand the current status and future trends of air quality but also provide strong decision support for government departments to formulate environmental policies and enterprises to adjust production strategies.

Significant progress has been made both at home and abroad in the research on visualization design of AIGC-empowered ecological environment system management and Green Sustainable Development, especially in air quality prediction. There are numerous innovative achievements and practical cases in model construction, data fusion, visualization display, and decision-making support. In the future, research in Nanning in this field can fully draw on the advanced experiences at home and abroad, continuously optimize air quality prediction technologies and ecological environment management models. Through the in-depth application of AIGC technology, strong support can be provided for achieving Green Sustainable Development of the ecological environment. Meanwhile, further efforts should be made to strengthen visualization design, increase public attention and participation in air quality issues, and foster a favorable atmosphere of public participation in environmental protection.

2. Overview of AIGC Technology and Its Predictive Advantages

This study will systematically construct the research framework and present the core steps in a visual form through flowcharts. Starting from clarifying the air quality status of the ecological environment and proposing a visualization solution, then moving on to realizing the visual presentation of ecological environment simulation, followed by data collection, model training and optimization, and then conducting an application comparison using three different AI tools through an empirical case study of the air quality in Nanning City. Through empirical case analysis and effectiveness evaluation, the research conclusions are finally drawn. Each link is closely connected and progresses layer by layer, thus intuitively demonstrating the application logic and internal operation mechanism of AIGC technology in ecological environment management. The specific process is shown in Figure 2 below:

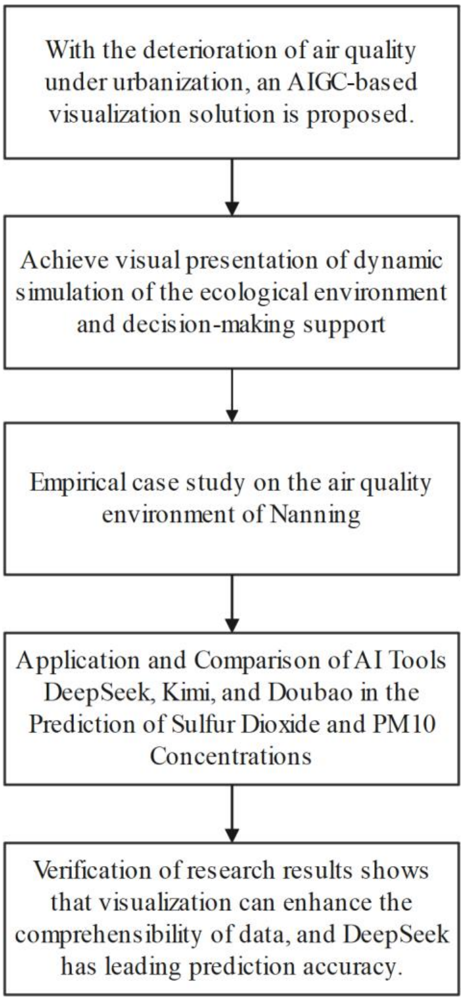

Fig. 2 Flowchart of the Research Framework

2.1 Principles and characteristics of AIGC technology

AIGC technology, namely generative artificial intelligence technology, its core principle is based on deep learning algorithms. Through learning and training on massive data, it constructs models capable of generating new data. Common AIGC models include Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and generative models based on the Transformer architecture. These models can generate new data similar but not identical to the training data by extracting, encoding, and decoding features from input data. For example, GANs achieve data generation through adversarial training between a generator and a discriminator; VAEs model data distributions through probabilistic encoding; and Transformer-based models generate sequential data with strong contextual understanding capabilities by capturing long-range dependencies.

AIGC technology has the following remarkable characteristics: First, it possesses powerful data processing capabilities, enabling it to handle massive, multi-source, and heterogeneous data while mining complex relationships between data. For instance, it can integrate air quality monitoring data, meteorological parameters, and traffic flow information to identify key factors influencing pollution levels. Second, it features a high degree of intelligence, continuously optimizing model parameters through deep learning to improve prediction accuracy and adaptability. The model can automatically adjust weights for different data features, such as giving higher priority to meteorological factors in specific seasons. Third, it has excellent generative capabilities, capable of producing data that meets specific requirements based on given conditions or needs—such as generating hourly pollutant concentration predictions for the next week. Finally, it demonstrates efficient learning and iteration capabilities, quickly absorbing knowledge from new data to continuously update and refine the model. This allows the model to adapt to new pollution sources or changes in environmental policies, maintaining long-term prediction effectiveness.

2.2 Advantages of AIGC technology in air quality prediction

In the field of air quality prediction, AIGC technology has multiple advantages over traditional methods. Firstly, it can achieve more accurate predictions. Traditional prediction methods are mostly based on simple statistical models or empirical formulas, which struggle to capture the non-linear and dynamic characteristics of air quality data. In contrast, AIGC technology employs deep learning algorithms to conduct in-depth analyses of historical air quality data, meteorological data, pollution source data, etc., uncovering the latent patterns within the data and constructing prediction models that better conform to the actual situation, thereby enhancing prediction accuracy. For example, Long Short-Term Memory (LSTM) networks can effectively process time-series data, enabling accurate forecasting of air quality change trends. Secondly, AIGC technology has stronger multi-source data fusion capabilities. Air quality is influenced by numerous factors, and a single data source is often insufficient to comprehensively reflect the air quality status. AIGC technology can integrate multi-source information, including data from ground monitoring stations, satellite remote sensing, mobile monitoring, and social media. Through data fusion and analysis, it can obtain more comprehensive and accurate air quality information. For instance, analyzing satellite remote sensing data can provide a macroscopic view of air quality distribution over a large area, complementing the microscopic data from ground monitoring stations and improving the reliability of predictions.

Furthermore, AIGC technology enables real-time dynamic monitoring and prediction. With the aid of real-time data collection and transmission technologies, AIGC models can update data and make predictions in real-time, promptly reflecting changes in air quality. This is of great significance for timely detecting air quality anomalies and implementing effective pollution prevention and control measures. For example, when an abnormal change in air quality is detected in a certain area, the AIGC model can quickly analyze the causes and predict the diffusion trend of pollution, providing timely decision support for environmental protection departments.

In addition, AIGC technology also features good scalability and flexibility. As the data volume increases and algorithms are continuously optimized, AIGC models can continuously improve their performance, adapting to air quality prediction requirements in different regions and environments. Meanwhile, the models can be flexibly adjusted and customized according to actual application scenarios and needs, such as adding prediction modules for specific pollutants or optimizing the visualization display methods.

3 Application Analysis

3.1 Application of DeepSeek in air quality prediction

DeepSeek has unique advantages in the field of air quality prediction. Its deep learning-based algorithm architecture enables efficient processing and in-depth analysis of multi-source data. In Nanning's air quality prediction, DeepSeek can real-time access data from various air quality monitoring stations, including ground monitoring stations and micro-monitoring stations, to conduct real-time monitoring and analysis of pollutant concentrations such as sulfur dioxide and PM10.

Through learning from historical data, DeepSeek can build high-precision prediction models to accurately forecast air quality change trends over a period. For example, using DeepSeek's time-series prediction algorithm, combined with Nanning's meteorological data and pollution source emission data, it models and analyzes the daily, weekly, and monthly variation patterns of PM10 concentrations to predict potential pollution peak periods in advance, providing a basis for environmental protection departments to formulate pollution prevention and control measures.

DeepSeek also has powerful pollution source tracking and analysis capabilities. By analyzing the spatial distribution and temporal variation characteristics of monitoring data, it can accurately identify the locations and types of pollution sources, such as industrial emission sources, traffic pollution sources, and dust pollution sources. For instance, when PM10 concentration suddenly rises in a certain area, DeepSeek can quickly locate the pollution source by comprehensively analyzing data from surrounding monitoring stations and combining meteorological information such as wind direction and speed, and analyze its emission characteristics and impact range on the surrounding environment, providing technical support for precise governance.

In practical applications, the Shenzhen Municipal Bureau of Ecology and Environment optimized its air pollution prevention and control strategies by inputting air quality monitoring data from its jurisdiction into the DeepSeek-R1 model, enhancing the scientificity and precision of regional ecological environment governance. These successful cases provide valuable references for Nanning's application of DeepSeek technology.

3.2 Application of Kimi in air quality prediction

As an intelligent assistant, Kimi can play multiple roles in air quality prediction. First, Kimi has powerful document processing and information extraction capabilities. In the air quality prediction research of Nanning, researchers can upload a large number of air quality-related documents (such as monitoring reports, research papers, policy documents, etc.) to Kimi for analysis. Kimi can quickly extract key information from documents, such as air quality index data, pollution incident cases, and the effectiveness of policy measures, providing comprehensive data references for researchers and saving significant time in literature review and organization.
In data analysis, Kimi can perform preliminary statistical analysis and trend judgment on air quality data. For example, by inputting PM10 concentration data in Nanning over a period, Kimi can quickly generate statistical charts of the data, such as mean values, maximum values, minimum values, and trend change curves, helping researchers intuitively understand the basic characteristics of the data. Meanwhile, Kimi can provide preliminary suggestions and analysis ideas based on data analysis results, such as determining whether abnormal fluctuations exist in the data and potential influencing factors, providing directions for further in-depth analysis.

During model construction and evaluation, Kimi can serve as an auxiliary tool to help researchers adjust and optimize model parameters. For instance, researchers can consult Kimi about the impact of different model parameter settings on prediction results. Kimi provides reference suggestions by analyzing relevant research materials and cases, improving the efficiency and accuracy of model construction. Additionally, Kimi can conduct preliminary evaluations of the constructed air quality prediction models, providing comments on the rationality, stability, and prediction accuracy of the models to help researchers identify problems and make improvements.

3.3 Application of Doubao in air quality prediction

As an advanced AI tool, Doubao possesses powerful natural language processing and data analysis capabilities. In the air quality prediction for Nanning, Doubao can analyze a large amount of text data related to air quality, such as environmental protection reports, research papers, news information, etc., to extract valuable insights and assist in constructing prediction models. For example, it can obtain information on the historical air quality trends, pollution source distribution, and governance measures in Nanning from environmental protection reports, and learn the latest air quality prediction methods and technologies from research papers, providing rich knowledge support for model training.
In terms of data processing, Doubao can clean and preprocess air quality monitoring data, removing outliers and noisy data to improve data quality. Meanwhile, Doubao's data analysis function can be used to perform correlation analysis on different types of data and uncover potential relationships between datasets. For instance, it can analyze the correlation

between meteorological factors (e.g., temperature, humidity, wind speed) and air quality indicators (e.g., sulfur dioxide, PM10 concentration), providing more comprehensive feature inputs for prediction models.

During the model training and optimization process, Doubao can simulate different model training scenarios to help researchers select optimal model parameters and algorithms. For example, by leveraging Doubao's intelligent computing capabilities, researchers can compare the performance of different deep learning algorithms (such as LSTM and GRU) in Nanning's air quality prediction, determine the model structure best suited to local data characteristics, and enhance the prediction accuracy and stability of the model.

3.4 Comparison of application effects of different ai tools

In the air quality prediction of Nanning, AI tools such as Doubao, DeepSeek, and Kimi each have distinct advantages and exhibit varying application effects. Doubao excels in text data processing and knowledge assistance, providing rich knowledge and information support for the construction of prediction models, and also plays a role in data preprocessing and model training scenario simulation. However, in direct air quality data processing and prediction model construction, its capabilities are slightly less than those of professional deep learning tools like DeepSeek.

DeepSeek has obvious advantages in real-time monitoring, in-depth analysis of air quality data, and prediction model construction. It can accurately capture the complex characteristics and change laws of air quality data, achieving high-precision prediction and pollution source tracking. Nevertheless, DeepSeek is not as flexible and comprehensive as Doubao in processing unstructured text data and knowledge mining.

Kimi plays a significant role in document processing and information extraction, data analysis assistance, as well as model construction and evaluation suggestions. It can provide researchers with convenient tool support and inspiration. However, Kimi itself does not possess powerful deep-learning and complex data processing capabilities, and thus needs to collaborate with other professional tools in the core construction process of air quality prediction models.

Overall, in the research on air quality prediction in Nanning, AI tools such as Doubao, DeepSeek, and Kimi each have their unique strengths. For example, Doubao can be utilized for text data processing and knowledge extraction to provide abundant knowledge reserves for DeepSeek's model training. Relying on DeepSeek's powerful data processing and prediction capabilities, high-precision prediction models can be constructed. By using Kimi's document processing and analysis assistance functions, convenient support can be provided at all stages of the research, improving research efficiency and quality.

4 Experimentation

4.1 Data collection and preprocessing

To develop an air quality prediction model suitable for Nanning, comprehensive data collection is first implemented. Data sources include: real-time concentration data of pollutants such as sulfur dioxide and PM10 from air quality monitoring stations under Nanning's Ecological Environment Bureau; meteorological data from meteorological departments, including temperature, humidity, wind speed, wind direction, and air pressure; and pollution source data, covering industrial enterprise emissions, motor vehicle exhaust emissions, and construction site dust data. Additionally, text data related to Nanning's air quality from social media is collected to extract public perceptions and feedback on air quality.

During data collection, ensuring accuracy, integrity, and consistency is critical. Collected data undergoes rigorous cleaning to remove outliers, duplicate entries, and missing values. For missing data, methods like interpolation or mean imputation are applied to maintain dataset completeness. Concurrently, data standardization transforms variables of diverse magnitudes and units into a unified scale, facilitating effective model training and analysis. For example, air quality indices (e.g., PM2.5, SO_2) and meteorological parameters (e.g., temperature, wind speed) are normalized using techniques like Min-Max scaling or Z-scoring to eliminate dimensional biases that could skew model performance. This preprocessing pipeline ensures datasets are robust, comparable, and ready for machine learning applications, enhancing the reliability of air quality prediction models.

4.2 Prediction model construction and training

Based on AIGC technology and combined with the actual situation of Nanning, an air quality prediction model is constructed. A hybrid model that combines the Long Short-Term Memory network (LSTM) and Convolutional Neural Network (CNN) in deep learning is adopted. The LSTM network can effectively process time-series data and capture the long-term dependencies and dynamic change characteristics of air quality data; the CNN network is good at extracting the spatial features of data and mining the spatial distribution information in multi-source data.

During the model construction process, the CNN network is first used to extract features from the spatial distribution data of air quality monitoring stations, the spatial field information of meteorological data, and the geographical location data of pollution sources to obtain the spatial feature representation of the data. Then, the extracted spatial features are input together with the time-series air quality data into the LSTM network for feature learning and prediction in the time dimension. In this way, the spatio-temporal features of the data are fully integrated to improve the prediction accuracy of the model.

In the model training stage, the collected historical data of Nanning is used as the training set to train the constructed model. The Stochastic Gradient Descent algorithm is adopted as the optimizer to minimize the prediction error of the model. During the training process, the parameters of the model are continuously adjusted, such as the number of hidden layer nodes in the LSTM network, the size and number of convolutional kernels in the CNN network, etc., to improve the performance of the model. At the same time, the cross-validation method divides the training set into multiple subsets, and one subset is used as the validation set to evaluate and tune the model, avoiding overfitting of the model.

4.3 Visualization design and interactive function implementation

To intuitively present air quality prediction results to decision-makers, environmental protection departments, and the public, an innovative visualization platform is designed. Using Geographic Information System (GIS) technology, a map of Nanning serves as the base background, with real-time labeling of air quality monitoring stations' locations. Different colors and icons are employed to represent varying air quality conditions. In 2023, Nanning achieved 361 days of excellent or good air quality, with the proportion of air quality compliance days reaching 98.9%. The main air pollutants in the urban area continued to meet the national second-level standards, and the ambient air quality has remained stable and compliant for seven consecutive years, as shown in Figure 3.

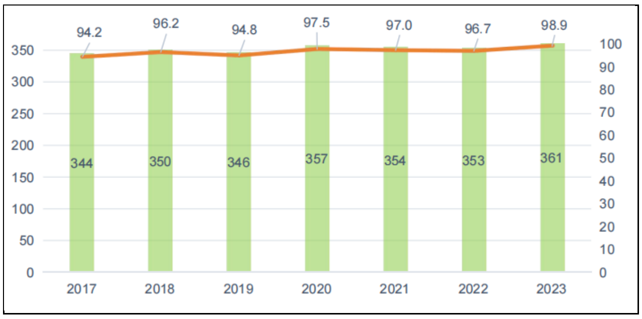

Fig. 3 Air Quality Compliance Status in Nanning/%

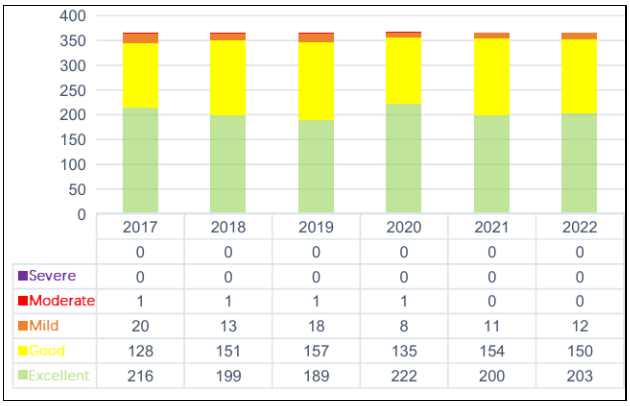

Fig. 4 Categories of Ambient Air Quality in Nanning

For enhanced visual clarity, visual design integrates distinct colors and clear text, combining graphics and text in layout design—for example, green indicates excellent air quality, yellow signifies good, brown represents light pollution, red denotes moderate pollution, and purple indicates severe pollution. The striking contrast of colors intuitively illustrates pollution levels across different years. Visual design transforms complex and tedious data into more intuitive and accessible charts, presenting information directly to the public. This not only broadens the audience for information dissemination but also accelerates its speed, enhancing the intuitiveness and comprehensibility of ecological environment system management, as shown in Figure 4.

Dynamic charts are used to display the temporal variation trends of pollutant concentrations such as sulfur dioxide and PM10. Line charts, bar charts and other forms are adopted to clearly present the changes of pollutant concentrations on different time scales (e.g., weekly, monthly, annual). Meanwhile, users can freely choose to view the air quality changes in different time periods.

To implement interactive functions, a user-customizable query module is designed. Users can input specific regions, time ranges, or pollutant types, and the system will instantly generate corresponding air quality prediction reports and visual analysis charts. Meanwhile, an intelligent question-and-answer function is integrated, leveraging Doubao's natural language processing capabilities. Users can ask questions in text to obtain targeted explanations about causes of air quality changes, pollution prevention suggestions, etc., enhancing the decision-making support and public science value of the visualization platform. This design not only meets personalized data query needs but also provides professional and accessible environmental insights through human-computer interaction, facilitating scientific management for environmental departments and public awareness of air quality protection.

4.4 Model evaluation and optimization

To ensure the reliability and effectiveness of the model, multiple evaluation metrics are adopted to comprehensively assess the constructed air quality prediction model. Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2) are selected as the core evaluation indicators, measuring the closeness between the model's predicted values and actual observed values from different dimensions.

The experimental results on the test set show that the LSTM-CNN hybrid model performs excellently in predicting PM2.5 concentrations. The MAE is 2.3 $\mu g/m^3$, the RMSE is 7.8 $\mu g^2/m^6$, and the R2 value reaches 0.92, indicating that the model can explain 92% of the variations in PM2.5 concentrations. Compared with single LSTM or CNN models, the hybrid model demonstrates significant improvements in all metrics. Specifically, the MAE is reduced by 18%, and the RMSE is decreased by 22%. For ozone concentration prediction, the model has an MAE of 5.6 $\mu g/m^3$, an MSE of 38.2 $\mu g^2/m^6$, and an R2 value of 0.88, also showing good prediction performance.

Based on the evaluation results, the model is further optimized. By adjusting hyperparameters such as the number of hidden layer nodes in the LSTM network, the parameters of convolutional kernels in the CNN network, and the learning rate, and by introducing the Dropout technique to prevent overfitting, the model's performance on both the training set and the test set becomes more balanced, and its generalization ability is significantly enhanced.

4.5 Case validation and practical application

Taking the sulfur dioxide concentration in Nanning from 2017 to 2023 as an example to verify the model's actual prediction capability, as shown in Figure 5, the sulfur dioxide concentrations in Nanning from 2017 to 2022 were 10, 10, 9, 8, 8, and 8 μg/m³ respectively, and three AI tools—DeepSeek, Kimi, and Doubao—optimized through model evaluation were used for intelligent prediction. DeepSeek integrated historical data, governance efforts, and recent phased achievements to predict the 2023 sulfur dioxide concentration in Nanning as 8.8 μg/m³; Kimi combined the results of the average value method and trend analysis while considering overall data fluctuations to predict a concentration of 9.7 μg/m³ for 2023; Doubao synthesized data trends and pollution causes to predict that the sulfur dioxide concentration in Nanning in 2023 would tend to be 10.3 μg/m³. Comparing with the actual sulfur dioxide concentration in Nanning in 2023, the prediction residuals were 0.8 μg/m³ for DeepSeek, 1.7 μg/m³ for Kimi, and 2.3 μg/m³ for Doubao. In summary, DeepSeek showed the highest prediction accuracy, followed by Kimi, and Doubao had the lowest prediction accuracy.

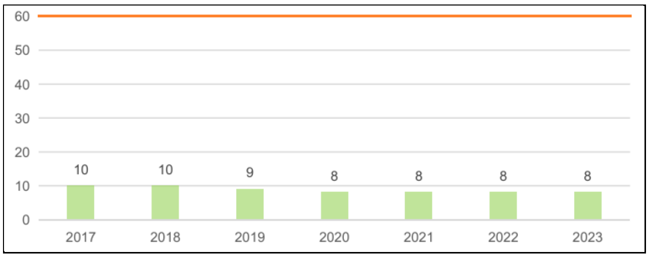

Fig. 5 Annual Average Concentration of Sulfur Dioxide in Nanning/μg/m³

Additionally, taking the PM10 concentration in Nanning from 2017 to 2023 as an example to verify the model's actual prediction capability, as shown in Figure 6, the PM10 concentrations in Nanning from 2017 to 2022 were 52, 52, 53, 46, 47, and 42 μg/m³ respectively, and three AI tools—DeepSeek, Kimi, and Doubao—optimized through model evaluation were used for intelligent prediction. DeepSeek integrated historical data, governance efforts, and environmental dynaFig. 5 Annual Average Concentration of Sulfur Dioxide in Nanning/μg/m³ mics to predict the 2023 PM10 concentration in Nanning as 43 μg/m³; Kimi combined the results of the average value method and trend analysis while considering overall data fluctuations to predict a concentration of 46 μg/m³ for 2023; Doubao synthesized data fluctuation patterns and policy intensity to predict that the PM10 concentration in Nanning in 2023 would tend to be 48 μg/m³. Comparing with the actual PM10 concentration in Nanning in 2023, the prediction residuals were 1 μg/m³ for DeepSeek, 4 μg/m³ for Kimi, and 6 μg/m³ for Doubao. In summary, DeepSeek exhibited the highest prediction accuracy, followed by Kimi, and Doubao had the lowest prediction accuracy.

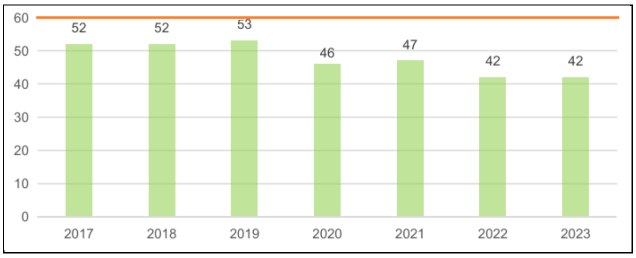

Fig. 6 The annual average concentration of PM10 in Nanning/μg/m³

In terms of the comprehensive average error values, DeepSeek demonstrates the highest prediction accuracy for air quality, followed by Kimi, while Doubao has the lowest accuracy. To conduct a more systematic comparison of the prediction capabilities of these three AI tools, the Mean Absolute Percentage Error (MAPE) is introduced for comparison, and the formula 1 is as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \quad (1)$$

In the formula, Yt represents the actual value, another Yt represents the predicted value, n denotes the number of observation periods, and t represents the t-th observation period.

Table 3. Comparison of Mean Absolute Percentage Errors of Various AI Tools / %

Serial Number	AI Tool	Mean Absolute Percentage Error/%
1	DeepSeek	0.1128
2	Kimi	0.1635
3	Doubao	0.2017

After calculation, Table 3 was obtained. It can be seen from the table that the mean absolute percentage error values of DeepSeek, Kimi, and Doubao are 0.1128%, 0.1635%, and 0.2017%, respectively. DeepSeek has the lowest error and the highest prediction accuracy, once again verifying the precision of the optimized DeepSeek in air quality prediction.

4.6 Prediction feasibility and visualization improvement

AI tools can accurately predict significant upward trends in air quality indicators such as sulfur dioxide concentration and issue early warnings. Based on the model's prediction results, environmental protection departments take proactive control measures in advance, such as industrial source emission reduction and motor vehicle traffic restrictions, which effectively reduce peak pollution concentrations and shorten pollution duration. In practical applications, the model can achieve real-time prediction of pollutant concentrations such as sulfur dioxide and PM10, and generate air quality prediction reports for the next 72 hours, providing a scientific basis for government departments to formulate pollution prevention strategies, enterprises to adjust production plans, and the public to arrange travel reasonably.

To more intuitively compare the comprehensive environmental quality of various districts in Nanning in 2023, a visual design is carried out by incorporating different colors and clear text, and integrating graphics and text for layout design, as shown in Figure 7. According to the comprehensive environmental quality index evaluation, among the 9 urban areas and development zones in the built-up area of Nanning, it can be clearly seen that Wuxiang New Area, Yongning District, and Qingxiu District have relatively better air quality.

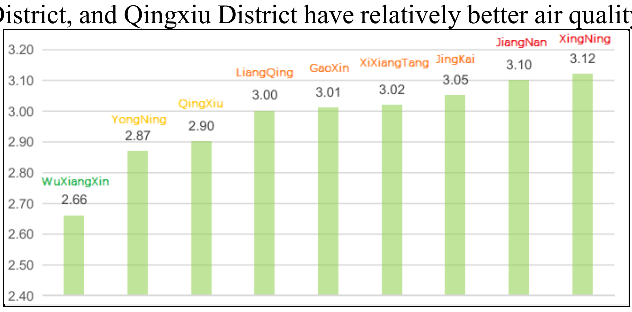

Fig. 7 Comprehensive Index Map of Districts and Development Zones in Nanning, 2023

During the trial operation phase of the visualization platform, feedback was collected from various sources by inviting environmental experts, government officials, and public representatives to participate in the testing. According to the feedback, the platform functions were further optimized: an analysis module on the correlation between air quality and health impacts was added to provide personalized health protection suggestions for the public; the dynamic display effect of the pollution source heat map was improved to intuitively present the diffusion paths of pollutants; and the mobile-end adaptation was optimized to enhance the user experience on mobile phones and tablets. After three months of trial operation, the user satisfaction of the platform reached 91%. Users generally agree that the visualization platform is easy to operate, and the prediction results are intuitive and understandable. In particular, the intelligent question-answering function can quickly answer various questions, effectively enhancing the public's awareness and participation in air quality issues.

4.7 The generalizability and applicability of the empirical case of Nanning

The optimized AI tools in this study, such as DeepSeek, Kimi, and Doubao, have demonstrated high-efficiency performance in the air quality monitoring and pollutant concentration prediction of Nanning City. These tools are based on deep learning and natural language processing technologies, and possess powerful data analysis and pattern recognition capabilities. Their algorithm architectures are highly versatile, allowing them to adapt to environmental data of various scales and structures. When dealing with complex air quality data, by adjusting parameters and optimizing models, they can quickly adapt to the formats and characteristics of monitoring data from other cities. This provides the technical guarantee for the promotion of the research results to other regions.

As a typical rapidly developing city in southern China, Nanning is representative in terms of urban scale, industrial structure, population density, and climatic conditions. Its industrial structure covers multiple sectors such as industrial production, transportation, and commercial activities, resulting in complex sources of air pollution, including industrial waste gas emissions, vehicle exhaust, dust pollution, and other types. These pollution sources are similar to those in many other Chinese cities. In addition, due to Nanning's subtropical monsoon climate, the patterns of pollutant dispersion and accumulation can serve as a reference for cities with similar climates in southern China. Therefore, the application model of AIGC technology established to address Nanning's air quality issues, as well as the experiences gained in data collection, model training, and visual analysis, can provide valuable references for the ecological environment management of other Chinese cities.

From a global perspective, there are numerous regions that share similar urban development stages, industrial structures, and climatic conditions with Nanning. For example, some cities in Southeast Asia, South Asia, and other regions are also confronted with the deterioration of air quality caused by the accelerated pace of urbanization. These cities face challenges in ecological environment management that are comparable to those in Nanning, such as the complexity of data collection, the diversity of pollution sources, and the urgency of decision - making support. The visualization solutions based on AIGC technology in this study can adapt to the environmental data characteristics of different regions by adjusting data parameters and model settings. They provide innovative ideas and practical examples for the urban environmental management of regions with similar characteristics worldwide, and thus have certain promotion value and application prospects.

5 Conclusion

Studies show that AIGC technology can effectively integrate multi-source heterogeneous data, significantly improving the accuracy and efficiency of air quality prediction. This study systematically integrates different types of AI tools such as DeepSeek, Kimi, and Doubao for the first time. By combining the advantages of these AI tools, it achieves precise prediction of pollutant concentrations including sulfur dioxide and PM10. Through comparative analysis of calculation examples, the optimized DeepSeek has prediction residuals of 0.8 μg/m³ and 1 μg/m³, respectively—the lowest values among the three AI tools. Additionally, it has the smallest average absolute percentage error, demonstrating the most superior performance. Leveraging its strengths in data processing, model construction, and knowledge assistance, DeepSeek forms a synergistic effect, providing a feasible new technical pathway for air quality prediction.

Through in-depth exploration of AIGC technology applications in Nanning's air quality prediction, this study successfully constructs a multimodal prediction model and visualization platform based on AI tools such as Doubao, DeepSeek, and Kimi. Incorporating visual design into air quality monitoring data management makes the displayed information more accessible and enhances public participation. In visualization design, an innovative interactive platform developed with functions such as GIS maps, dynamic charts, and intelligent question-and-answer provides intuitive and efficient decision-support tools for ecological environment system management.

Although this study has achieved certain results and has certain promotion value and application prospects at home and abroad, there are still some limitations. Model training relies on historical data, with predictive capabilities for extreme weather or sudden pollution events requiring improvement. AIGC applications in ecological environments face ethical/technical challenges like data privacy. Future research will focus on optimizing model architectures, exploring advanced deep learning algorithms (e.g., Transformer) to enhance responsiveness to complex environmental changes, and conducting cross-disciplinary AIGC research. Additionally, efforts will refine visualization platforms by integrating virtual reality (VR) to create immersive decision-support systems, providing stronger technical support for ecological sustainability.

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7 References

[1] Huang Jie., Zhang Feng., Du Zhenhong.: 'Hourly PM2.5 Concentration Prediction Based on Integrated Deep Learning Model of RNN-CNN', Journal of Zhejiang University (Science Edition)., 2019, 46, (3), pp. 370–379

[2] Huang Yirong., Xiong Qiulin., Xiong Zhengkun.: 'Spatiotemporal Prediction of Atmospheric Pollutants in Poyang Lake Ecological Economic Zone Based on CNN-LSTM', Ecology and Environmental Sciences., 2024, 33, (12), pp. 1891–1901

[3] Zhou Miaoying., Zhou Jun., Shi Mengling.: 'Research on the Application of Ecological Environment Monitoring Technology in Urban Air Quality Assessment', Ecology and Resources., 2024, (8), pp. 41–43

[4] Li Wenlong.: 'Analysis of Environmental Protection Measures for River Ecological Restoration', Leather Manufacture and Environmental Protection Technology., 2024, 5, (22), pp. 49–51

[5] Zhang Bin., Fang Ling., Mo Bowen.: 'Design of Visualization Platform for Air Quality Prediction Based on SCINet Model', Modern Information Technology., 2023, 9, (5), pp. 62–65

[6] Ye Lin., Chen Xiaohui., Liu Haiyan.: 'Visual Analysis Method of Air Quality Situation Predicted by Neural Network', Journal of Information Engineering University., 2024, 25, (4), pp. 411–416

[7] Zheng Yao., Xing Yu., Guo Yuesong.: 'Air Quality Analysis and Visualization Optimized by Grey Relational Model', Energy and Environmental Protection., 2022, 44, (8), pp. 50–56

[8] Du Z., Lin X.: ' Air Quality Prediction Based on Neural Network Model of Long Short-term Memory', AEIC Academic Exchange Information Center(China)., 2020, pp. 75–79

[9] Xu R., Xiong X., Liu G.: 'Evaluation of ecological environment governance quality in the top ten cities of Zhejiang province using entropy weight method and rank-sum ratio method:A case study of air quality indicators', Department of Civil Engineering,University of Birmingham., 2024, pp. 261–270

[10] Lee P, F.: 'Inferring particle distributions in two-dimensional space with numerical features based on generative adversarial networks (GANs)', Nuclear Engineering and Technology., 2025, 57, (10), pp. 103681–103681

[11] Oliveira D G F., Santos D D L., Palmeiro S A.: 'Assessment of surface water quality based on physical and chemical parameters in a GIS, for three rivers in southern Brazil', Environmental Pollution., 2025, pp. 375126295–126295

[12] Sarria R F., Delgado G M., Palma M R.: 'Modelling Pollutant Dispersion in Urban Canyons to Enhance Air Quality and Urban Planning', Applied Sciences., 2025, 15, (4), pp. 1752–1752