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A new integrated 3D modeling method based on multisource heterogeneous geological data and its application

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ABSTRACT

With continuous advancement in geological studies, three-dimensional (3D) geological modeling technology based on big data and artificial intelligence (AI) has become a prominent focus in the interdisciplinary field of earth and information sciences. Through the analysis and comparison of existing 3D modeling methods, this study introduces a high-precision 3D geological modeling approach. The new method leverages advanced computing technologies, including multisource heterogeneous data processing, integrated model databases, seamless splicing of local models, and cluster analysis. Furthermore, it enables unified 3D visualization of subsurface and surface conditions, providing new insights into disaster prevention, mitigation, and intelligent mineral exploration. To validate its practicality, this study conducts 3D geological modeling of the X area within the Sichuan Basin, China. The data sources include remote sensing images, geological maps, geophysical data, borehole data, and X-ray fluorescence (XRF) spectroscopy data. Preliminary exploration in the X area has successfully identified new mineralization belts, verifying the feasibility and effectiveness of the new 3D geological modeling method that integrates big data processing and intelligent techniques.

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1. Introduction

As new strategic initiatives for prospecting breakthroughs advance, there is an increasingly urgent need to explore the deeper and peripheral areas of mineralization belts. Specifically, the focus of exploration has shifted from outcrops, shallow layers, and easily identifiable ore bodies to concealed, deep, and challenging targets. Given the rising complexity of exploration, it has become imperative to adopt innovative theories, technologies, and methods to improve the efficiency of mineralization prediction and exploration. A recently developed 3D geological modeling method that integrates surface and remote information has emerged as a crucial tool in mineralization prediction (Yu RQ et al., 2013).

Combining remote sensing images, digital elevation models (DEMs), and 3D geological modeling effectively enhances the visualization of geobodies. The key aim of 3D geological modeling is to provide an accurate and objective representation of geological conditions by integrating multisource data. Currently, popular 3D modeling software packages such as Petrel, Surpac, and Micromine suffer from a common limitation: they fail to simultaneously load and process multiple data types (Zhou F et al., 2022). In recent years, many researchers have proposed and improved various 3D geological models based on extensive studies and practical applications. Typical examples include a borehole-based stratigraphic boundary model (He HJ et al., 2002), an object-oriented vector-raster integrated 3D model for ore bodies (Liu YJ et al., 2012), a profile-based method using tunnel-stratigraphy intersections (Zhang ZH et al., 2014), and a virtual generalized triangular prism (GTP) model (Li CL et al., 2013). Although these models have advanced the modeling of complex geobodies, they remain limited by dependence on single data sources and low precision.

Using big data and AI, this study proposes a novel 3D

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modeling method based on multisource heterogeneous geological data processing and high-precision constraints. To validate its practicality, this method is employed to conduct the 3D geological modeling of the X area within the Sichuan Basin using remote sensing images, geological maps, geophysical data, borehole data, and XRF spectroscopy data. Modeling and visualizing the X area reveals a new mineralization belt, confirming the feasibility and effectiveness of the new approach.

2. Key technologies of the new 3D modeling method

2.1. Overview

Information technology (IT) is rapidly transforming production, lifestyles, and thought while also advancing Earth system science and modernizing geological practices. Since the establishment of the China Geological Survey, the digitalization of geological surveys has been one of its key priorities (Li CL et al., 2015). Recently, traditional methods for representing geological information, such as maps and cross sections, have struggled to meet the demands of big data and digital transformation. Research on 3D geological modeling and visualization has attracted wide attention across multiple disciplines, supporting the ‘Glass Earth’ strategy and the integration of multisource heterogeneous data in geological big data in several countries (Zhang Y et al., 2022). Moreover, 3D visualization has increasingly become a significant component of the digitalization of geological surveys. New 3D geological modeling methods are systematic approaches that integrate technologies including multisource heterogeneous data processing, holistic model databases, seamless local modeling, remote sensing, and the convergence of big data with AI.

2.2. Technology for multisource heterogeneous data processing

2.2.1. Characteristics of geological data

Geological big data technology is a technical system that integrates cloud computing, information and communication technology, and internet platforms to collect, manage, analyze, and apply geological data. By employing advanced data processing and analysis techniques, this technology reveals potential value in geological data, thus providing robust support for geological studies, resource exploration, early warning of geologic hazards, and environmental protection. Its application to 3D modeling enhances data processing while also ensuring model integrity (Wang Y et al., 2021). However, the data employed are characterized by multiple sources and heterogeneity. Specifically, geological phenomena are represented using various data types, including remote sensing, borehole, cross-sectional, and geophysical exploration data. Furthermore, each of the data types potentially has multiple sources. As a result, even for the same geological phenomena in a given area, it is challenging to ensure the consistency of multisource heterogeneous geological data. The resulting uncertainties in

data quality necessitate thorough processing to construct accurate 3D geological models.

2.2.2. Isomerization of heterogeneous data

The fusion of multisource remote sensing data is a technology that comprehensively processes and analyzes these data, particularly facilitating the integration of these data with other multisource information in geoscience research. Multisource heterogeneous data processing plays a fundamental role in geological modeling. Regardless of the data source, the key to the processing is to convert heterogeneous data into isomorphic vector data (points and lines), thereby providing foundational data on surface features such as ground, fault planes, and rock mass surfaces.

2.2.3. Data conflict priority

During geological modeling, when data conflicts occur, the multisource heterogeneous data processing technology determines the priority of conflicting data, with higher-accuracy data corresponding to higher priority. In other words, the usage of the original data is positively correlated with their accuracy.

2.3. Large-scale and high-precision holistic modeling

2.3.1. Working principle

Large-scale, high-precision holistic modeling contributes to the establishment of a continuous 3D geological model that meets the accuracy demands of various geological research fields. This approach depends primarily on model database and data expansion technologies. Model database technology facilitates the integration of different strata in a large area, ensuring that local models achieve accuracy comparable to traditional block models. In contrast, data expansion technology allows for the splicing and fusion of boundary faults and strata, thus improving fault delineation. Using complex structures, large-scale and high-precision holistic modeling ensures consistent model information, high-precision fusion across areas, and effective inheritance of existing modeling achievements. Additionally, holistic modeling enables unified storage of data and models while establishing a unified management and communication platform. This technology is suitable for exploration and exploitation in the study or mining areas that offer extensive, diverse geological data. The model constructed using this technology can accurately represent all geological structures in the study area. Besides, the holistic model can serve as the basis for fine-scale geological management. Lastly, large-scale, high-precision holistic models can provide accurate geological descriptions, rapid computations, and dynamic updates. Fig. 1 shows the working principle of large-scale, high-precision holistic modeling. Initially, raw data are stored in a database. Then, a holistic model is constructed using holistic model database technology, seamless local modeling, and a collaborative parallel working pattern. Third, cluster visualization technology is used to describe the entire model, supporting the development of various professional

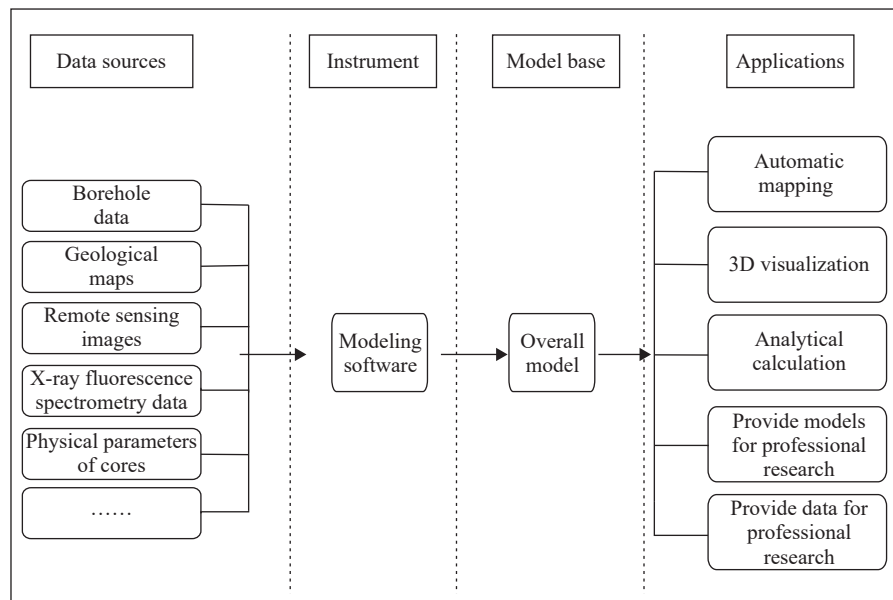


Fig. 1. Working principle of large-scale, high-precision holistic modeling.

applications (Ma ZY et al., 2022).

2.3.2. Holistic model database technology

The holistic model database technology employs a chip storage mode to generate and store models as field data, transforming the traditional storage file mode of models. This represents the core of holistic model databases. During model storage, users specify and separate model cells in the external display first, and the model cells separated are then saved to the database file. Specifically, each cell is stored in a corresponding table, whose information is recorded as fields. When a local model is downloaded, the system identifies the locked cells of the model. Therefore, an established local model is derived into multiple slice or cell models after being processed. In the database, the information of these models is recorded as fields in corresponding cell tables. The call process of models is similar to the storage process. Specifically, the locked cell models are initially extracted from the database and then processed to form a complete model (Fig. 2).

2.3.3. Seamless splicing technique for local modeling

The splicing of areas with few splices can be achieved using traditional modeling methods. However, excessive and overly large splices will lead to an overlarge working area to be processed by conventional software. In this case, model database technology should be adopted. This technology enables seamless splicing of local models using local splicing and extended grids, thus achieving the splicing of multiple or large working areas. The seamless splicing technique for local models involves loading all the data of an overlapping area into the database to achieve a unified understanding of structures. Then, the model of the overlapping area is updated, during which the updated model and its surrounding models can be seamlessly spliced using extended grids. In this manner, seamless splicing and fusion across multiple working areas can be achieved.

In local modeling, it is necessary to select proper splicing methods for various splicing sites. For the splicing sites involving faults, splicing can be achieved as follows: (1) When faults at the splicing sites remain unchanged, seamless splicing can be performed automatically; (2) when faults at the splicing sites change without affecting adjacent blocks, seamless splicing can also be executed automatically; (3) when faults at the splicing sites change and adjacent blocks are affected, an additional block at the fault should be downloaded and remodeled to achieve seamless splicing. The stratigraphic models in the splicing areas can be established only when the fault and stratigraphic data are consistent. This allows for a unified understanding of boundary faults across adjacent blocks, effective integration of modeling results, and avoidance of repetitive modeling (Ma ZY et al., 2022). Fig. 3 shows the identification of boundary faults in an overlapping area.

2.3.4. Collaborative parallel working pattern

During holistic modeling, the collaborative parallel working pattern can be applied to divide the working area into multiple segments, allowing the parallel construction of a holistic model by multiple people. This pattern overcomes the limitations of the conventional single-person method in achieving regional modeling.

2.3.5. Cluster visualization system

The cluster visualization system is a platform focusing on cluster graphics processing. It can provide the visualization of both the large-scale holistic model and local models of any size and location while also allowing the generation of the geological plans and sections of any location.

2.4. Application of remote sensing technology

2.4.1. Overview

Remote sensing technology employs various types of

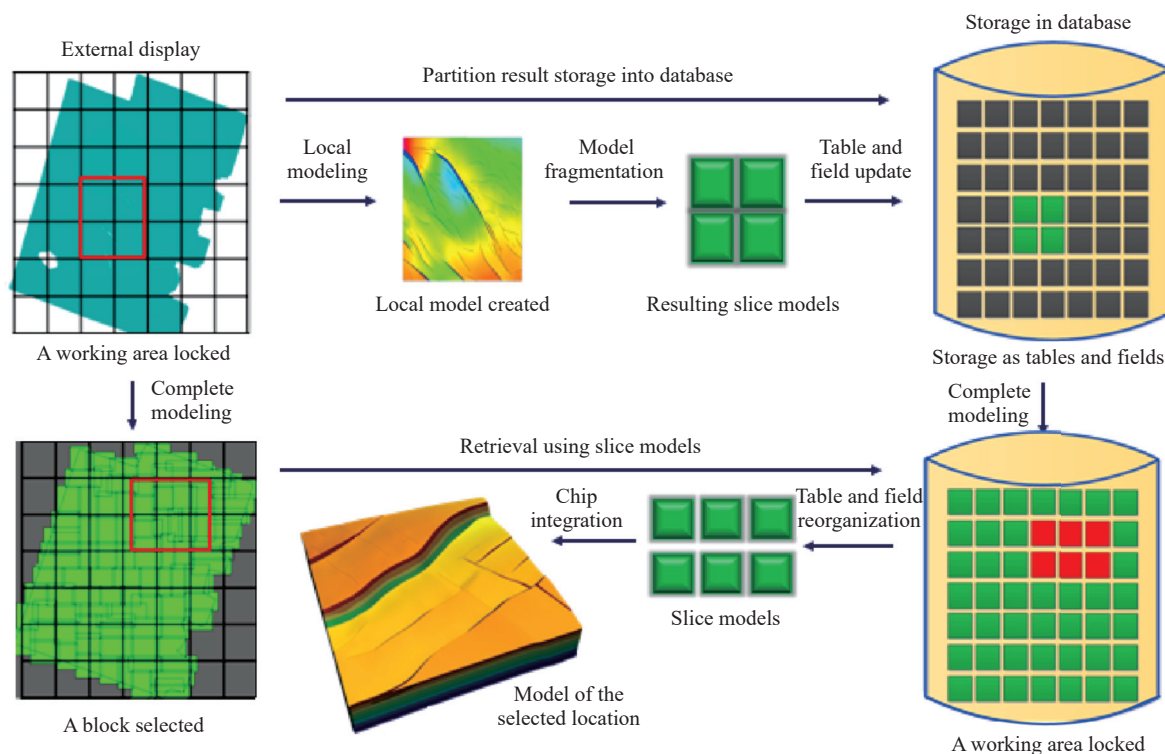


Fig. 2. Holistic model database technology.

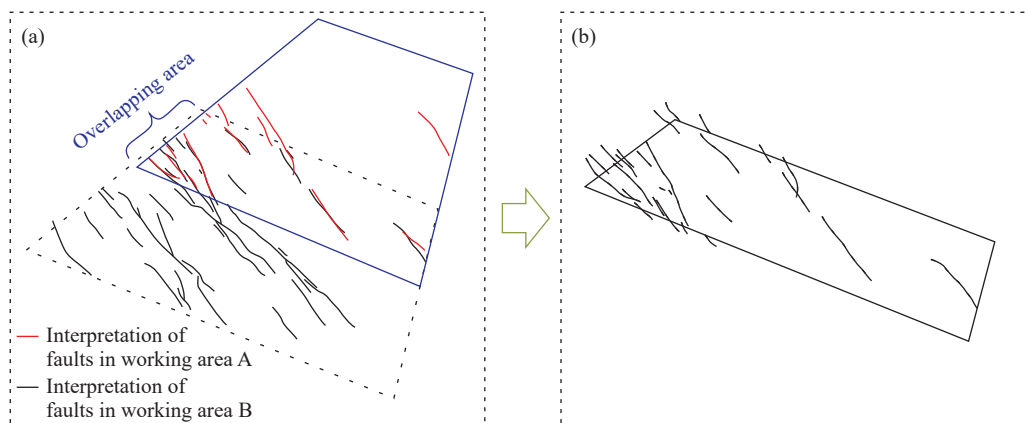


Fig. 3. Schematic diagram showing the selection of overlapping areas. a–Inconsistent boundary faults identified in varying working areas; b–finally identified boundary faults.

sensors located at different distances to obtain the Earth's information. Since the acquisition of the first remote sensing image, this technology has been applied to land use, hydrology, geology, meteorology, climate studies, and vegetation studies (Slonecker ET et al., 2001; Horning N et al., 2008). Its evolution has significantly broadened the horizon of field-related technologies, establishing it as an indispensable tool for geological studies and 3D modeling. The development of sensor parameters has significantly improved the observation scale, resolution, and identification accuracy. Remote sensing geology has transitioned from macroscopic to microscopic detection and from qualitative interpretation to quantitative inversion, resulting in elevated applications (Wang RS, 2011). Its primary research directions include remote sensing image processing, multi-spectral alteration anomaly extraction, and hyperspectral mineral

identification and mapping. Additionally, it also involves surface deformation survey and monitoring based on interferometric synthetic aperture radar (InSAR), remote sensing-based ore prospecting models, and remote sensing-based geologic hazard investigation and monitoring. In this context, the research results of remote sensing technology are essential for predicting the structural morphology, lithology, and attribute distribution of 3D geological models (Du XF, 2018). A major advantage of this technology is its ability to identify and extract the spatial extent and elemental characteristics of built-up areas, thus supporting planning and resource management, risk assessment, and the early warning of disasters (Bhaskaran S et al., 2010; Ge W et al., 2018).

2.4.2. Remote sensing image processing

Given the close relationship between fault formation and

rock mass interactions, the fault structures of adjacent rock masses can be analyzed and compared based on their spatial distributions. For instance, using the Enhanced Thematic Mapper Plus (ETM+) remote sensing images as a data source, information about linear structures can be extracted from the remote sensing images of rock masses. By comprehensively analyzing isodensity maps, trend surfaces, and stress field distributions, the genetic relationships of rock masses can be determined. Remote sensing image data are images that are acquired from various sensors and undergo error processing and radiometric correction. After constant advancement, modern remote sensing technology has become a significant tool for extracting information from images due to its macroscopic, dynamic, rapid, accurate, and comprehensive nature (Li XC, 2005). Satellite image products play a crucial role in map-assisted datasets (Stevens FR et al., 2015). Surface DEMs are primarily acquired using methods including field surveys, map digitization, and InSAR (Waskiewicz T et al., 2013; Zhang W et al., 2016). Moreover, with the rapid development of IT, many DEM datasets can be downloaded directly on the Internet (Woodcock CE et al., 2008; Malenovský Z et al., 2012).

In the new 3D modeling method developed in this study, a major improvement in remote sensing image processing is the registration of remote sensing images with DEMs. This registration serves as the basis of 3D geomorphologic image mapping. For the superposition of remote sensing image data and DEMs, geometric registration is performed initially to transform the coordinate spaces into a unified projection coordinate system. In practice, a control point-based registration method is employed to match the control points and estimate the geometric transformation parameters for registration. Then, the registered remote sensing images are mapped as texture data onto the DEM-based 3D model surface, enabling realistic and objective landscape simulation. The spectral characteristics of remote sensing images can directly affect the visual quality of 3D geomorphologic models, while the accuracy of image-DEM overlapping can determine the accuracy of the 3D model reconstruction. Therefore, remote sensing image processing is crucial to improving the overall accuracy and fidelity of 3D models. Regarding 3D terrain visualization, with the remote sensing images of a certain area as textures, the DEM and the images are superimposed while ensuring coordinate registration among different datasets. As a result, data elements like text symbols, geographic features, and images of the area from various sources are transformed to share a unified coordinate system, contributing to the generation of the real-time 3D terrain of the area. The integration of remote sensing images with DEMs involves three key processes: The generation of the DEMs from remote sensing images, the correction of remote sensing images using the DEMs, and the registration between remote sensing images and DEMs (Hao M et al., 2014).

2.4.3. Remote sensing image interpretation

Remote sensing-based geoscience analysis aims to

provide more intuitive information, identify deeper spatial relationships, and enhance the accuracy of image classification and special feature extraction by integrating remote sensing data, geographic information, and geoscience knowledge. Developing spatial geodetic techniques is crucial for measuring surface displacement, thus increasing the number of detectable areas subjected to deformations (Biggs J et al., 2014, 2017; Huang Y et al., 2015; Yu M, 2017; Fernández J et al., 2018). In geology, remote sensing interpretation comprises four major aspects. (1) Interpretation of vertical faults: It involves assessing the changes in both their elevation differences and stratigraphic properties. For instance, NASA's Landsat 7, equipped with ETM+ sensors, provides data with higher spatial resolution and spectral richness compared to earlier emissive and land cover data. Such satellite data can serve as a reference for validating various methods in the future (Ma XL et al., 2017; Jiang W et al., 2017). Therefore, Landsat—with its long time series and high spatial resolution—can serve as a valuable data source (Wang KL, 2019). (2) Interpretation of horizontal strike-slip faults: Horizontal displacements produced by strike-slip faults have a wide range and long-time span. Features such as offset ridges, asymmetric valley slopes, and synchronous turning of water streams and terraces are key indicators for identifying horizontal strike-slip faults (Li JC, 2014). (3) Interpretation of multistage faults: Multistage faults are complex fault structures formed by multistage tectonic movements, occurring as T- or Y-shaped structures. (4) Interpretation of strata: Remote sensing images can vividly capture the structural traces and spatial framework of crustal movements, providing multi-level, multi-scale, and multisource structural landscapes for research on regional structures.

2.5. Technology of cutting for man-made structures, DEMs, and geobodies

Urban development and construction lead to increasing use of underground spaces, altering geobody shapes. To accurately characterize geobodies and assess their interactions with man-made structures, the impacts of man-made structures on geobodies must be examined first. The fusion of geological models and DEM data aims to address the mismatch between high-precision DEM surfaces and low-precision geological model grids. This can be achieved by cutting the geological mesh using a high-precision DEM surface. As a result, a new, complex polyhedral mesh that integrates the DEM and geobody data can be formed.

3. Applications of large-scale 3D geological models

3.1. Overview

Traditional large-scale 3D geological models are only applied to simple macroscopic visualization due to their low accuracy. In contrast, the new 3D geological modeling method developed in this study can satisfy diverse needs at both macroscopic and microscopic scales.

3.2. Assessment of geological suitability

Holistic structural modeling technology is crucial to the geological suitability assessment of large-scale engineering projects. This technology enables the integration of multisource data under the foundational framework of a holistic structural model. As a comprehensive platform for collaboration among multidisciplinary professionals, holistic structural models meet assessment needs in both the scale and precision dimensions. The processing technology for multisource heterogeneous data provides an accurate geological model for assessment. Notably, the construction of attribute models supplies a wealth of spatial attribute data, supporting quantitative assessments.

3.3. Analysis and research of geological big data mining

Remote sensing-based image data mining technology is to discover the information hidden in remote sensing images using image analysis, pattern recognition, AI, geographic information systems, and spatial data mining theories. This technology is the application of image data mining to remote sensing. The analysis of geological big data mining has become a hot research topic, especially with the increasing maturity of machine learning. The most fundamental requirement of geological big data mining is to establish a set of deep neural networks through machine learning to predict changes in geobodies and underground mineral distribution based on the structure and attribute distribution data of geobodies. The attribute model enables the unified storage and management of the structure and attribute distribution data of geobodies, providing effective support for various analysis methods of geological big data.

3.4. Gridding

3.4.1. Technical difficulties

Gridding serves as the technical foundation of attribute modeling, quantitative analysis, and numerical simulation. It is also the research focus of the new generation of 3D geological modeling technology. The grid type and gridding quality produce significant impacts on 3D geological modeling. 3D gridding faces two technical challenges. First, geologic conditions cannot be simplified during the 3D gridding of geobodies. Second, it is difficult to simplify the geological information when the 3D geological mesh is cut by man-made structures. Gridding can be achieved using most 3D geological modeling software, which, however, yields 3D mesh models using varying algorithms. This significantly affects the accuracy of subsequent analyses and calculations, determining whether the numerical simulation of solid mechanics can be performed. It is challenging to employ traditional gridding technologies to construct a 3D mesh that allows for accurate characterization of geological structures, as well as complex analyses and calculations. In contrast, the new 3D modeling method proposed in this study is more effective in gridding due to its integration of truncated

rectangular, perpendicular bisection (PEBI) grids, and corner-point grids.

3.4.2. Truncated rectangular grids

Truncated rectangular grids are irregular, allowing faults to be expressed using polygonal grids without losing their structural information. Besides, these grids are simple and efficient, supporting gridding under the constraint of complex structures.

3.4.3. PEBI grids

PEBI grids are unstructured grids that remain smooth without serrations at the stratigraphic and fault levels. These grids can be densified around boreholes, leading to more accurate simulation results. PEBI grids also support gridding under the constraint of complex structures.

3.4.4. Corner-point grids

Corner-point grids are commonly used in the geological modeling and numerical simulation of oil reservoirs. However, these grids will lose structural information where strata pinch out or faults intersect. Besides, it is inapplicable to the local updating of a 3D geological model.

3.4.5. Rasters

Rasters are simple regular grids characterized by simple spatial position expressions. They have a limited ability to express complex geobodies. Furthermore, they typically represent structural information using attribute interfaces, failing to express structures effectively.

3.5. Key techniques for attribute modeling

3.5.1. Attribute interpolation methods

Attribute modeling is to establish attribute models based on structural models by conducting calculations using a geostatistical method. The attributes involved consist of discrete attributes (sedimentary facies and lithofacies) and continuous attributes (water content, weight, permeability, and saturation). The commonly used interpolation algorithms include Kriging, sequential simulation, and inverse distance weighting (IDW).

3.5.2. Data analysis methods

Data analysis refers to data research and preprocessing using many methods before modeling. Attribute data for modeling can be classified into discrete data (for facies modeling) and continuous data (for physical property modeling), which correspond to varying analysis methods. The variogram function is a method to describe the variations in reservoir properties. This method follows the principle that samples in close proximity exhibit a stronger correlation than those farther apart. Furthermore, the further change in the distance, after exceeding a certain value, exerts minimal influence on the correlation. Discrete attributes can be directly analyzed using the variogram function. In contrast, continuous attributes should be transformed first. In this study, many

transformation algorithms have been developed, including input and output truncation, logarithmic and exponential transformation, standardization, and 1D, 2D, and 3D trend removal algorithms. The variogram function analysis yields experimental variogram functions, which need to be fitted. Previous studies indicate four major theoretical variogram models for fitting (Fig. 4). Of these, the spherical model, the most widely used in geostatistics, can effectively determine many variables through fitting. A variogram function contains three pivotal parameters: Sill, range, and nugget. Nugget C_0 is the Y-intercept of the function, indicating the discontinuous change of a variable below the sampling scale. Sill C_0+C is the maximum of the variogram function, representing the maximum variation in attributes. Range a is the minimum lag distance where the value of the function remains unchanged, indicating that the spatial correlation of the variable vanishes in the case of a lag distance greater than a . Therefore, range a reflects the influence range of the variable. With the continuous advancement in science and technology, the computing power of computers has been enhanced constantly, promoting the rapid development of numerical methods. These numerical methods can combine material and structural heterogeneity, supporting investigations into subsurface characteristics.

4. Application of 3D geological modeling in the X area

4.1. Overview

The X area, located in Southwest China, spans the Sichuan Basin and the Qinghai–Xizang Plateau, exhibiting an extensive area and complex geologic conditions. In this area, 56 types of mineral resources (with proven reserves for 30 types) and 620 mining areas have been identified. This study aims to construct a high-precision, large-scale 3D model for the X area using available geological maps, borehole data, and airborne remote sensing data. This model is expected to support future breakthroughs in mineral exploration.

4.2. Modeling scheme

The 3D geological modeling of the X area was conducted using four angular coordinates and the new 3D geological modeling method. Based on theories of geology and other related disciplines, this study investigated and assessed the primary structural features within the area, including topographic features, soil-rock interfaces, lithologic boundaries, lithologic assemblages, faults, folds, and structural planes, as well as subsurface stratigraphic distribution and structural morphologies at certain depths. This contributes to a detailed understanding of the spatial distribution and changes of surface and subsurface geobodies in the X area. The new 3D modeling method was applied to establish a high-resolution holistic 3D geological model of the area through gridding and multiple attribute modeling. The technology roadmap is shown in Fig. 5.

4.3. Data sources

4.3.1. Layer data from boreholes

Modeling was conducted using layer data (basic geological ages and formation data) from nearly 1960 boreholes with depths ranging from 300 m to 1600 m (Table 1).

4.3.2. Geological maps

Two 1 : 1000000 maps of the X area are available, and their splicing part was selected for modeling (red box in Fig. 6). Specifically, the modeling area covers an area of 31104 km² along the margin of the Sichuan Basin, exhibiting significant terrain differences and complex structures. This area is dominated by deep-lying hills and mountains, with elevations ranging from 1000 m to 3000 m and relative elevation differences of around 1000 m.

Fig. 6 illustrates the Chamdo H-47 and Chengdu H-48 maps. The area covered by the Chamdo H-47 map is located at 96°06'E–102°05'E and 28°06'N–32°06'N primarily in Chamdo, Xizang, with elevations ranging from 2296 m to 5460 m (average about 3500 m). This area exhibits complex

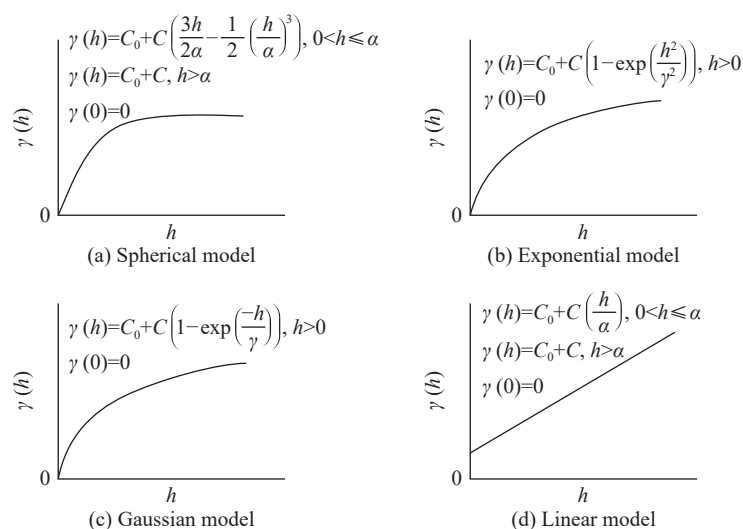


Fig. 4. Theoretical variogram models.

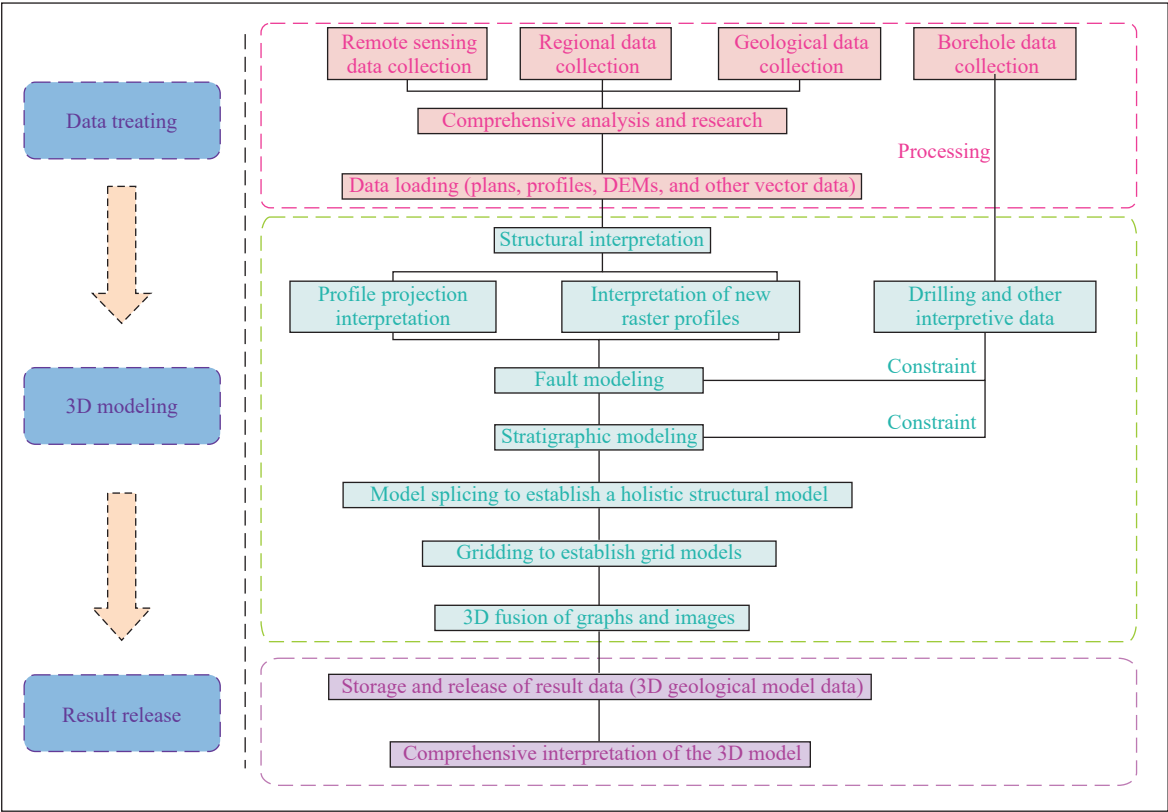


Fig. 5. Technology roadmap of the novel 3D geological modeling method..

Table 1. Examples of layer data from boreholes.

Borehole No.	Layer No.	Layer depth		Thickness	Age on the stratigraphic column	Formation
		From	To			
13-2	1	0	1.6	1.6	T ₁ ^{v3}	Jiujitanzu
13-2	2	1.6	132.76	131.16	T ₁ ^v	Yulongshanduan
13-2	3	132.76	288.8	156.04	T ₁ ^v	Yulongshanduan
13-2	4	288.8	299.97	11.17	P ₃ ^c	Changxingzu
13-2	5	299.97	364.61	64.64	P ₂ ^l	Longtianzu
...	...	...	...	...	...	...

and diverse geological characteristics and contains relatively complete strata except for the pre-Sinian and Cambrian strata. The strata in this area show a significant regional distribution and distinct contact relationships. Minerals in this area are dominated by copper and iron.

The area covered by the Chengdu H-48 map is located at 102°54'E–104°53'E and 30°05'N–31°26'N. This area is dominated by deep-lying hills and mountains, with elevations mostly ranging between 1000 m and 3000 m. The tectonic belt in this area primarily contains faults and folds, which significantly control the distribution and deformations of the strata within. Over 60 types of mineral resources have been discovered in Chengdu H-48, with primary minerals including iron, titanium and vanadium, copper, lead, zinc, aluminum, gold, silver, strontium, and rare earth.

4.3.3. Remote sensing image data

High-precision remote sensing images of the X area were used for modeling, covering 93°6'E–104°53'E and

28°30'N–32°28'N (Fig. 7). They serve as a reference for modeling and the visualization of the surface integration of 3D models, supporting professional studies. Remote sensing images can objectively reflect the morphologies, structures, spatial relationships, and other features of surface scenes, providing macroscopic, comprehensive insights into surface features. A high spatial resolution is generally preferred (Sousa AMO et al., 2015, 2017). High-quality land cover data like high-resolution optical remote sensing images serve as critical data sources of surface information (Xu H, 2008; Amarsaikhan D et al., 2009; Waqar MM et al., 2012; Xiang D et al., 2016; Liu S et al., 2017). These data sources can provide true and objective records of surface scenes, significant for 3D terrain simulation.

4.3.4. XRF spectroscopy data from cores

XRF spectroscopy data were obtained through the analysis of core samples. These data provide detailed information about the elemental composition of the samples, including the types and concentrations of elements, playing an essential role in constructing accurate geological models. Hence, they are of critical application value in 3D geological modeling. As a complex process involving the precise description and visualization of subsurface geological structures, stratigraphic distribution, and mineral resources, 3D geological modeling necessitates the combination of multiple data sources and technical means. As an important data source, the XRF spectroscopy data can complement and verify other data, contributing to the construction of more accurate and comprehensive geological models. The visualization of 3D

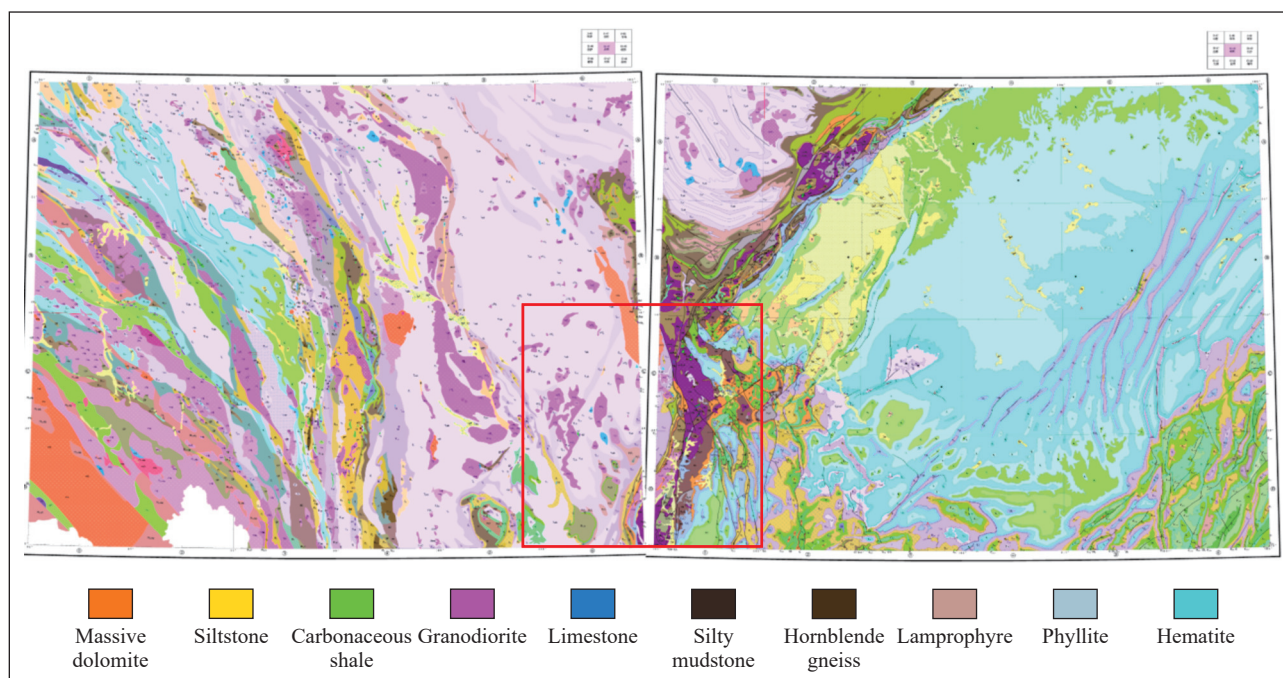


Fig. 6. Area for modeling.



Fig. 7. Remote sensing image of the X area.

geological models allows for a more intuitive presentation of subsurface geological structures, thus offering valuable decision support for geological exploration and mineral exploitation. In this study, the XRF spectroscopy data of core

samples from 200 boreholes were used (Table 2).

4.3.5. Physical parameters of cores

The physical parameters of cores play a significant role in

subsurface complex geological structures and reservoirs can be achieved by combining these data with 3D modeling technology. In this study, the physical parameters of core samples from 200 boreholes were used (Table 3).

The borehole data were organized in a uniform data format, with points of various layers arranged into three groups. These data were used to construct models of varying scales and precision to overcome overly thin layers within a too large working area. The coordinate system of the borehole location data was transformed from the World Geodetic System 1984 (WGS 84) to the China Geodetic Coordinate System 2000 (CGCS2000) using the Gauss-Krüger projection. Regarding the organization of geological maps, the 1 : 100000 Chengdu and Chamdo maps were projected onto the CGCS2000 to ensure consistency between projection parameters and borehole data. For the organization of surface elevation data, 90 m-resolution data were downloaded from the Geospatial Data Cloud initially and were then clipped and sparsified. The raster data were transformed into point data, followed by projection onto the CGCS2000. The high alignment among datasets (Fig. 8) indicates correct projection.

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4.3.7. Convolutional neural network design for geological data processing

To design a convolutional neural network (CNN) for geological data processing, it is necessary to carefully consider the characteristics of geologic data, modeling requirements, and computational resources. In this study, a CNN architecture was designed to process prime geologic data and identify and classify geobodies. This architecture consisted of multiple convolutional layers, pooling layers, fully connected layers, and activation functions, aimed at extracting features and classifying geologic data.

The input data of the CNN architecture included borehole data, physical parameters of cores, XRF spectrometry data, geological maps, and remote sensing images. These data were used to train the CNN model after preprocessing, typically represented as 2D or 3D matrices. Data preprocessing included data standardization and augmentation. Data standardization was performed to ensure that all feature values were within the same range, thereby accelerating training and enhancing model performance. Data augmentation was conducted using techniques like flipping, rotating, and cropping, aiming to increase data diversity and improve the model's generalization ability. The input data were divided into the training, validation, and test sets, with

the training set comprising 70% to 80% of the input data. The validation and test sets, each representing 10% to 15% of the input data, were used to tune model hyperparameters and assess final model performance, respectively.

The designed CNN framework consisted of an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. The input layer accepted geologic data as input, including borehole data, the physical parameters of cores, XRF spectrometry data, geological maps, and remote sensing images. The channel dimension and number in the input layer were adjusted according to the dimensions and resolution of the input data. Multiple convolutional layers were used to perform convolution operations on the input data to extract local features. Specifically, five convolutional layers were employed to extract features at different levels. A Rectified Linear Unit (ReLU) activation was applied after each convolutional layer to introduce nonlinearity. Pooling layers were inserted between convolutional layers to reduce both the dimensionality of feature maps and the computational load using average pooling. After convolution and pooling operations, three fully connected layers flattened the feature maps into a one-dimensional vector, followed by the gradual extraction of global features and classification. In the output layer, the number of neurons was determined based

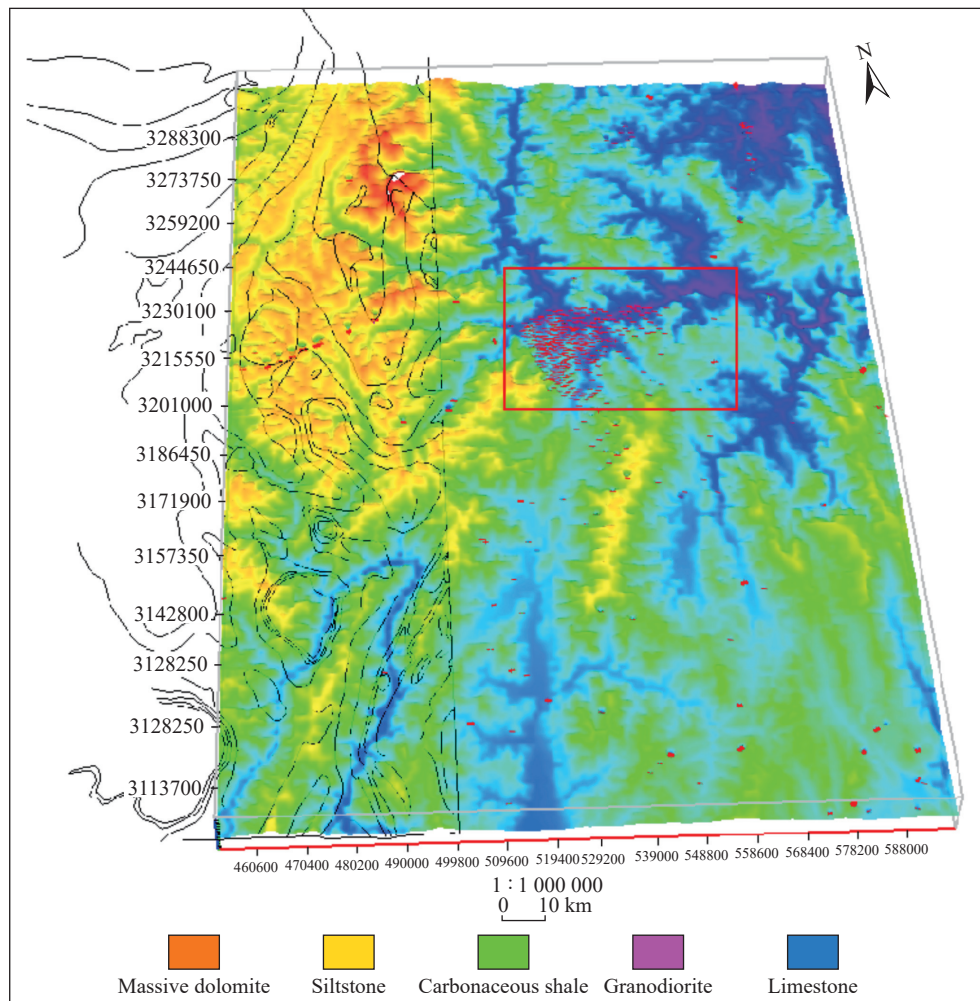


Fig. 8. Matching effects of surface elevations, boreholes, and map boundaries.

on the classification task. The Softmax activation function was used to output the probability distribution of each class.

In the design of the CNN architecture, the loss function was the focus of the training and optimization strategies. Based on the task requirements, the cross-entropy loss function was selected for classification. An appropriate Adam optimizer was used to update the network parameters, thereby accelerating the model's training process. Additionally, L1 and L2 regularization was employed to prevent overfitting and enhance the model's generalization performance. The following aspects were considered in the design. First, for the network structure design, it is crucial to balance the actual computational resources and time constraints to avoid the training difficulty and high computational costs caused by an overly complex network. Second, in the training process, close attention should be paid to the model's convergence and overfitting issues, and a timely adjustment of the training strategy and network structure is required. The CNN framework designed in this study is illustrated in Fig. 9.

4.4. Project results

4.4.1. Large-scale and high-precision 3D geological model based on multisource heterogeneous data

A 3D geological structural model of the X area was established using advanced 3D geological modeling methods. The data sources for modeling include borehole data, geological maps, and remote sensing images. Through multisource heterogeneous data processing, large-scale and high-precision modeling, gridding, and attribute modeling, a high modeling accuracy was achieved, with each grid representing an area of 50 m×50 m on average. Considering the large scale of the modeling area, the large-scale, high-precision holistic modeling technology was employed. The modeling area was divided into four parts for independent modeling. Then, the resulting models were seamlessly integrated to form a comprehensive 3D geological model.

Finally, the comprehensive model was demonstrated through OpenGL 3D rendering and the superimposition of oblique photogrammetry models. The constructed 3D geological model of the X area is shown in Fig. 10.

4.4.2. Model gridding under the constrain of the structural model

Under the constraint of the structural model, geobodies were divided into truncated rectangular grids. Such gridding can ensure the highly consistent geometric morphology between the geological attribute models and the structural model, as well as smooth grids at the stratigraphic and fault levels (Fig. 11). The resulting grid model is a multi-precision model that supports multi-resolution grids, rendering it well-suited for visualization in a level of detail (LOD) mode.

4.4.3. 3D high-precision modeling based on remote sensing data

After spatial coordinate transformation, the large-scale high-precision geological model and the remote sensing image were fused seamlessly. Their perfect agreement suggests high modeling accuracy (Fig. 12).

4.4.4. Visualization based on remote sensing image fusion

The complex and irregular surface landscapes of the X area render it challenging to achieve satisfactory 3D surface morphologies using simple texture mapping. The realism of 3D terrain simulation can be significantly improved by pasting processed remote sensing images on the 3D terrain surface as textures (Bhaskaran S et al., 2010). Surface texture mapping that combines remote sensing images with DEMs emerges as an effective approach to enhance the realism of 3D terrain simulation. Most especially, this approach holds promising application prospects for the 3D landscape visualization of areas with inconvenient traffic and a sparse population (Bhaskaran S et al., 2010). Fig. 13 illustrates the 3D geological model combined with remote sensing images.

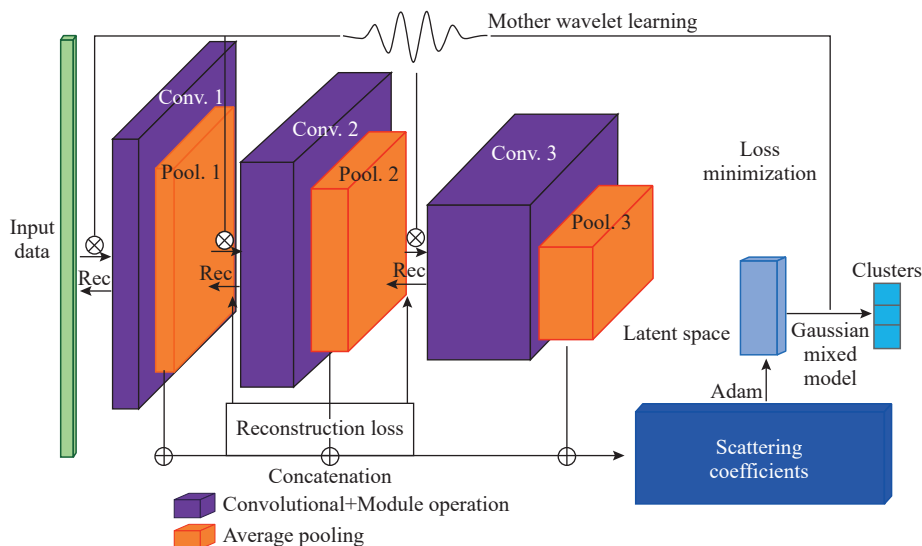


Fig. 9. Schematic diagram of the CNN framework.

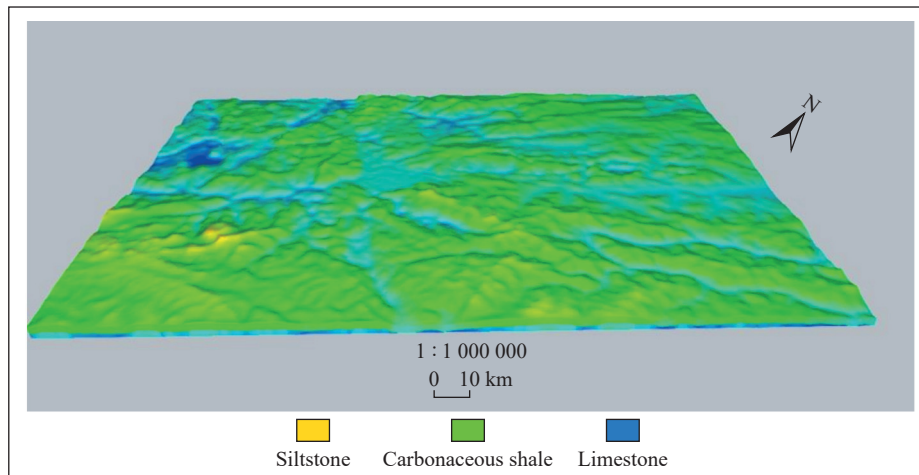


Fig. 10. 3D geological model of the X area.

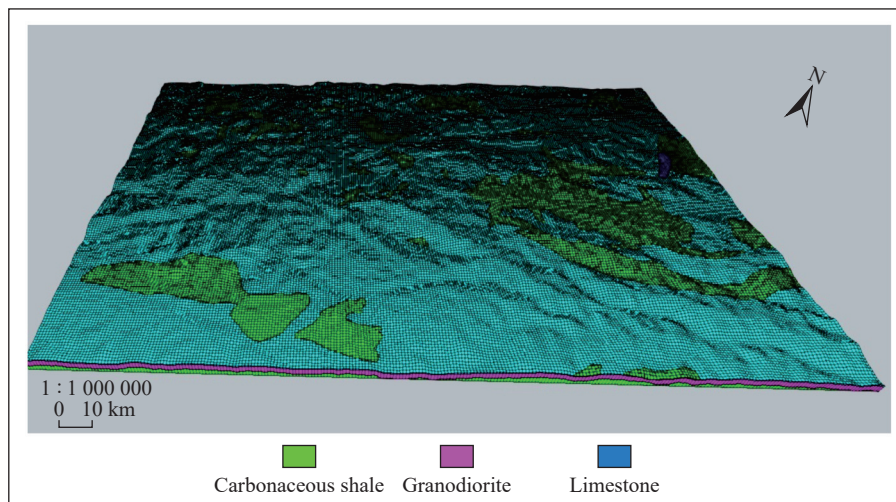


Fig. 11. Grid model under the constraint of structures.

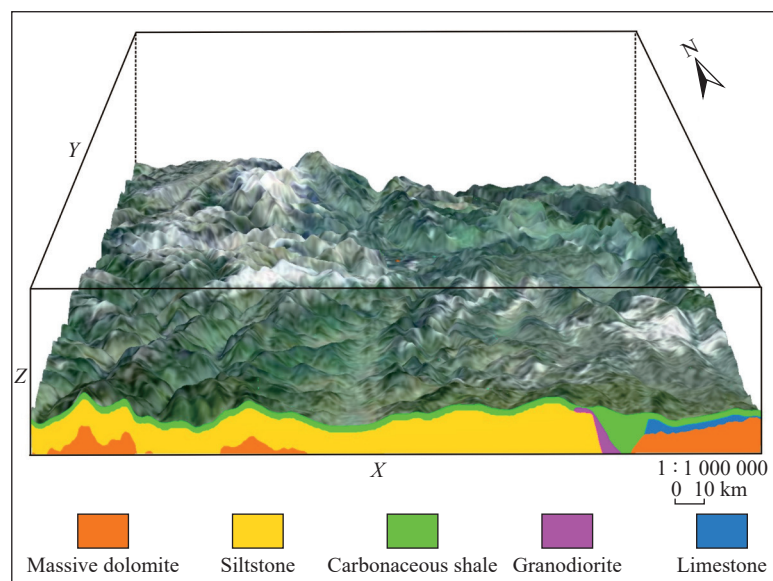


Fig. 12. Fusion of remote sensing image and the geological model.

This model enables interactions such as cutting and excavation. This facilitates geological studies and also provides a reference and basis for determining the rationality of the geological structures and the accuracy of sedimentary

area division and geotechnical property description in the model.

4.4.5. Application of new 3D geological modeling

The new 3D geological modeling method plays a crucial role in exploration breakthroughs. This method integrates complementary information from multiple data sources while also presenting geological structures and ore body distributions three-dimensionally, as exemplified by the ore body marked by a red box in Fig. 14. This will significantly enhance the accuracy and efficiency of exploration prediction.

The new 3D geological modeling method has played a critical role in delineating a metallogenic target area in a region in Southwest China, as denoted by the red box in Fig. 15. This method enables more accurate identification of key information, such as mineral deposit distribution and the morphologies and distributions of geological structures. Accordingly, potentially favorable structures subjected to mineralization can be determined more accurately. This contributes to reduced target area ranges, increased success rates of mineral exploration drilling, and enhanced discovery rates of new mineral deposits.

4.4.6. Investment and efficiency of the 3D geological modeling project

3D geological modeling is a complex process, and its achievements and cost depend on multiple factors such as the extent of the modeling area, the complexity of geological structures, and data types. For instance, the size of the 3D geological model is closely related to the extent of the modeling zone and the complexity of geological structures. A larger modeling area requires more data and more complex computations, resulting in larger model files. For the 3D geological modeling project in this study, the modeling area covers an area of 31104 km², and a data volume of up to 972 GB is required. Furthermore, the model area is situated in the Sichuan Basin, exhibiting complex geological structures such as multiple faults, inclined strata, and magmatic intrusions.

Primary costs of 3D geological modeling include data acquisition, labor, and time costs. The data acquisition cost is related to the high-expense methods, such as drilling and satellite remote sensing. The labor cost is a significant cost component, as the involvement of professional geological engineers is essential for modeling. Moreover, complex modeling projects typically require collaboration among

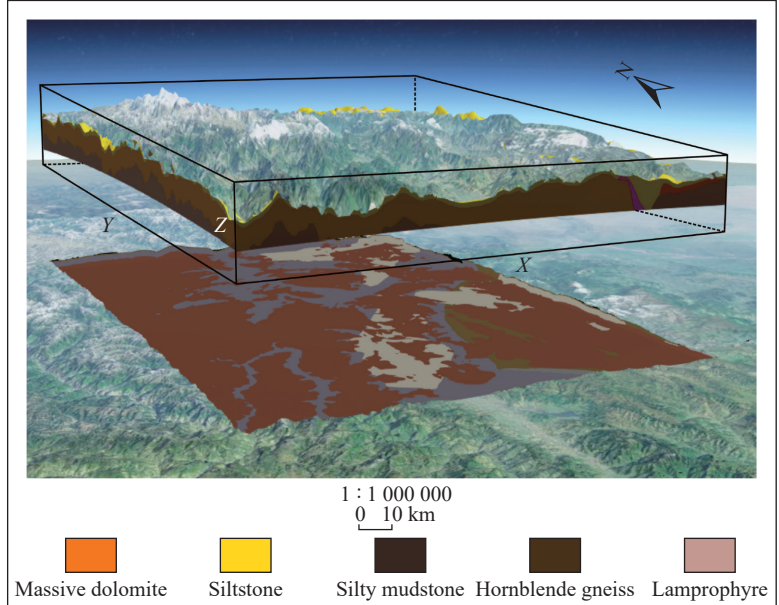


Fig. 13. Interactions of the model combined with remote sensing images.

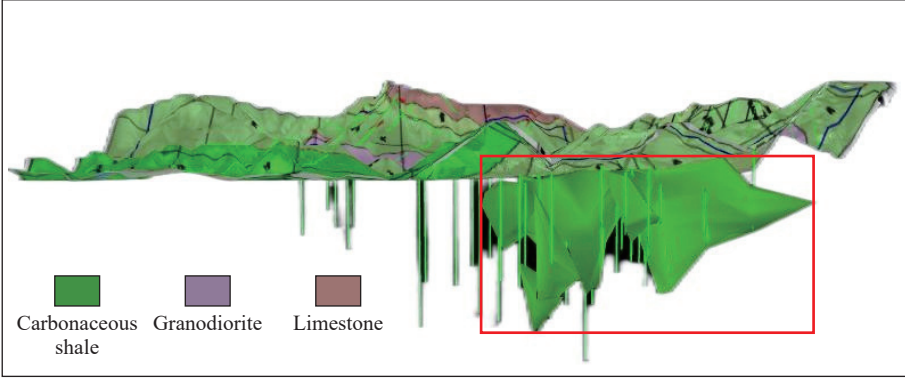


Fig. 14. 3D diagram of a metallogenic target area.

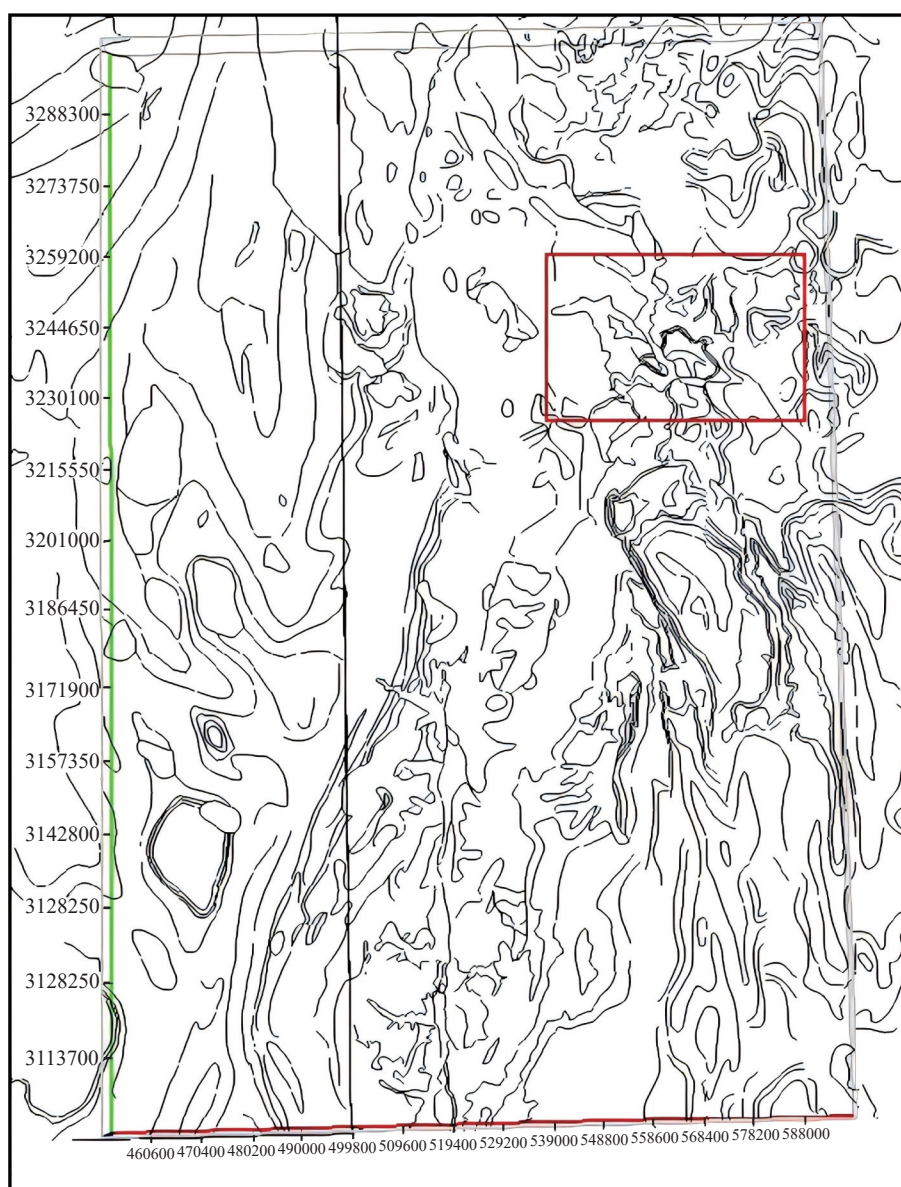


Fig. 15. Schematic diagram of a metallogenic target area.

multidisciplinary teams. The time cost warrants much attention since the construction and optimization of a complex model generally take several months. Generally, the total cost of 3D geological modeling varies from hundreds of thousands to millions of Chinese Yuan (CNY), depending on the project's scale and complexity. Based on previous work experience, it was initially estimated that the 3D geological modeling in this study required three people, four months of work, and a budget of 200000 CNY. However, by applying the new 3D geological modeling method, the modeling was completed by only two people in two months, with a cost of merely 80000 CNY. The modeling process proves efficient due to data and algorithm optimization. The data optimization is attributed to advanced technology for multisource heterogeneous data processing. This technology converts heterogeneous data into homogeneous vector data (points and lines) to provide foundational surface data of ground, sections, and rock mass surfaces. The algorithm optimization

includes parallel modeling, large-scale and high-precision modeling, seamless splicing of local models, and cluster analysis. All of these algorithm optimization measures can reduce manual intervention and repetitive tasks, thereby reducing the modeling time and labor cost. The data and algorithm optimization ensure that the new 3D geological modeling approach produces high-quality geological models while significantly reducing the model size and overall cost. Therefore, the 3D geological modeling method holds great value in geological engineering and resource exploration.

5. Conclusion

The structural modeling practice of the X area highlights the importance of the novel 3D geological modeling method, which can significantly enhance the effectiveness of geologic data application and the accuracy of 3D geological models. The future development of 3D geological modeling technology should focus primarily on two aspects. The first is

to reduce modeling costs and improve modeling efficiency, and the second is to enhance model quality to meet user needs more comprehensively. By integrating remote sensing images and borehole data, the new modeling method can produce a complete and detailed 3D representation of the subsurface conditions nationwide. This will substantially facilitate the work of global researchers. The authors will continue to make technical and methodological improvements while closely monitoring relevant progress.

With the continuous development of human society and the increasing exploitation of surface mineral resources, major mining nations in the world have turned their attention to the more challenging deep mineral resource exploitation. Notably, 3D geological modeling technology can provide robust support for the exploration of deep mineral resources. With the progress in a new round of strategic mineral exploration initiatives, big data and machine learning have demonstrated significant advantages in addressing challenges such as mineral resource localization and prediction. Therefore, deep geologic data mining by integrating big data, machine learning, and 3D visualization modeling might be an effective method to make key breakthroughs in mineral exploration.

CRedit authorship contribution statement

Zhao-yang Ma, Sen Zhang, and Ya-kai Qiao conceived of the presented idea. Zhao-yang Ma and Hua-feng Sun developed the theory and performed the computations. Zhao-yang Ma, Ming Jing, and Jie Li verified the analytical methods. Zhao-yang Ma encouraged Fateh Bouchaala to supervise the findings of this work. All authors discussed the results and contributed to the final manuscript.

Declaration of competing interest

The authors declare no conflicts of interest.

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