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Application of artificial intelligence recognition model methods in the analysis characteristics of closed/abandoned mine resources

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Abstract

With the continuous development of China's social economy and exploitation of coal resources, some mines have reached the end of their life cycle. The precise intelligent recognition of the types, boundaries, and scope of closed/abandoned mines is a fundamental issue for energy resources, low carbon development and ecological protection. The study constructed a method for real-time live automated identification of spatial characteristics of closed/abandoned mines to obtain high-precision and high-quality information. The research included:

1. *Integrating multi-source remote sensing data such as Google Images, GF-6, Sentinel-2 and artificial intelligence technology to establish four datasets:*

    a. *coal mine sites (open pit)*

    b. *coal mine sites (underground)*

    c. *coal-power sites*

    d. *coal chemical sites.*

    The dataset covered 21 categories of samples. Configured with six cuboids for each sample type, 6 × 10 × 21 samples were created, totalling 1,260 site samples. The optimal confidence interval ranges from 80% to 86%.

2. *Developing a closed/abandoned mine site classification quantitative model (CSCQM) and a closed/abandoned mine site range characteristic model (CSRCM). The average accuracy of the models is 0.837.*

3. *Take the example of China's closed shaft mine Shaanxi Zhujiahe coal mine – a quantitative and precise identification of the surface resource types of closed mines was conducted. The office area is 2,375.7 m^2, residential area is 5,073.8 m^2, production area occupies 5,696.2 m^2, and auxiliary production area occupies 9,951.6 m^2.*

4. *Based on open-source 3D geographic information system (GIS) technology, coupled with artificial intelligence recognition models and other cutting-edge technologies such as web databases, a comprehensive GIS database platform for closed mines has been developed using a B/S architecture. This platform encompasses system architecture design, scene design, and functional design.*

The study aims to provide methodological references and practical support for quantifying spatial resources of closed mines.

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1 Introduction

Mineral resources form an essential base for human existence, playing a pivotal role in the progress of society through their exploration and exploitation (Xi et al. 2020; Zou et al. 2021). Concurrently, the extraction of minerals has its downsides, including alterations to the geological structure, deterioration of the natural environment, and potential threats to the safety of nearby communities (Feng et al. 2021; Morris et al. 2005; Zhang & Xi 2020). In the context of dwindling resources and escalating mining expenses, steps are being taken towards mine decommissioning. Yet, hasty mine closures not only result in resource loss but also provoke new forms of environmental pollution and geological hazards (Rezki et al. 2021). Developed nations and regions prioritise this issue, undertaking comprehensive studies and innovative practices in the management, redevelopment, and regulation of inactive or abandoned mines (Bandopadhyay & Packee 2000; Getty & Morrison-Saunders 2020; Monosky & Keeling 2021).

Statistical data revealed that by 2018, the worldwide tally of decommissioned mines had surpassed one million (Huo et al. 2019). These inactive mines are predominantly located in regions such as Europe, North America, Australia, South Africa, and East Asia (Yuan et al. 2018). In nations known for their established mining sectors and cutting-edge subterranean technologies, such as Canada, the United States of America, and Germany, innovative approaches to mine closure have been in progress starting from the mid-20th century (He et al. 2018). These initiatives have shown effectiveness in reducing the negative effects of mine shutdowns. The escalating count of decommissioned mines around the globe, along with an intensified focus on the concept of sustainable development, has spurred global bodies and academics to broaden their investigation and feasible work concerning the reclamation and repurposing of closed mines. This has led to the accumulation of an extensive array of case studies, theoretical models, and legal standards related to the redevelopment strategies for these sites (Chang & Zou 2014; Liu et al. 2018; Bayanmunkh 2022).

Resource characterisation of closed/abandoned mines is the basis for transformation and utilisation. With the continuous development of artificial intelligence technology, the mainstream approach for precise identification of mining feature information currently involves the use of high spatial resolution imagery combined with deep learning methods. The representative algorithms in deep learning are neural networks, and Convolutional Neural Network (CNN) is widely used for remote sensing image target recognition and classification (Shi & Zhang 2021; Gu et al. 2023). Representative algorithms include Faster R-CNN (Faster Region-based Convolutional Neural Network), Mask R-CNN, You Only Look Once-v5 (YOLO), U-Net, Transformers for Object Detection (DETR), and others (Ren et al. 2017; He et al. 2017; Redmon et al. 2016; Ronneberger et al. 2015; Carion et al. 2020). However, the complexity of remote sensing image backgrounds and the diversity of scenes restrict the versatility and adaptability of these algorithms. The DETR model is capable of directly predicting the categories and bounding boxes of objects from input images without the need for intricate intermediate steps. Moreover, the DETR model utilises transformer architecture, affording it a global contextual understanding capability, thereby enabling more precise object recognition and localisation. Due to its ability to consider full context, the DETR model can effectively handle occluded and overlapping objects. The DETR model has advantages in the process of predicting complex scenes.

In recent years, foundational models such as Generative Pre-trained Transformer-4 (GPT-4), Flamingo, and Segment Anything Model (SAM) have made significant advancements (Alayrac et al. 2022). SAM is a visual model trained through the annotation of 1.1 billion marks on 11 million images. SAM can segment any object in any image without requiring additional training. However, it necessitates the provision of points, bounding boxes, or masks as cues alongside input images and the recognition outcomes of SAM are independent of categories. These limitations make SAM unsuitable for fully automatic identification of features from remote sensing images. The study establishes a coal-based site target recognition frame using conventional deep learning algorithms. These identified coal site recognition boxes serve as input cues for SAM, ultimately yielding precise information about coal-related sites.

Optimal data was selected from multiple sources including Google Images, GF-6 imagery, GF-2 imagery, etc. to construct a dataset of closed/abandoned mine samples. Establishing a coal-based site classification quantitative model (CSCQM) and a coal-based site range characteristic model (CSRCM) that integrates multiple data sources with deep learning algorithms, and conducts accuracy validation of the models. The model was used to quantitatively and accurately analysed the types, distribution, and quantities of resources at the Zhujiahe closed mine in Shaanxi, China. A model assessing the suitability for transitioning closed mines has been constructed. Establishing a comprehensive geographic information system GIS management system for closed mines to manage the spatial assets above-ground such as factories, machinery, equipment, and extensive land, as well as underground resources including remaining coal, water, and mine shaft spaces.

2 Intelligent analysis of coal-related industrial sites in closed/abandoned mines

2.1 Definition of mine closure/abandoned mine

In China, 'mine closure' is commonly defined as the permanent cessation of operations of a mining enterprise attributed to the depletion of resources, intricate geological conditions, macroeconomic control measures, market fluctuations, and business circumstances (Hu et al. 2005). As well, a lot of scholars consider that the concepts of 'mine closure' 'abandoned mine' and 'mine shutdown' are synonymous. They defined them as:

> *'The destruction or occupation of the original landform resulting from mining activities, leading to the formation of economically valueless lands such as open pit mines, subsidence areas, spoil heaps, and tailings ponds' (Lin et al. 2018).*

The concept of 'mine closure' is often described using various terms abroad, including mine closure, disused mine, abandoned mine, discarded mine and shutdown mine, etc. Among these, 'mine closure' and 'abandoned mine' are the most commonly used interpretations. In foreign mining operations, particularly open pit mines, studies on mine closure primarily focus on environmental restoration and land reclamation issues. For instance, Subodh (2013) defines 'mine closure' as the process that occurs when the operational stage of a mine is ending or has ended, and final decommissioning and mine rehabilitation activities are being carried out.

2.2 Data samples and datasets delineation

2.2.1 Data sources

The study focuses on the Zhujiahe closed mine in Shaanxi province, China. The primary data sources utilised include remote sensing data and point of interest (POI) data. The detailed sources are outlined in Table 1. Remote sensing data is utilised for coal site identification at the Zhujiahe closed mine, while POI data is employed for supplementary accuracy validation of coal site identification in closed/abandoned mines. The remotely sensed data are pre-processed in the order of image fusion, image cropping, image stitching, and image segmentation. The POI data was used for data cleansing to obtain the coordinates of the points of interest of the coal-related sites.

Table 1 List of data sources

Source	Time	Accuracy	Resources
Sentinel-2	2023	Spatial resolution: 10 m	https://scihub.copernicus.eu/dhus/#/home
GF-6	2020	Spatial resolution: 2 m	https://www.chinageoss.cn/aircas/
Google Images	2022，2023	Spatial resolution: <0.8 m	https://earth.google.com
Point of interest data	2023	–	Map website

2.2.2 Sample collection and type classification

Based on the characteristics of production-living-ecological space, the background of the Zhujiahe closed mine and relevant literature, the sample data was categorised into four datasets:

1. coal sites (open pit)
2. coal sites (underground)
3. coal-power sites
4. coal chemical sites.

These datasets encompass 21 types of samples. The dataset for coal sites (open pit) includes various components:

- open-pit mining areas
- coal storage yards
- dumping site
- coal gangue stacking sites
- production auxiliary facilities
- other solid waste disposal sites, such as waste rock piles, tailings ponds, tailings dams, etc.

The dataset for coal sites (underground) includes several elements as well. This includes:

- industrial squares
- coal processing facilities such as: coal selection workshops, coal washing workshops, coal storage yards, coal conveyor belts
- subsidence areas, and damaged sites, such as: collapse, landslides, mudslides, cracks, deformations and encroachments.

The dataset for coal-power sites consists of:

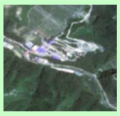
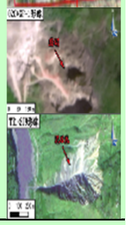
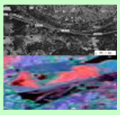
- management areas
- waste disposal sites
- production equipment
- fly ash
- chimneys.

The dataset for coal chemical sites includes:

- comprises coal chemical industry surface production management areas
- condensation towers
- surface equipment for coal chemical industry sites
- disposal sites for coal chemical industry waste, such as desulphurisation gypsum and coal chemical industry slag.

The 21 sample types are configured with 6 × 10 samples per sample type, resulting in a total of 1,260 site samples. The detailed information of the dataset is provided in Table 2. Selecting data with high image quality and clear object boundaries is crucial for modelling and validation purposes.

Table 2 Samples and datasets

Source	Dataset	Samples type	Information	Samples /6 × 10	Samples type	Information	Samples /6 × 10
Google Images, GF-6, Sentinel-2	Coal sites (open pit)	Open pit mining areas	Uniformly toned black or light black with large plaques and well defined borders		Coal storage yards	Black or light black in colour, regular in shape and thicker in texture	
		Dumping site	Subtrapezoidal or regular subcircular patches that are concave inwards		Coal gangue stacking sites	Light grey in colour with high brightness and distinctive patchy marks	
		Production auxiliary facilities	Located around the open quarry, reddish-blue in colour, regular in shape		Other solid waste disposal sites	Generally characterised by a light-toned patchy, orthogonal topography	
	Coal sites (underground)	Industrial squares	A site for a series of sorting and transport of minerals extracted, accompanied by a mine building		Coal processing facilities	Generally located in areas with good transport links and characterised by industrial buildings	
		Coal storage yards	Black or light black in colour, regular in shape and thicker in texture		Coal conveyor belts	Long, regular shape	
		Subsidence areas	Ground collapse craters are round or oval in shape, with rough texture, varying shades of colour, unevenly distributed vegetation		Damaged sites	The surfaces of the landslides are uneven and rough, often with large boulders jutting out from underneath	
	Coal-power sites	Management areas	Including coal powerplant offices and living quarters, such as office buildings, hospitals, staff dormitories, etc.		waste disposal sites	Located in the coal powerhouse, rough textured and irregular in shape	
		Production equipment	Reddish-blue in colour, regular in shape, mostly square or rectangular, concentrated, with neatly distributed equipment		Fly ash	Appears grey or grey-black, piled up in hill-like shapes. mauve, blue in TM images, uneven in tone	
		Chimneys	Built near the coal trestle bridge, the building has a red and white circular strip				
	Coal chemical sites	Coal chemical industry surface production management areas	Including coal chemical industry office and living quarters, such as office buildings, hospitals, staff dormitories, etc.		Condensation towers	Black circular area with high height and distinctive shadows, the tower is made of concrete and has distinctive areas of high brightness	
		Surface equipment for coal chemical industry sites	Black and bright blue in colour, with a concentrated distribution of industrial facilities, regular shape and distinct borders		Disposal sites for coal chemical industry waste	Greyish-white in colour with smooth texture and distinct accumulations	

2.3 Site feature identification modelling

The process of model establishment is divided into four steps (Figure 1):

1. data screening
2. establishment of sample dataset
3. model training and accuracy verification
4. establishment of optimal model.

First, the optimal data sources were selected by screening from multiple sources such as Google Images, GF-6 imagery, Sentinel-2 imagery, and others. Second, samples of coal-based sites from the Zhujiagou closed mine were collected to construct four datasets: coal mining sites (open pit), coal mining sites (underground), coal-power sites, and coal chemical sites; covering 21 types of samples. Third, the samples from the dataset were used as training data, input into the DETR to obtain the optimal quantified model for coal-based site types; which is then subjected to accuracy verification. Subsequently, the four datasets (coal mining sites [open pit], coal mining sites [underground], coal-fired powerplant sites, and coal chemical industry sites) were individually input into the DETR model for training. Fourthly, the output of the DETR model was input into SAM to obtain the coal-based site extent characterisation model.

The model application process was divided into data acquisition and pre-processing, site type quantification and site extent identification (Figure 2). Firstly, the obtained raw images were pre-processed, including fusion, cropping, splicing and chunking of the images. Secondly, the target frame information of the coal base site was obtained by using the quantitative model of the coal base site type and, again, the obtained target frame was inputted into the model of the range features of the coal base site, to obtain the range information of the coal base site. The model implements an application process for accurately identifying coal sites (open pit), coal sites (well construction), coal-power sites, and coal chemical sites using 21 site samples as a basis for identifying coal-based site boundaries, and using 21 site samples as a basis for determination.

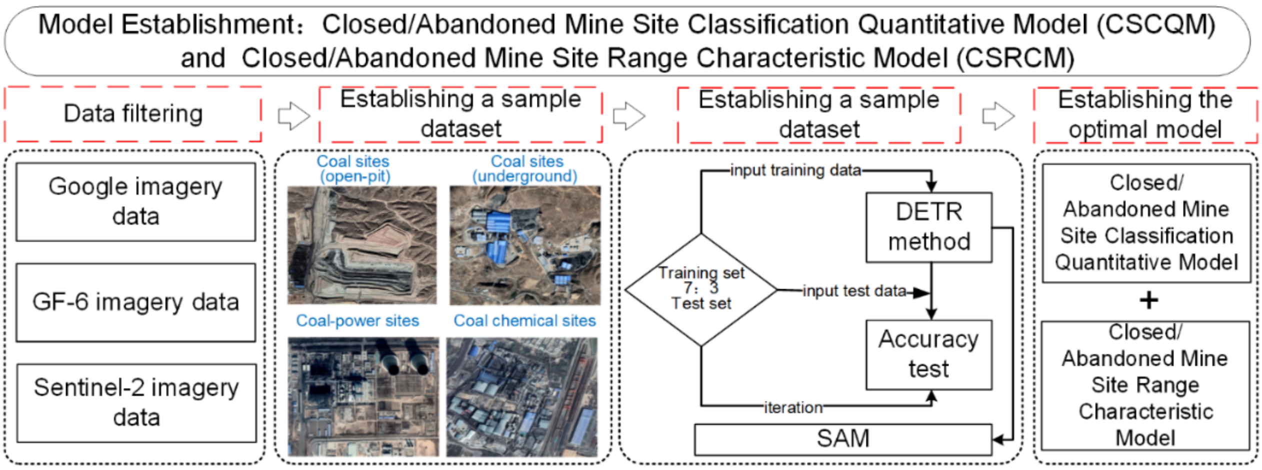


Figure 1 Process diagram for establishing coal-based site classification quantitative model and coal-based site range characteristic model

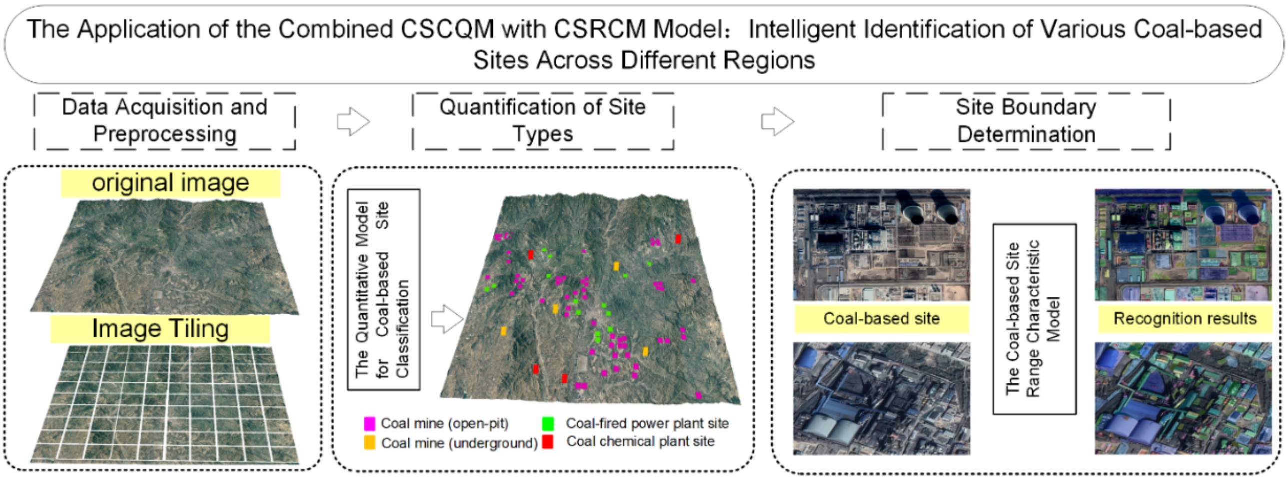


Figure 2 Application flow chart of coal-based site classification quantitative model and coal-based site range characteristic model

Figure 3a depicts the schematic diagram of SAM, which includes an image encoder, prompt encoder, and mask decoder. The original SAM framework generates corresponding object masks based on the provided input prompts (points, boxes, masks). However, this manual intervention is not suitable for large-scale remote sensing object extraction. Therefore, the study replaces the manual input prompts required in SAM with object identification boxes established by the DETR model. This modification enables SAM to automatically extract objects from remote sensing images. Figure 3b illustrates the improved structure of SAM. Figure 3c shows the process of using the enhanced SAM for identifying coal sites (open pit).

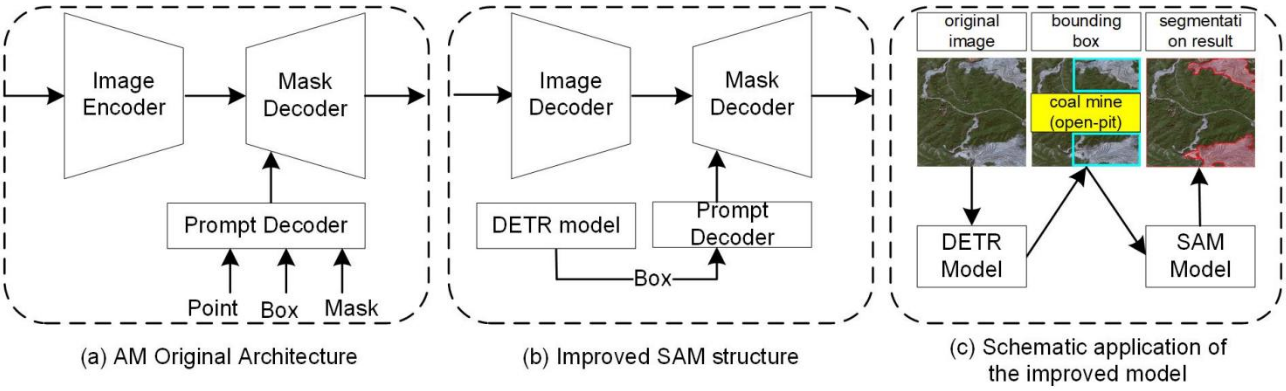


Figure 3 Segment anything model architecture and model improvement

To evaluate the accuracy of the model, the following metrics were used. Precision (P*)* refers to the proportion of actual positives among all samples predicted as positive by the model. Recall (R) refers to the proportion of samples correctly predicted as positive by the model among all actual positive samples. The calculation formulas are as follows (Equations 1 and 2):

$$P=\frac{T_{\mathrm{P}}}{T_{\mathrm{P}}+F_{\mathrm{P}}} \tag{1}$$

$$R=\frac{T_{\mathrm{P}}}{T_{\mathrm{P}}+F_{\mathrm{n}}} \tag{2}$$

where:

T_P = the number of samples that are actually positive and predicted as positive.

F_P = the number of samples that are actually negative but predicted as positive.

F_n = the number of samples that are actually positive but predicted as negative.

Additionally, $T_P + F_P$ denotes the total number of samples predicted as positive, and $T_P + F_n$ denotes the total number of actual positive samples.

P(r) is the curve representing the relationship between *R* and *P.* Average precision (P_A) is the mean precision (Equation 3).

$$P_A = \int_0^1 p(r)\mathrm{d}r \tag{3}$$

The degree of overlap between the classification results and the labels was assessed using the mean m_{IoU} of the intersection over union (IoU). The calculation formulas in Equation 4:

$$m_{IoU} = \frac{T_\mathrm{P}}{T_\mathrm{P} + F_\mathrm{P} + F_\mathrm{n}} \tag{4}$$

In this study, P_A is used to evaluate the accuracy of the coal-based site type quantification model, while m_{IoU} is used to evaluate the accuracy of the coal-based site range feature model.

2.4 Accuracy of coal-related industry site type identification results

First, an analysis of the recognition accuracy of the DETR model and the SAM model on the validation dataset. The CSCQM and CSRCM both had good accuracy. The P_A for all 21 sample types in the four dataset categories of coal sites (open pit), coal sites (underground), coal-power sites, and coal chemical sites were all above 0.8. The P_A for the coal sites (open pit) dataset was 0.832, with m_{IoU} of 0.823. For the coal sites (underground) dataset, the P_A was 0.830, with m_{IoU} of 0.836. The coal-power sites dataset had a P_A of 0.824, with m_{IoU} of 0.842. Lastly, for the coal chemical sites dataset, the P_A was 0.858, with m_{IoU} of 0.849.

Second, the overall average precision for the CSCQM was 0.836, and for the CSRCM was 0.838. The DETR model is a transformer-based object detection model, and its decoder does not use autoregression. This makes the prediction process of the DETR model more concise and efficient. As a result, the DETR model demonstrated excellent recognition performance for complex mining scenes in the context of closure/abandoned mine site recognition. The goal of SAM was to establish a foundational model for image segmentation. Due to its outstanding generalisation capability, the SAM model has achieved good results in practical applications.

Finally, the quantitative model of coal-based site types and the coal-based site extent feature model, established using sample from closed/abandoned mines. These models were practically applied to identify feature information for various coal sites, including coal sites (open pit), coal sites (underground), coal-power sites, and coal chemical sites at Shaanxi Zhujiahe closed mine. The accuracy of these models was verified using POI data. The model accuracy reached 86.7%, with the lowest identification accuracy of 80.1%. The average accuracy was 83.6%. The accuracy of the model on the validation dataset is shown in Table 3.

Table 3 List of data sources

Dataset	Samples	DETR /P_A	SAM /m_{IoU}	Dataset	Samples	DETR /P_A	SAM /m_{IoU}
Coal sites (open pit)	Open pit mining areas	0.821	0.814	Coal sites (underground)	Industrial squares	0.843	0.856
	Coal gangue stacking sites	0.812	0.831		Coal conveyor belts	0.867	0.843
	Dumping site	0.856	0.824		Coal storage yards	0.810	0.824
	Coal storage yards	0.845	0.833		Coal processing facilities	0.842	0.862
	Production auxiliary facilities	0.856	0.831		Subsidence areas	0.814	0.826
	Other solid waste disposal sites	0.801	0.804		Damaged sites	0.803	0.806
Total average		0.832	0.823	Total average		0.830	0.836
Coal-power sites	Management areas	0.814	0.856	Coal chemical sites	Coal chemical industry surface production management areas	0.854	0.835
	Fly ash	0.801	0.814		Surface equipment for coal chemical industry sites	0.863	0.864
	Production equipment	0.821	0.836		Condensation towers	0.859	0.865
	Waste disposal sites	0.823	0.845		Disposal sites for coal chemical industry waste	0.854	0.832
	Chimneys	0.863	0.859				
Total average		0.824	0.842	Total average		0.858	0.849

3 Type identification and spatial characteristics of closed mine resources in Shaanxi, China

3.1 Types and characteristics of closed mine resources

The resources in closed mine are generally divided into above-ground resources and underground resources. Based on the industrial characteristics of the mining area, the above-ground resources in the mining area include surface water resources, land resources, industrial squares, and residential area buildings. The land resources mainly include coal sites (open pit), coal sites (underground), coal-power sites, and coal chemical sites. There are many types of underground resources in closed mines, including space resources, underground equipment, and residual coal resources (Table 4).

Table 4 Type of resource above/under mine

	Type	Characteristics
Above-ground resource	Surface water	Ponds, rivers, lakes, reservoirs and other water bodies around the mining area
	Land resources	The abandoned land, subsidence caused by mining (waste disposal sites, waste rock piles, tailings, etc.), and the farmland surrounding the mining area
	Industrial squares	Buildings (office buildings, coal preparation plants, wellhead buildings, dispatching buildings, power and auxiliary facilities, etc.), and ground linear facilities (highways, railways, power, communication lines, etc.)
	Residential area buildings	Canteens, bathhouses, boiler rooms, clubs, mine hospitals, staff dormitories, etc.
Underground resource	Space resources	Shafts, chambers, roadways, and mining areas
	Residual coal resources	Protective coal pillars in alleys, shafts, workings, faults, field boundaries, etc.
	Underground equipment	Extraction equipment, transportation equipment, drainage equipment, ventilation equipment
	Underground water	Aquifer water, water in wellbore silos, water in void areas, water in roadways
	Space resources	Shafts, chambers, roadways, and mining areas

3.2 Estimation of building space of industrial square

To determine the available space of the industrial square's buildings, one can utilise Equations 5 and 6 for calculation (Li et al. 2023).

$$S_{buil} = \sum_{i=1}^{n} L_{buil} \times D_{buil} \, (i = 1, 2, 3, \ldots, n) \tag{5}$$

$$V_{buil} = \sum_{i=1}^{n} L_{buil} \times D_{buil} \times H_{buil} \, (i = 1, 2, 3, \ldots, n) \tag{6}$$

where:

S_{buil} = the floor area of the building, m^2.

L_{buil} = the length of the building, m.

D_{buil} = the width of the building, m.

H_{buil} = the height of the building, m.

V_{buil} = the available space of the building, m^3.

Taking the closed mine of Zhujiahe as an example, the buildings in the mining area were measured by actual measurement and statistics. The floor area and space volume of the buildings were calculated according to Equations 1 and 2, respectively. Among them, the building of office area occupies 238,000 m^2 and the space volume is 2,200,000 m^3; the building of living area occupies 507,000 m^2 and the space volume is 3,400,000 m^3; the building of production area occupies 570,000 m^2 and the space volume is 3,800,000 m^3; the building of auxiliary production area occupies 995,000 m^2 and the space volume is 1,000,000 m^3. The building space volume of the whole industrial square reaches 10,400,000 m^3 (Table 5).

Table 5 General situation of above-ground space resources in a closed mine in Shaanxi, China

Types of above-ground space resources	Floor area/m^2	Space volume/m^3
Office buildings (administrative office building, garage, office laboratory, etc.)	238,000	2,200,000
Living area building (dormitory buildings, staff canteens, gym, etc.)	507,000 × 10^3	3,400,000
Production area buildings (main transformation room, machine repair plant, warehouse, etc.)	570,000	3,800,000
Auxiliary production area buildings (circular coal storage yard, water treatment sedimentation tank, sewage treatment room, etc.)	995,000	1,000,000
Total amount	2,310,000 × 10^4	10,400,000

3.3 Feasibility analysis for repurposing closed/abandoned mining sites

3.3.1 Mine transformation constraints

The various modes for developing and utilising closed or abandoned mines are contingent upon meeting distinct resource requirements (Peila & Pelizza 1995). These requirements fall into four main categories:

1. natural conditions
2. mine resource conditions
3. economic feasibility
4. external factors.

Mine resource conditions encompass aspects such as the mining methods employed, available resources and facilities, the type of mine, its potential for transformation, and the mine's size. Natural conditions refer to factors like surface subsidence, soil erosion, the state of surrounding rocks, pollution levels, and mining depth. External factors take into account the mine's location, public support, market and technical demands, as well as the completeness of relevant policies. Lastly, economic feasibility involves analysing the industrial structure linked to the mine, its economic contribution, output value, employment impact, and the regional economic growth rate (Li et al. 2023), shown in Table 6.

Table 6 General situation of above-ground space resources in a closed mine

Target layer	Criterion layer	Index layer
Factors constraining the direction of mine transformation	Mine resource	Method of mining
		Resources and equipment
		Mine type
		Transformation potential
		Mine size
	Natural factors	Surface subsidence
		Surrounding rock conditions
		Soil erosion
		Pollution conditions
		Mining depth
	External factors	Location condition
		Technical demand
		Policy completeness
		Public support
		Market demand
	Economic sustainability	Industrial structure
		Employees
		Mining output value
		Economic share
		Economic growth rate

3.3.2 Model for evaluating the suitability of mine closures for transformation

According to different mining methods, the actual situation of the mine to select the transformation constraint factors, is chosen using the weight determination method and weighting, by calculating the transformation of the degree of suitability of the integrated constraint factor value (Equation 7):

$$T = \sum_{a=1}^{a} \omega_a \sum_{b=1}^{r} W_{ab} N_{ab} \tag{7}$$

where:

T = the value of comprehensive constraint factor.

ω_a = the weight of the first constraint factor.

W_{ab} = the weight of the bth sub-constraint factor of the first constraint factor.

N_{ab} = the value of the bth sub-constraint factor of the first constraint factor.

q = the total number of constraints.

r = is the number of sub-constraints included in the qth constraint factor.

3.3.3 Appropriateness of mine closure for transformation

Based on the degree of suitability for transformation, a preliminary determination was made as to whether a closed mine could be transformed and the feasible modes of transformation. Level I indicates a particularly difficult transition path, level II indicates a difficult transition path, level III indicates a more difficult transition path, level IV indicates a more suitable transition path, and level V indicates a suitable transition path (Table 7).

Table 7 Suitability of mine closures for transformation

Level I	Level II	Level III	Level IV	Level V
$0 < T \leq 20$	$20 < T \leq 40$	$40 < T \leq 60$	$60 < T \leq 80$	$80 < T \leq 100$
Particularly difficult	Difficult	More difficult	More suitable	Suitable

3.3.4 Proposal of development and utilisation modes of the closed mine

The mine has a beautiful environment, a superior geographical location, complete infrastructure and supporting facilities, and many mature scenic spots around it. The transformation and utilisation of the mine is in line with the requirements of mining tourism development. Taking mining tourism as the new economic growth direction of the mining area is of great significance to the economic diversification and sustainable development of mining towns. According to the preliminary evaluation of the suitability of the mine transformation, three transformation paths are put forward.

1. Transformation into mine park or resort mode (mode 1). The internal facilities of the mining area are complete, and there are scenic spots in the surrounding area, with superior geographical position and convenient transportation. This transformation path cannot only reflect the history of mining development, but also protect industrial relics.
2. Transformation into mine park or mine museum (mode 2). The mining area has rich industrial relics and cultural history, and the equipment in the mining area is well preserved, which can transform the mining area into a mode integrating mine park and mine museum, with research value and educational function.
3. Transformation into mine museum or underground material reserve (mode 3). The underground space of the mining area is large. Using the special nature of the mine, the underground space of the mine can be built into an underground greenhouse to store and preserve vegetables and fruits, breed special animals and plants, or store special substances. It can also be used for underground reservoir construction and mine groundwater storage. At the same time, the mine museum will be developed to organically integrate the above-ground and underground spaces to effectively promote the transformation of mining areas.

4 Construction of a geographic information system comprehensive database platform for the closed mine

4.1 System architecture and module design

4.1.1 System architecture design

The main framework of the integrated GIS management system for closing coal mines adopts the B/S architecture pattern. The basic geographic information data, image data, terrain data, and model data of the mines are stored in the data server. Clients can browse scenes and operate the system's functions through a browser on the web. The server of the system accesses various data in real-time through a C/S mode. The system architecture design is shown in Figure 4.

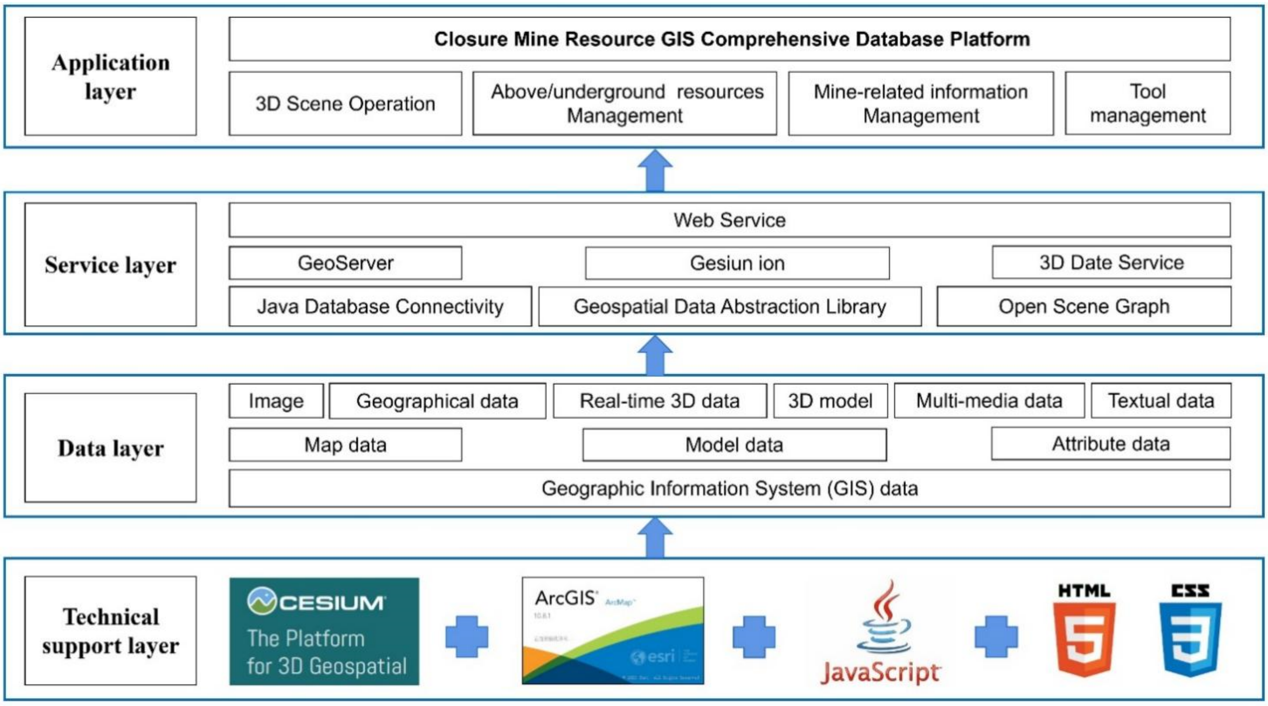


Figure 4 System architecture design

4.1.2 System scene design

The mine area's real-life 3D scene consists of two parts: the industrial square's real-life 3D scene and the underground tunnel 3D model. The industrial square's real-life 3D data is collected using unmanned aerial vehicles for low-altitude oblique photogrammetry. The underground tunnel 3D model is built using 3ds Max modelling software. By performing geographic registration, the integration of the mine area's real-life 3D scene is achieved.

4.1.3 System functionality design

The main functionalities of the integrated GIS management system for closing coal mines mainly include 3D scene operations, above-ground and underground spatial resource management, closed mine-related information management, and tool management. The system functional modules are shown in Figure 5.

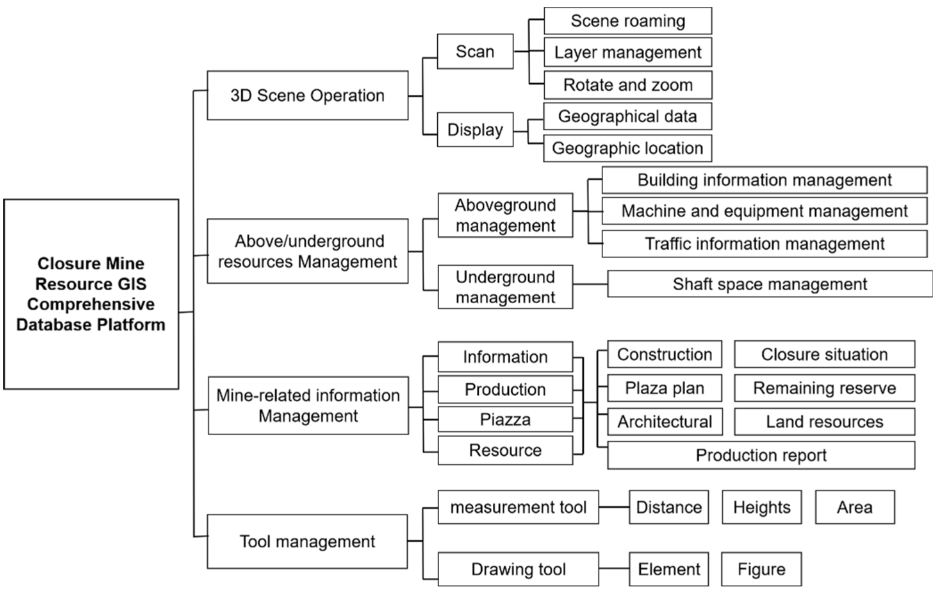


Figure 5 Schematic diagram of system function design

4.2 System practice case design

The system adopts a GIS secondary development approach, utilising ArcSDE as the spatial data engine and GeoServer and Cesium ion for publishing map data. The B/S part of the system is developed based on the open-source mapping engine, Cesium, to implement system functionality. Take Zhujiahe coal mine as an example.

4.2.1 3D Scene manipulation

This system utilises the Cesium API to load and navigate 3D scenes by accessing the mining area's real-time 3D data published through a Tomcat server. It also implements functions such as rotating, scaling, and other scene manipulations. In addition, the system displays mining area terrain and geographic location information using the terrain and image data provided by Cesium ion, combined with other image data from sources like Tianditu Map, and allows for switching and management of multiple image and terrain layers (Figure 6).

Figure 6 3D image of the mine site

4.2.2 Above/underground space resource management

Management of surface space resources primarily includes buildings, machinery and equipment, and land. The system enables individualised and layered queries for buildings. Individualised queries provide information such as the names, floors, and area of each building, while layered queries provide detailed information about each floor, including room numbers and names. The system also manages attribute information for machinery and equipment, allowing users to query various parameters of coal storage, coal washing, and coal transportation equipment. Additionally, the system facilitates querying and management of surrounding land resources in the mining area, categorised by land use types such as green space, arable land, and industrial land. Users can access information regarding land area, cultivation, and irrigation within the system. Furthermore, the system manages transportation information for the mining area and its surroundings, including railways and highways, based on a vector map provided by Tianditu Map. As for underground space resources, which mainly include tunnels and galleries, the system allows for the query and management of length and area information after establishing a georeferenced 3D model for the underground spaces.

4.2.3 Management of coal mining-related information

Management of coal mining-related information primarily includes the construction status, closure overview, production overview, square overview, resource overview, as well as mining and closure reports. This system presents the entire process of coal mine construction through web pages, showcasing the construction and closure overviews from the beginning of construction to the closure of the mine to users. For the production overview of coal mines, the system uses the Echarts.js plugin to display historical data about the production volume, coal seams, and water influx in a chart format on the client side. The square overview includes a plan view of the square, as well as the attribute information such as the name, length, width, and area of all buildings in the square. The resource overview mainly covers basic information about remaining coal reserves, land resources, and underground space resources; represented in statistical chart styles. Mining and closure reports are provided in PDF format for online browsing, downloading, and printing.

4.2.4 Tool management

Tool management includes the management of measuring tools and drawing tools. The measuring tools enable distance measurement, height measurement, and area measurement. Distance measurement includes both straight-line distance measurement and ground distance measurement. Height measurement includes vertical height measurement and triangle height measurement. The drawing tools include the drawing of point, line, and polygon features, as well as the drawing of geometric shapes such as rectangles and circles.

5 Conclusion

The study selected multi-source data, including Google Earth images, GF-6 images, and Sentinel-2 images, to determine the optimal data combination for identifying closed/abandoned mines. Specifically, Google Earth images were combined with GF-6 images to enhance the identification process. Based on existing research and practical needs, four datasets were constructed: coal sites (open pit), coal sites (underground), coal-power sites, and coal chemical sites. These datasets encompass 21 sample types. The research indicated that employing a method of setting up 6 ×10 × 21 samples for each type, totalling 1,260 site samples, can meet the accuracy requirements for identifying closed/abandoned coal-related mining sites. Analysis revealed the optimal sample quantity within the confidence interval for achieving the highest identification efficiency with an accuracy range of 80% to 86%. Training a multi-source coal-based site feature recognition model was achieved by utilising samples from four distinct datasets. This led to the establishment of the CSCQM and a CSRCM, yielding model accuracies of 83.50% and 83.70%, respectively. The innovative and efficient approach of overlaying Google Earth imagery with site intelligent recognition models for extracting coal-related site features, represents a notable advancement in this field.

The CSCQM and CSRCM were employed to quantitatively analyse the precise background data of the Zhujiagou closed mine. Based on constraint factors, transition suitability grades, and resource conditions, a model for evaluating the suitability of transition for closed mines was constructed. This model provides the optimal transition pathway for the Zhujiagou. Leveraging open-source 3D GIS technology in conjunction with artificial intelligence recognition models and advanced technologies such as web databases, a comprehensive GIS management system for closed mines was developed. This system, built on a B/S architecture, encompasses system architecture design, scenario design, and functional design components.

In the context of artificial intelligence recognition for coal-related industrial sites, the selection of sample datasets holds paramount significance. In future research endeavours, the establishment of a sufficiently large-scale and high-quality database pertaining to coal-related industrial sites emerges as a crucial avenue for enhancing the accuracy of boundary delineation and type identification models within this domain. Future research endeavours could utilise the abandoned open pit coal mine, Xinqiu, (located in Fuxin, Liaoning province, China) as a case study. This could involve intelligently identifying the boundary scope of abandoned mine landscapes, leveraging the advantages of artificial intelligence-based target object identification techniques in diverse and large-scale scenarios. Furthermore, it could facilitate the effective and precise identification of closed mines, thereby furnishing technical methodologies and practical examples for the governance and ecological restoration of closed mines.

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