Journal of Cleaner Production 418 (2023) 138135

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

A Bayesian network model for suitability evaluation of underground space development in urban areas: The case of Changsha, China

Zhiwen Xu[a,b], Suhua Zhou[a,b], Chao Zhang[a,b,*], Minghui Yang[c], Mingyi Jiang[a]

[a] College of Civil Engineering, Hunan University, Changsha, 410082, Hunan, China
[b] National Center for International Research Collaboration in Building Safety and Environment, Hunan University, Changsha, 410082, China
[c] School of Architecture and Civil Engineering, Xiamen University, Xiamen, 361005, China

ARTICLE INFO

Handling Editor: Zhifu Mi

Keywords:
Underground space resources
Bayesian network model
Suitability evaluation
Urban planning
GIS

ABSTRACT

Developing underground spaces has emerged as a crucial strategy for mitigating the pressure on urban land resources. Therefore, an appropriate evaluation of underground space is imperative for the sustainable utilization of urban underground space resources (UUSR). In this study, the Bayesian Network model was employed as a decision-support tool to evaluate the suitability of UUSR in Changsha. A spatial database was constructed to comprehensively understand the socio-economic, geological condition, and the current construction status that impacts UUSR suitability. Furthermore, the analytic hierarchy process (AHP) method was utilized to weigh the contributions of these factors, thereby constructing the conditional probability tables (CPTs). The Changsha urban area was rasterized into 116,554 evaluation units with a size of 100 m × 100 m, and the suitability of each unit was evaluated using Bayesian inference. Finally, the suitability of the UUSR in Changsha was classified into four levels: very high, high, low, and very low. They represented 16%, 30%, 37%, and 17% of the total area. It was discovered that the areas with high suitability were predominantly located in the Changshaxian district, whereas those with low suitability exhibited an inverted Y-shaped distribution in the study area. Based on Bayesian inference, it was revealed that an increase in socio-economic value is associated with a maximum 20% increase in the suitability of underground space. This study has enhanced the available assessment tools for decision-making support when evaluating UUSR and is a valuable reference for urban planners and other professionals working in related fields.

1. Introduction

The rapid pace of urbanization has resulted in a gradual depletion of urban land resources, thereby presenting formidable obstacles to urban development (Qian, 2016; Zhou et al., 2019; Xi et al., 2022). The recognition of underground space as a burgeoning resource for development and utilization is rising (Zhou et al., 2019). The exploitation of underground space holds promise for improving land use efficiency and augmenting public infrastructures and services, ultimately generating new opportunities for the advancement of sustainable urban development (Bobylev, 2009; Makana et al., 2016; Peng et al., 2021; Qiao et al., 2022a). Although urban underground space development has many benefits, it also faces several problems. Firstly, it is important to recognize that urban underground space is a non-renewable natural resource. Secondly, there may be conflicts between short-term and long-term demands for urban underground space. Lastly, there is a lack of unified planning in urban underground space (Zhou et al., 2019; Xi et al., 2022). To address these issues. Several promising development concepts have been proposed. One concept is geosystem services, which emphasizes balancing human requirements with responsible management and preservation of natural resources and ecosystems (Van Ree and van Beukering, 2016; Frisk et al., 2022). Achieving sustainability in the role of underground space requires finding a balance between exploitation and conservation. To achieve this objective. It is crucial to rationally assess the unseen underground space resources and implement comprehensive planning for urban underground space.

Therefore, the prudential evaluation and strategic planning of urban underground space are crucial for advancing sustainable urban development (Peng and Peng, 2018). The comprehensive assessment of underground space resources plays a pivotal role in identifying their developmental potential and sustainable utilization capacity, thereby aiding in the formulation of well-informed development strategies and

* Corresponding author. College of Civil Engineering, Hunan University, Changsha, 410082, Hunan, China.
E-mail address: chao_zhang@hnu.edu.cn (C. Zhang).

https://doi.org/10.1016/j.jclepro.2023.138135
Received 2 April 2023; Received in revised form 8 July 2023; Accepted 15 July 2023
Available online 18 July 2023
0959-6526/

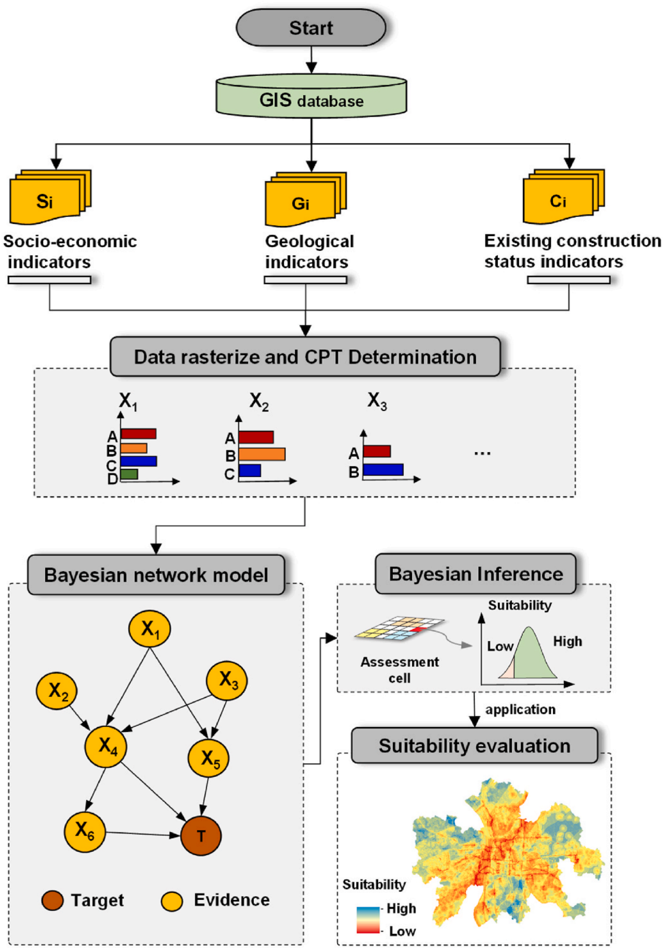

Fig. 1. The Flowchart of this study.

sustainable utilization plans to ensure long-term viability and environmental preservation (Li et al., 2016; Peng and Peng, 2018; Zhao et al., 2022). Despite its importance, several challenges make evaluating urban underground space resources difficult, such as the selection of factors and a lack of uniform assessment criteria for the evaluation model.

For the above reason, scholars have attempted to study the evaluation indicators and models for the suitability of urban underground space. Some scholars consider the engineering geological characteristics of underground space as an indicator for evaluating underground space resources (Li et al., 2013; Doyle, 2016). Another group of scholars determines evaluation indicators based on typical geological characteristics of the research area, such as mountainous (Xi et al., 2022), plateau (Duan et al., 2021), and plain (Zhou et al., 2019; He et al., 2012; Chen et al., 2021). At the same time, the scholars take care of the status of existing buildings and socio-economic values (Peng and Peng, 2018; Xi et al., 2022). In recent years, evaluation indicators have gradually developed from a few to a multi-level and multi-index evaluation system considering socio-economics, engineering geological, and construction status (Peng and Peng, 2018; Zhou et al., 2019; Xi et al., 2022).

Many evaluation models have been developed and well-used in UUSR evaluation in literature, such as the analytic hierarchy process (AHP) (Saaty, 1994; Doyle, 2016; Zhou et al., 2019), fuzzy comprehensive assessment methods (Vahidnia et al., 2009; Tang et al., 2020; Lyu et al., 2020), entropy weight (Tan et al., 2021). Also, some ensemble models or systems have been developed in this field, including the FAHP-TOPSIS model (Lu et al., 2016), underground space plan decision support system (USP-DSS) (Peng and Peng, 2018), and the multi-agent system (MAS) (Chen et al., 2021). All these methods mentioned above have proved their efficiency in UUSR evaluation. In recent years, there has been a growing popularity in the utilization of machine learning algorithms for addressing multi-criteria decision-making problems, notably the Bayesian Networks Model (BNM) (Hosseini and Barker, 2016; Marcot and Penman, 2019; Tang et al., 2020). Nevertheless, little application has been in the field of UUSR evaluation. BNM can effectively mine data, identifies and displays relationships among variables, and integrate expert knowledge and empirical data (Uusitalo, 2007; Hanea et al., 2010; Landuyt et al., 2013). It can also model the causal relationships among evaluation indices and goals (Hosseini and Barker, 2016; Tang et al., 2020).

Therefore, this paper attempts to apply the Bayesian Networks Model (BNM) to evaluate urban underground space resources (UUSR). The study area is divided into discrete evaluation units of 100 m × 100 m by ArcGIS 10.6. Subsequently, the collected data is assigned to the corresponding evaluation units. Then, the network structure of the BNM is constructed, and the conditional probability tables (CPTs) are determined using the analytic hierarchy process (AHP). Finally, the development potential of underground space in Changsha City is discussed as a case study. This study aims to present a novel approach for evaluating the suitability of urban underground space development and offering an aid decision-making tool for urban underground space planning.

Table 1
Factors of the underground space evaluation.

	Factors	Indicators	Data sources
Socio-economic value	Economy	S_1: Benchmark land price	Shell House (Beijing) Technology Co., Ltd. https://cs.lianjia.com
		S_2: Population density	University of Southampton https://www.worldpop.org
Geological condition	Landform	S_3: Relief	NASA https://www.nasa.gov
		S_4: Ground gradient	NASA https://www.nasa.gov
	Geology	S_5: Depth to bedrock	Scientific Data http://globalchange.bnu.edu.cn/
		S_6: Distance to a fault	National Geological Archive Data Center http://dc.ngac.org.cn
		S_7: Soil type	ISRIC -World Soil Information https://www.isric.org
	Hydrogeology	S_8: Distance to the river	OpenStreetMap https://www.openstreetmap.org
Construction status	Construction rate	S_9: Construction rate	Amap Software Co., Ltd. https://ditu.gaode.com
	Land use type	S_{10}: Land use type	Tsinghua University http://data.ess.tsinghua.edu.cn
	Existing traffic facilities	S_{11}: Road density	OpenStreetMap https://www.openstreetmap.org
		S_{12}: Distance to railway	OpenStreetMap https://www.openstreetmap.org

2. Methodology

This section presents the construction of a Bayesian network model for evaluating urban underground spaces. Firstly, we will show the flowchart of this study to evaluate UUSR. Subsequently, the evaluation indicators will be explored in detail. Finally, we will explain the fundamental concepts of the Bayesian network model by using a simple case study.

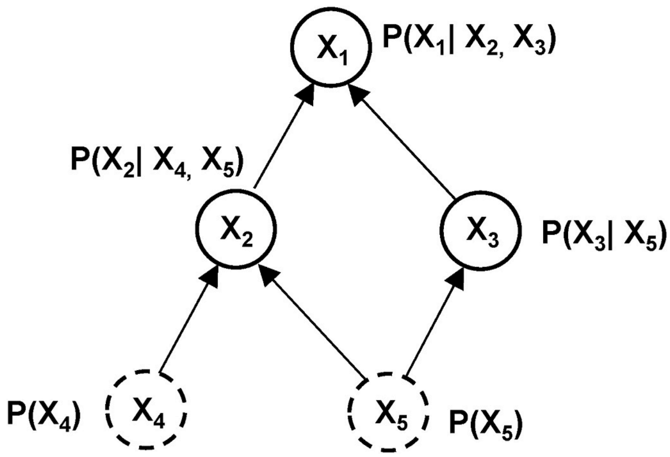

Fig. 2. An example of a Bayesian network model.

2.1. Flowchart of evaluation model

The flowchart in Fig. 1 outlines the process for assessing urban underground space resources. Firstly, multiple data sources are integrated into the ArcGIS platform, encompassing three aspects: socio-economic, geological, and existing construction status indicators. Secondly, the data is rasterized and classified into several levels. Thirdly, a Bayesian network model is established, with the conditional probability tables (CPTs) determined by expert knowledge. Finally, the Bayesian network model is used to analyze the suitability of urban underground spaces.

2.2. Indicator of UUSR evaluation

This section mainly introduces the evaluation indicators of the feasibility of underground space development. It explains in detail the impact of these indicators on the development and utilization of urban underground space. There are seven main factors and 12 indicators, as shown in Table 1. The following is a detailed explanation.

2.2.1. Socio-economic

Socio-economic factors significantly influence urban underground space development, with population density and benchmark land prices playing a key role. Researchers have conducted extensive studies to explore the optimal population density for various districts within urban areas. Resource allocation optimization has been suggested as a means to enhance the livable population density of cities. According to Wu et al. (2020), the appropriate population density for urban areas is 10, 000 to 30,000 persons per square kilometer. Benchmark land price is an indicator of the development value of a study area, with higher prices indicating more significant exploitative potential.

2.2.2. Landforms

A landform is a feature on Earth's surface. The most notable landforms include mountains, hills, plateaus, and plains. These landforms are characterized by distinct topographic relief and slopes that significantly impact their appearance and suitability for various human activities. When selecting a site for a city, it is crucial to avoid low-lying areas prone to flooding and regions with large topographic fluctuations. The presence of such places can pose significant challenges to the development of underground urban spaces. For instance, the risk of flooding in subway stations situated in low-lying areas could jeopardize their security. Additionally, constructing infrastructure in undulating areas can be prohibitively expensive due to the complex engineering and geological considerations required.

2.2.3. Engineering geology

Engineering geology is critical in determining the viability of underground space development and utilization. The engineering properties of geological materials, such as bedrock depth, the thickness of soft soil, the liquefaction index of sandy soil, distance from active fault zones, and rock compressive strength, among others, play a pivotal role in assessing the feasibility and safety of underground space development. The engineering geological characteristics of a site provide valuable insights into the level of risk and complexity involved in construction. Bedrock, for instance, typically exhibits low weathering and high natural compressive strength, rendering it stable and safe for development, albeit challenging to excavate. Conversely, fracture zones near fault lines pose a significant hazard and should be avoided as much as possible when planning underground space utilization.

2.2.4. Hydrogeology

Hydrology constitutes a critical aspect that requires careful attention in underground space development. Hydrological characterizations, such as the phreatic water table, artesian head elevation, artesian water head, groundwater corrosion, and watery faults in bed, are essential in assessing the feasibility and safety of underground space development. The excavation of underground spaces often results in groundwater seepage, which can cause soil subsidence and induce uneven settlement of building foundations and structures, leading to building damage. This phenomenon is determined by the soil permeability and proximity to the water body, with closer proximity increasing the likelihood of danger. Hence, a thorough understanding of hydrological characteristics is essential for successful and safe underground space development.

2.2.5. Construction rate

In evaluating underground space development, the construction rate is an essential indicator of the degree of construction achieved. Specifically, it is defined as the ratio of V_u (the developed underground space volume) to V_t (the total volume of underground space). The V_t of each unit is the volume from the surface to the depth of 50 m below the ground surface. The determination of the developed underground space volume V_u is based on the influence of the building foundation. The National Standards of the People's Republic of China (2019) provide guidelines for establishing the relationship between the building foundation's depth of influence and the building's height. For instance, when the height of the building is less than 9 m, the influence depth is 10 m, while for buildings with heights ranging from 9.1 m to 30 m, the influence depth is 30 m. As for buildings with heights ranging from 30 m to 100 m, the influence depth is more than 50 m. It is worth noting that the higher the construction rate, the less remaining underground space is available for development.

2.2.6. Existing traffic facilities

Transportation infrastructure plays a pivotal role in urban development, encompassing road networks, high-speed railways, conventional railways, and subways. One of the key concerns when developing underground spaces near urban transportation facilities is maintaining a safe distance during construction, thereby preserving the integrity of the existing public transportation infrastructure. From the aspects of construction difficulty and safety, the underground spaces located in low-density road areas and outside the safety impact zone of the subway demonstrate greater potential for development.

2.2.7. Land use type

Land use type refers to the plans made by the urban planning department to develop the urban surface. The main categories of land use include commercial, residential, industrial, and ecological. There are well-established planning and design specifications for surface land use types. However, the planning of underground space requires further investigation. Typically, surface planning also influences the planning of urban underground space. For instance, developing the urban

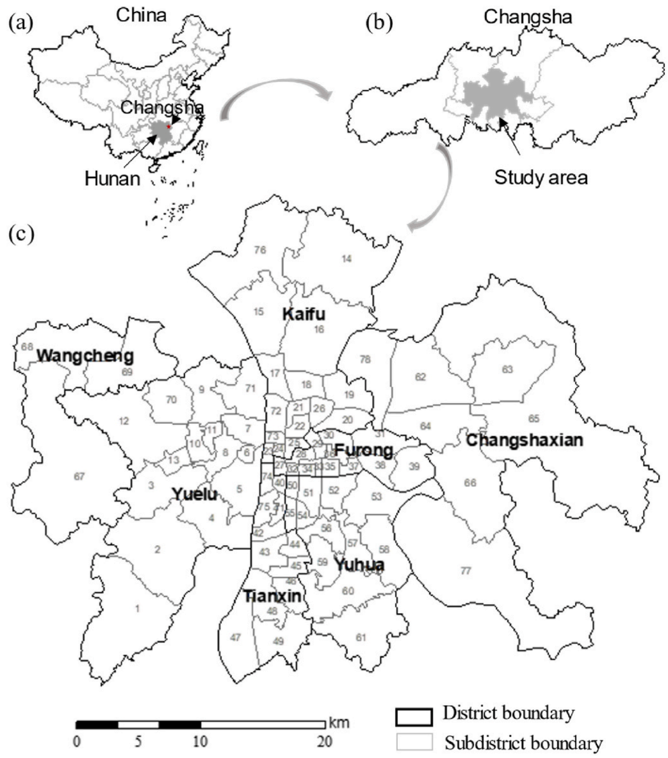

Fig. 3. Administrative divisions of the Study area.

Table 2
The abbreviation of subdistricts.

No.	Name	No.	Name	No.	Name	No.	Name
1	GQ.ST	21	TD.ST (2)	41	NL.ST	61	WYH.ST
2	YHT.ST	22	XiH.ST	42	WLY.ST	62	DFL.ST
3	DT.ST	23	HX.ST	43	WJL.ST	63	XL.ST
4	GSL.ST	24	TS.ST	44	DWT.ST	64	JCY.ST
5	CNL.ST	25	WYue.ST	45	YNJ.ST	65	FRBL.ST
6	HJY.ST	26	QST.ST	46	JZZ.ST	66	WY.ST
7	SZT.ST	27	MWD.ST	47	JSQ.ST	67	DTP.ST
8	HHY.ST	28	HP.ST	48	YH.ST	68	HS.ST
9	PZJ.ST	29	CL.ST	49	SP.ST	69	LT.ST
10	CYJ.ST	30	HJT.ST	50	TTL.ST	70	WYL.ST
11	DTD.ST	31	MPL.ST	51	XYL.ST	71	XueS.ST
12	GHP.ST	32	DH.ST	52	MXH.ST	72	TongS.ST
13	XH.ST	33	LDH.ST	53	ZJT.ST	73	QT.ST
14	LYH.ST	34	QY.ST	54	XS.ST	74	HH.ST
15	HXing.ST	35	WLP.ST	55	TD.ST (1)	75	XianF.ST
16	XinH.ST	36	QZF.ST	56	YPL.ST	76	WCP.ST
17	DA.ST	37	LG.ST	57	DS.ST	77	SFP.ST
18	YL.ST	38	XKP.ST	58	GT.ST	78	LF.ST
19	HSP.ST	39	JWZ.ST	59	CLL.ST	–	–
20	JPL.ST	40	XF.ST	60	XJH.ST	–	–

underground space to create a three-dimensional business district can increase commercial land availability and promote urban development.

2.3. Bayesian network model (BNM)

This section introduces the Bayesian network model and its basic principles. It is an artificial intelligence algorithm with causal inference capabilities, and it is a directed acyclic graph where each node represents a random variable. When constructing a Bayesian network model, the first step is to evaluate whether any two nodes are correlated. Correlated nodes are connected with a straight line. The next step is to determine the direction of the arrow, which points from the cause to the effect.

Fig. 2 shows a simple Bayesian network model containing five variables. The nodes can be divided into two categories: the nodes pointed to by the arrows are called child nodes, and the nodes pointing to other nodes are called parent nodes. X_4 and X_5 are parent nodes, while X_1, X_2, and X_3 are child nodes. The nodes can be classified into three categories based on their connectivity states. The first category is the root node, which has no parent nodes. The second category is the leaf node, which has no child nodes. The third category is the intermediate node, which has both child and parent nodes. X_4 and X_5 are the root nodes, X_2 and X_3 are intermediate nodes, and X_1 is the leaf node. Based on the Bayesian network structure and the conditional probability table between each node, we can complete the Bayesian network modeling.

The generic form of the Bayesian net joint probability is as follows.

$$P(X_1, X_2, \dots, X_n) = P(X_1|X_2, X_3, \dots, X_n)P(X_2|X_3, \dots, X_n)\dots P(X_{n-1}|X_n)P(X_n) = \prod_{i=1}^{n} P(X_i|X_{i+1}, \dots, X_n) \tag{1}$$

Following the above general form, we can write the joint probabilities of the Bayesian network model in Fig. 2. Once the states of the nodes are determined, the joint probability formula allows inferential calculations on the unknown variables. Here, we introduce a case.

$$P(X_1, X_2, X_3, X_4, X_5) = P(X_1|X_2, X_3)P(X_2|X_4, X_5)P(X_3|X_5)P(X_4)P(X_5) \tag{2}$$

For example, suppose nodes $X_1 \sim X_5$ have two states, “Yes”and “No”. When the states of X_1, X_3, X_4, and X_5 are “Yes”. How can we get the probability of X_2 with the state of “Yes”? Here, $E = \{X_{1y}, X_{3y}, X_{4y}, X_{4y}\}$. According to Bayes’s theorem, its probability can be solved by equation (3).

$$P(X_{2y}|E) = P(X_{2y}|X_{1y}, X_{3y}, X_{4y}, X_{5y}) = \frac{P(X_{1y}, X_{2y}, X_{3y}, X_{4y}, X_{5y})}{\sum_{X_2} P(X_{1y}, X_{3y}, X_{4y}, X_{5y})} \tag{3}$$

$$= \frac{P(X_{1y}|X_{2y}, X_{3y})P(X_{2y}|X_{4y}, X_{5y})}{P(X_{1y}|X_{2y}, X_{3y})P(X_{2y}|X_{4y}, X_{5y}) + P(X_{1y}|X_{2N}, X_{3y})P(X_{2N}|X_{4y}, X_{5y})}$$

The values of $P(X_{1y}|X_{2y}, X_{3y})$、$P(X_{1y}|X_{2N}, X_{3y})$、$P(X_{2y}|X_{4y}, X_{5y})$, and $P(X_{2N}|X_{4y}, X_{5y})$ can be found by conditional probability table (CPT). The probability that X_2 is “Yes”. When the states of X_1, X_3, X_4, X_5 are “Yes”. It can be solved by bringing the above values into Equation (3). The state of each node can be inferred using the method above.

3. Case study of Changsha

Changsha is located in the Hunan Province of China. The study area encompasses seven districts of Changsha: Kaifu District (KF), Wangcheng District (WC), Yuelu District (YL), Furong District (FR), Tianxin District (TX), Yuhua District (YH), Changshaxian District (CSX). Furthermore, the study area is divided into 78 subdistricts, as depicted in Fig. 3 and Table 2. To obtain more detailed assessment results regarding the suitability of underground space, it is often necessary to divide the study area into a series of evaluation units. The size of these units needs to take into account several factors, including the visualization effect, computing efficiency, and the data source (Li and Openshaw, 1993; Zhou et al., 2019; Qiao et al., 2022b). Considering these factors, we employed ArcGIS 10.6 to discretize the study area into evaluation units measuring 100 m × 100 m. In total, 116,554 units were created.

3.1. Data

This section pertains to acquiring and processing data in the study. Table 3 expounds on the criteria for classifying each level of the examined indicators. We can find further details data about the 12 indicators under investigation in the study area in Fig. 4.

Table 3
The categorization and labels of the indicators.

	Indicators	Unit	Evaluation Labels				
			1	2	3	4	5
Socio-economic value	S_1: Benchmark land price	yuan/m^2	≤6000	6000–8000	8000–10000	10000–12000	>12000
	S_2: Population density	persons/km^2	≤6000	6000–12000	12000–18000	18000–24000	>24000
Geological condition	S_3: Relief	m	≤8	8–15	15–25	25–45	>45
	S_4: Ground gradient	°	≤5	5–10	10–20	20–30	>30
	S_5: Depth to bedrock	m	≤20	20–40	40–60	>60	–
	S_6: Distance to a fault	m	≤500	500–2000	2000–5000	5000–10000	>10000
	S_7: Soil type	–	Extremely soft rock	Soft rock	Hard rock	Extremely Hard rock	–
	S_8: Distance to the river	m	≤100	100–200	200–500	500–1000	>1000
Construction status	S_9: Construction Rate	–	≤0.2	0.2–0.4	0.4–0.6	0.6–0.8	>0.8
	S_{10}: Land use type	–	Commercial	Residential	Infrastructure	Industrial	Ecological
	S_{11}: Road density	km/km^2	<5	5–15	15–28	28–47	>47
	S_{12}: Distance to railway	m	≤100	100–200	200–500	500–1000	>1000

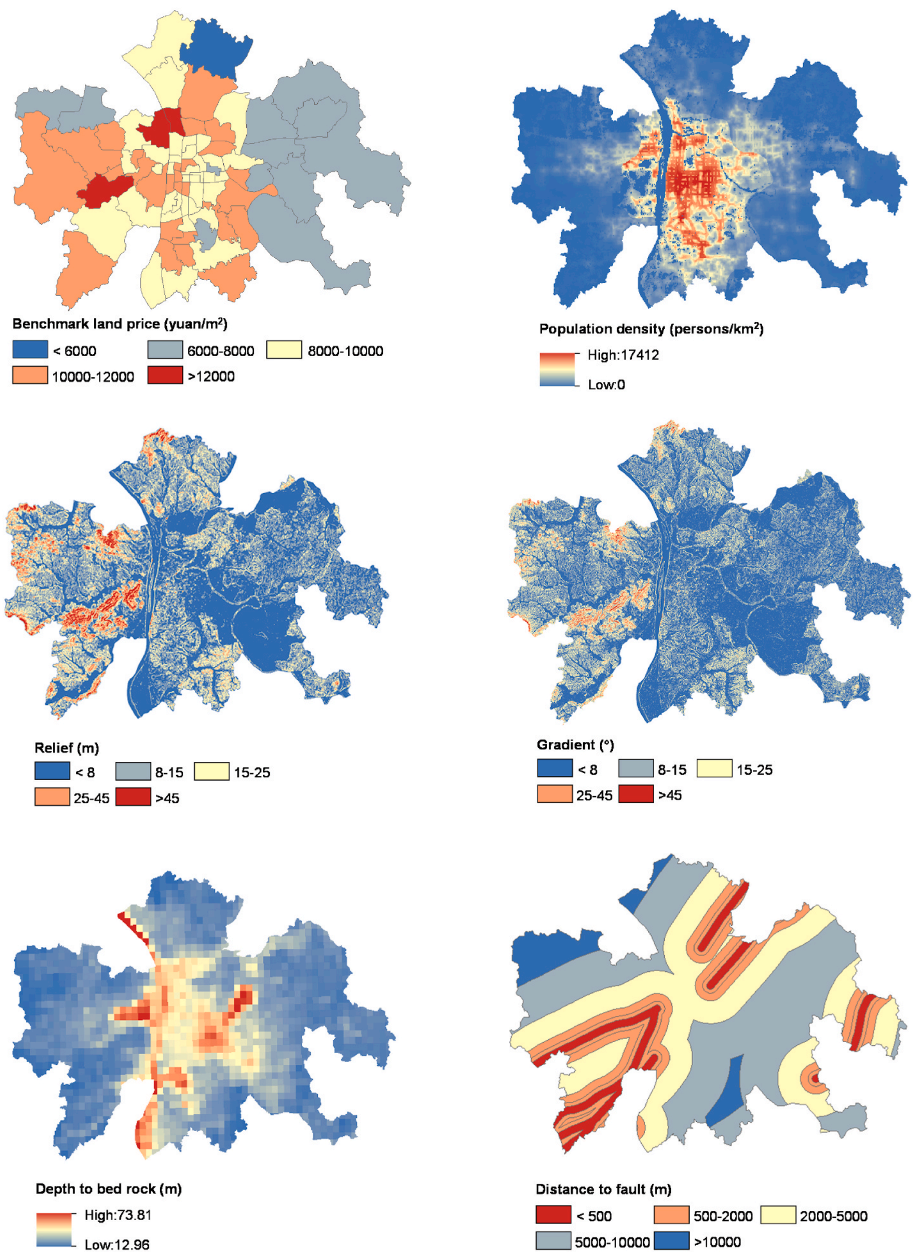

Fig. 4. Factors used to assess the suitability of the study area.

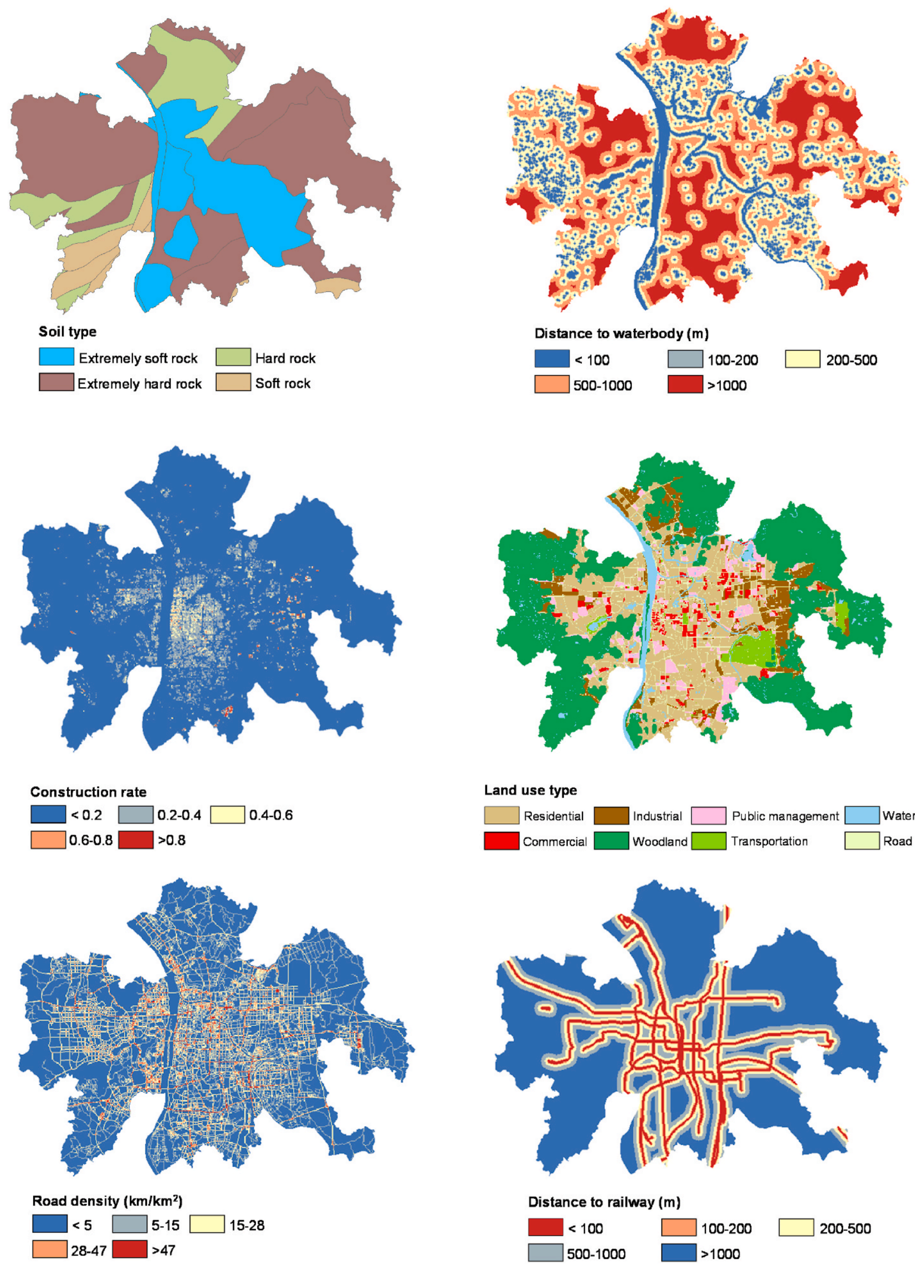

Fig. 4. (*continued*).

3.1.1. *Benchmark land price*

The benchmark land price data was sourced from the website (https://cs.lianjia.com), which provides house price data for new and second-hand houses in Changsha. The study presents median house price statistics for subdistricts, which have been divided into five categories. The subdistrict with the highest median benchmark land price is MXH.ST, at 17,530 yuan/m^2, while the subdistrict with the lowest median benchmark land price is SP.ST, at 5710 yuan/m^2.

3.1.2. *Population density*

Population density data for Changsha in 2020 was sourced from World Pop (https://www.worldpop.org/) using a raster size of 100 m × 100 m. The population density data was cropped to extract data specific to the region. The highest population density was observed in the urban center of Changsha, reaching a value of 17,412 persons/km^2. Based on the analysis, the population density was categorized into five levels, with the 5th level having a density greater than 24,000 persons/km^2, while the remaining levels gradually decreased by a gradient of 6000 persons/km^2.

3.1.3. *Relief*

Landform relief measures the difference between the maximum and minimum elevation values within a given area. This information can be analyzed using ArcGIS software to perform focal statistics of the digital elevation model (DEM). In the present study, the maximum relief value observed was 97 m, and the relief was categorized into five distinct classes using the natural interruption point method. Notably, higher relief values indicate more significant challenges for developing and utilizing urban underground spaces. Therefore, careful consideration of terrain relief is essential for efficiently planning and managing underground infrastructure in urban areas.

3.1.4. *Ground gradient*

The ground gradient is calculated from the Digital Elevation Model

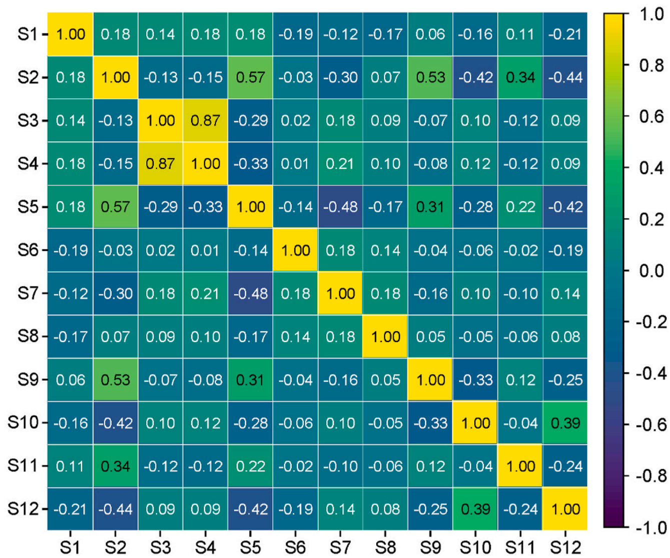

Fig. 5. Correlation of factors.

(DEM). The study area exhibits large gradient values in Yuelu Mountain to the west, Wangcheng District in the northwest, and Kaifu District in the north direction. Areas with smaller gradient values are generally more suitable for urban construction. In this study, the gradient of the study area is categorized into five classes based on the natural breaks.

3.1.5. Distance to bedrock

The data on distance to the bedrock was obtained from Yan et al. (2020). The bedrock depth is most significant at the center of the study area, with a maximum depth of 73.81 m. The bedrock depth is shallower in the surrounding areas, with a minimum depth of 12.96 m.

3.1.6. Distance to fault

The fault distribution data was obtained from OpenStreetMap, which identified five significant faults within the study area. The overall orientation of the fault zone is northeast-southwest. The proximity to the fault zone is directly proportional to the difficulty and risk associated with underground construction. Consequently, the planning of underground spaces should endeavor to minimize the presence of the fault zone. This study classifies the area into five categories based on the distance to the fault.

Table 4
Expert group information.

Name	Field/Profession	Affiliation
Li S. G.	Underground space/Professor (Registered Geotechnical Engineer)	Henan Communications Planning& Design Institute Co., Ltd, China
Tan X.	Geotechnical Engineering/ Associate Professor	Hunan university, Changsha, China
Li H. Q.	Urban Planning and Management/Senior Engineer	Hunan Provincial Communications Planning, Survey & Design Institute Co., Ltd, China

Table 5
The weight of two states of X_2.

X_2-Economy	Favorable	Unfavorable	Weight	Normalization (%)
Favorable	1	5	0.8333	100
Unfavorable	1/5	1	0.1667	0

Table 6
The weight of two states of X_3.

X_3-Geoploitability condition	Favorable	Unfavorable	Weight	Normalization (%)
Favorable	1	5	0.8333	100
Unfavorable	1/5	1	0.1667	0

Table 7
The weight of two states of X_4.

X_4-Construction status	Favorable	Unfavorable	Weight
Favorable	1	5	0.8333
Unfavorable	1/5	1	0.1667

Table 8
The weight of factors.

	X_2	X_3	X_4	Weight
X_2	1	1/2	1/2	0.2
X_3	2	1	1	0.4
X_4	2	1	1	0.4

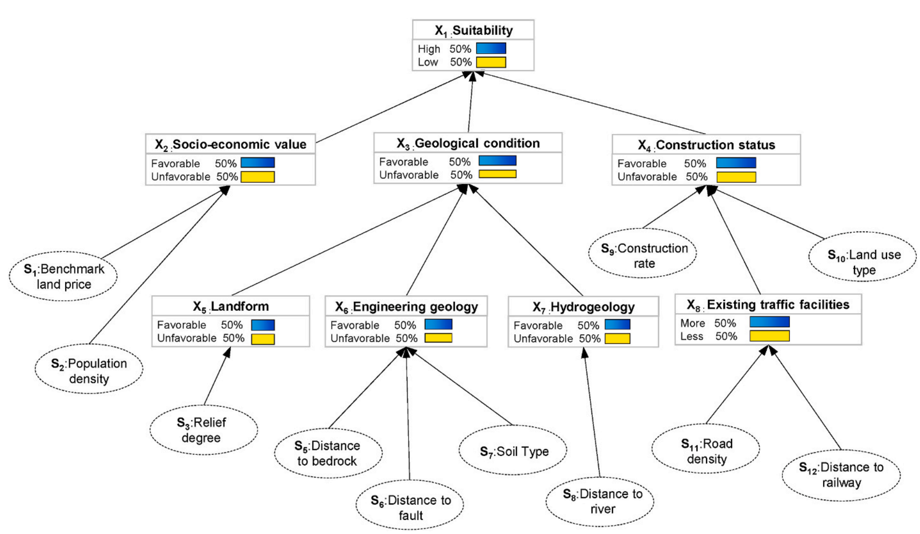

Fig. 6. Structure of evaluation model.

Table 9
The conditional probability of X_1.

X_1-Suitability								
X_4	Favorable	Favorable	Favorable	Favorable	Unfavorable	Unfavorable	Unfavorable	Unfavorable
X_3	Favorable	Favorable	Unfavorable	Unfavorable	Favorable	Favorable	Unfavorable	Unfavorable
X_2	Favorable	Unfavorable	Favorable	Unfavorable	Favorable	Unfavorable	Favorable	Unfavorable
High	100	80	60	40	60	40	20	0
Low	0	20	40	60	40	60	80	100

Table 10
The weight of factors.

	S_1	S_2	Weight
S_1	1	1/2	0.33
S_2	2	1	0.67

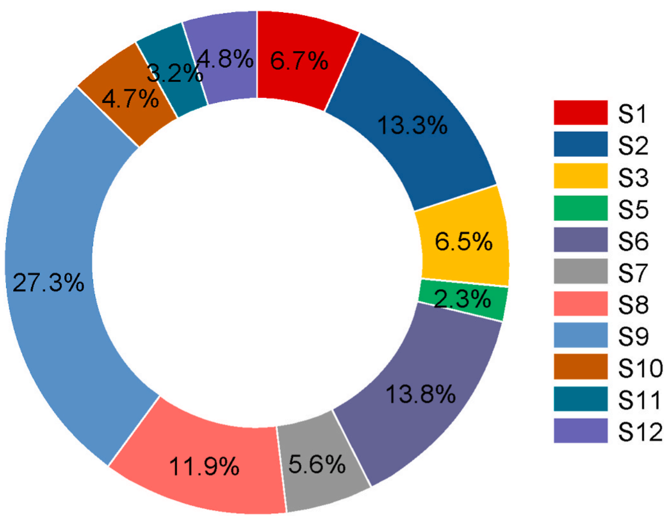

Fig. 7. Proportion of impact of factors.

3.1.7. Soil type

The geotechnical data were obtained from ISRIC - World Soil Information, which identified the presence of clay, sandstone, conglomerate, slate, tuff, and granite distributed throughout the study area. This study categorized the geotechnical soils into four distinct classes: extremely soft rock, soft rock, hard rock, and extremely hard rock, based on the National standards of the People's Republic of China (2015). In terms of construction safety, it is imperative to prioritize the strength of the rock, as it is directly proportional to the level of safety.

3.1.8. Distance to river

The primary rivers traverse Changsha include the Xiangjiang River, Liuyang River, and Ladao River. Additionally, the city boasts several wetland parks, such as Meixi Lake and Yang Lake. The development of underground spaces in the region is hindered by significant groundwater challenges. In particular, areas close to water bodies tend to present more substantial construction risks. The present study utilizes an evaluation system that quantifies the construction risk associated with underground space development by measuring the distance of evaluation units from water bodies. A five-level classification system categorizes grid units based on their distance from water bodies.

3.1.9. Construction rate

The construction rate refers to the proportion of developed area to the total area. The developed area is determined by collecting building outlines in the urban area from Amap Map and OpenStreetMap. In terms of depth, this study considers a depth of 50 m. The influence range of the building foundation is estimated based on the height of the building.

3.1.10. Land use type

The land use types data was obtained from Chen et al. (2021). The land use types within the central urban area include residential, industrial, public management and services, commercial, woodland, transportation, road, and water. These land use types were classified into five major categories based on their impact on underground space to facilitate statistical analysis, as presented in Table 3.

3.1.11. Road density

The road data was obtained from OpenStreetMap. The function fishnet of ArcGIS is to quantify road length and organize the data. The maximum road density of Changsha is 108.67 km/km^2. Based on natural interruption points, the data were classified into five levels of road density. A higher road density indicates a greater degree of construction in the area.

3.1.12. Distance to railway

The railway infrastructure comprises high-speed rail, ordinary rail, and subway systems and requires a certain safety distance to ensure safety and prevent disruptions. Construction projects near railway infrastructure, especially subways, and high-speed railways, can potentially disturb or damage the infrastructure. The closer the distance to the existing railway infrastructure, the more challenging to develop. This study has classified the area into five categories based on the distance from the railway infrastructure, as presented in Table 3.

3.2. Correlation of factors

This study employs the Pearson correlation coefficient to assess the relationship between the variables. Fig. 5 presents the corresponding correlation coefficients, where the absolute values between most parameters are less than 0.5, indicating a weak correlation. Specifically, factors S_2 and S_5 exhibit a low correlation, which satisfies the conditional independence assumption. Conversely, factors S_3 and S_4 are strongly correlated, as both are derived from DEM. As S_3 is a statistical index that more aptly represents landforms' impact on underground space, it will be used in the evaluation model. Therefore, the overall assumption of conditional independence among the factors is satisfied.

3.3. Implementation of BNM

This section is dedicated to constructing a Bayesian network model involving two key steps. The first step entails determining the network structure, while the second involves deciding the conditional probability tables (CPTs) of the nodes in the network structure. The Bayesian network structure is established through two approaches. The first approach is data-driven, while the second relies on expert knowledge.

3.3.1. Structure of BNM

This paper thoroughly examined the hierarchical relationships among factors through a comprehensive analysis of expert opinions and literature (Xi et al., 2022; Zhou et al., 2019). Then, a network evaluation structure for underground space suitability evaluation is constructed in Fig. 6.

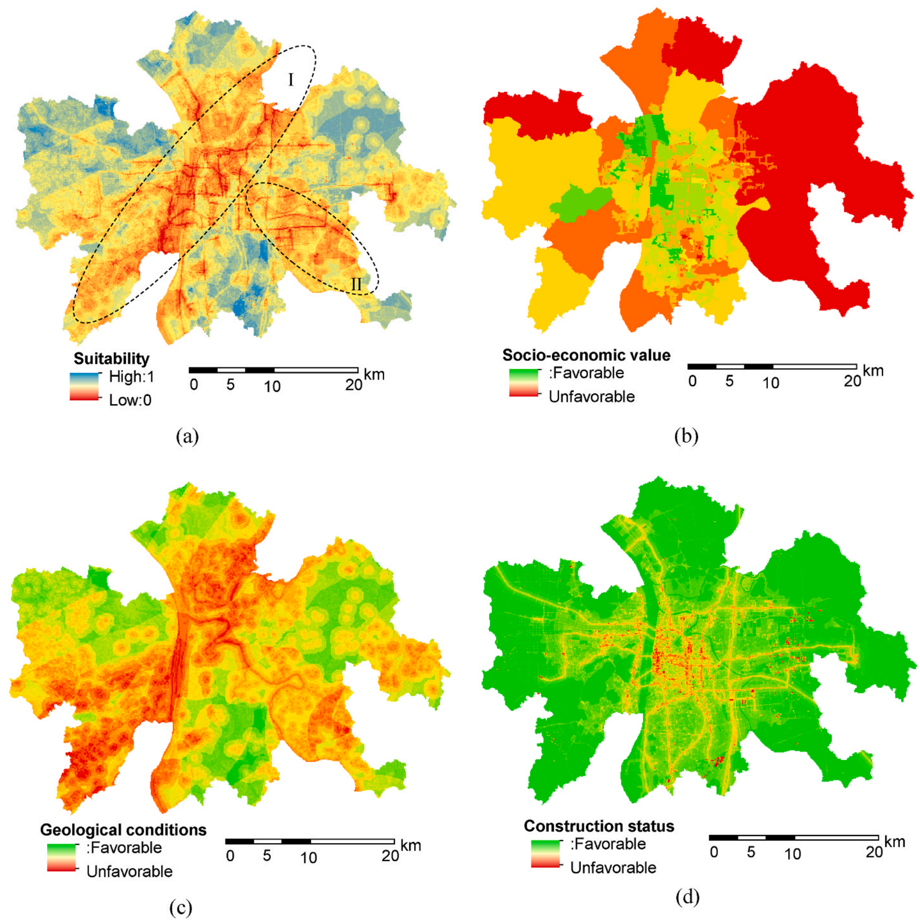

Fig. 8. (a) Suitability; (b) Socio-economic value; (c) Geological conditions; (d) Construction status.

Table 11
The categorization criteria.

Category	Suitability
Very High	1~0.75
High	0.75–0.5
Low	0.5–0.25
Very Low	0~0.25

X represents the node for decision, and S represents the node for data input. Node X_1 is the Bayesian network's leaf node, representing the degree of suitability. Node X_1 has two states, High and Low. X_2, X_3, X_4, X_5, X_6, X_7, and X_8 are intermediate nodes with two states. X_2 represents socio-economic value, mainly determined by benchmark land price and population density. X_3 represents geological adaptability, with two states of Favorable and Unfavorable. It mainly includes engineering geology, landform, and hydrogeology. X_4 stands for construction status, with two states of "Favorable" and "Unfavorable". S_1 to S_{12} are the input data. The states of each data are shown in Table 3.

3.3.2. The conditional probability of BNM

After the Bayesian network structure is established, it is necessary to determine the conditional probability table of nodes. There are usually two ways to determine a conditional probability table. The first method is data-based training. This method is suitable for all observable, objective variables and needs to be trained under complete data. However, variables X_1-X_8 in this paper cannot be directly observed. Therefore, the network structure constructed in this paper cannot be trained by data. The second method is based on expert knowledge, which can fuse multi-source information (Tang et al., 2020). This paper uses the second scheme to determine the conditional probability table, and the information of experts can be seen in Table 4. The main process to get the CPT of X_1 is as follows:

Step 1: Obtain the importance of the node's two states to support underground space development through Tables 5–7. Solve the weight through the AHP judgment matrix by Matlab code, and normalize it to 0–100%. For example, as shown in Table 5, X_2 (Economy) state of "Favorable" supports the development and utilization of underground space more than the state of "Unfavorable". Step 2: Through the AHP method, the relative weights of X_2, X_3, and X_4 nodes can be obtained in Table 8. Step 3: Solve the conditional probability of X_1 (the states of High) under the different state combinations of nodes X_2, X_3, and X_4. For example, as shown in Table 9, solve when X_4 is "Favorable", X_3 is "Favorable", and X_2 is "Favorable", the conditional probability of X_1 (the states of High). The solution formula is $X_1 = X_4{*}0.4{+}X_3{*}0.4{+}X_2{*}0.2$. The results are shown in Table 9. The conditional probability tables of $X_1 \sim X_8$ can obtain by the above method.

Following the above method, we can acquire the CPTs for each node. Moreover, we can calculate the weights of various factors within each level. In Table 10, we can establish the relative weights of factors S_1 and S_2 within node X_2, where S_1 is 0.33 and S_2 is 0.67. By multiplying these weights with the weight of X_2, we can derive the weights of S_1 and S_2 about X_1. This methodology allows us to obtain the weights of $S_1 \sim S_{12}$ about X_1.

Fig. 7 shows the degree of influence of each factor on the suitability of underground space. The top 3 factors with greater influence are S_9, S_6, and S_2, which account for 27.3%, 13.8%, and 13.3%. The factor with the least influence is S_5, which accounts for 2.3%.

3.4. Suitability analysis

This section employs the forward inference of BNM to evaluate the probability of underground space suitability in Changsha. Decision-makers often lack a comprehensive understanding of the overall suitability performance of Changsha before conducting forward inference. BNM forward inference can evaluate the suitability probability with input data prepared for root nodes. The proposed model utilizes prior probability values as evidence for each unit (100 m × 100 m), and the probability of suitability is obtained as unit evaluation outcomes. The BNM is constructed using MATLAB (R2021a) software, and 116,554 units in Changsha are evaluated. The evaluation results are presented below.

3.4.1. Suitability

Fig. 8a shows the suitability value of underground space development in Changsha. Red represents low suitability. Area I represents the area of Changsha from northeast to southwest. Area II represents the southwest of Changsha. Area I and Area II show the low suitability area of Changsha. The evaluation results for the second-level suitability index can be seen in Fig. 8b–d. Specifically, Fig. 8b depicts the evaluation results of X_2, the node representing socio-economic value, which is determined by S_1 and S_2. The results reveal that some subdistricts in the central area have higher potential value, while certain subdistricts in the east and north exhibit a lower socio-economic value. In Fig. 8c, the evaluation results of node X_3 are illustrated, which are based on landform, engineering geology, and hydrogeology. The region from the northeast to the southwest is characterized by poor geological adaptation, primarily due to the distribution of faults and water bodies. Finally, Fig. 8d shows the evaluation results of X_4, where the node represents the construction status, indicating that the central area has a higher degree of development. Moreover, the more built-up areas exhibit a grid-like pattern determined by the metro lines.

3.4.2. Quantitative analysis

We analyzed the distribution characteristics of underground space suitability in districts and subdistricts of the study area, and the suitability was categorized into four categories: Very High, High, Low, and Very Low. The categorization criteria can be seen in Table 11. The assessment results are tabulated based on districts and subdistricts.

Fig. 9 displays the results of the subdistrict statistics. The horizontal axis represents the subdistrict area, while the vertical axis represents the subdistrict names arranged in descending order of size. The largest subdistrict is LF.ST (145.4 km^2), and the smallest subdistrict is LDH.ST

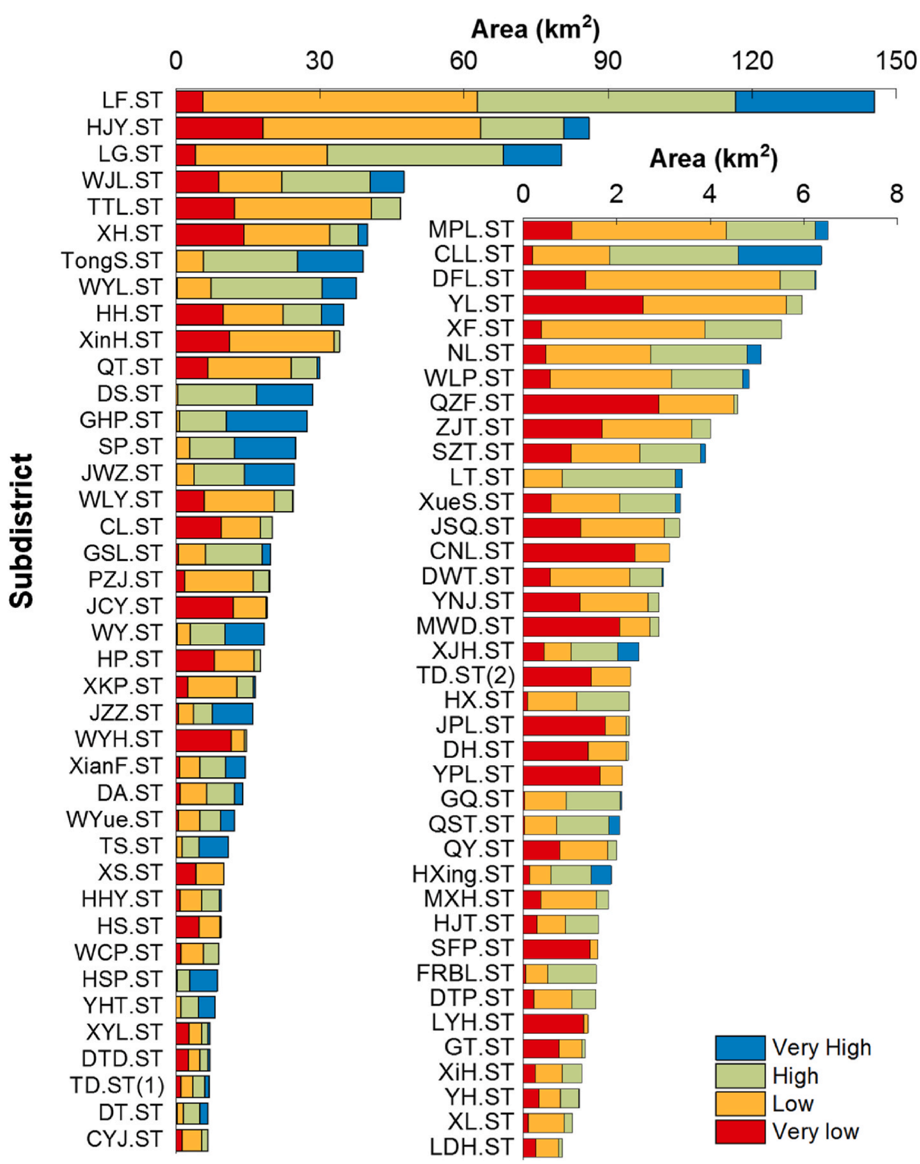

Fig. 9. Suitability of each subdistrict.

(0.84 km^2). The evaluation results for each subdistrict exhibit significant differences. Approximately 14 subdistricts do not fall under the Very Low class, including TongS.ST and WYL.ST. The subdistricts such as LYH.ST and SFP.ST are categorized as Very Low.

Fig. 10 presents the results of district-level statistics. In Fig. 10a, the horizontal axis represents district names, while the vertical axis shows the percentage of each district's suitability level. The results demonstrate that each district exhibits a distinct suitability level. The YH and WC districts have a relatively high percentage of Very High at 33% and 26%, respectively, while having a lower percentage of Very Low. In contrast, the FR district had the highest Very Low percentage at 30% but no Very High classification. Fig. 10b displays the statistical results of each district's area classified into four evaluation levels. The rectangular area in the graph represents the relative size of each district's area. The results indicate that the Low category has the largest area, followed by the High.

4. Discussions and implication

4.1. Bayesian forward inference

The primary objective of this paper is to assess the sustainable development of underground space and provide a forward-looking evaluation of its suitability in urban areas. The Bayesian network model is employed to forecast the possible changes in the suitability of urban underground space under different input parameters. This capability to anticipate potential changes is a critical advantage of the Bayesian network model. In this section, we concentrate on the anticipated impact of changes in socio-economic value on the suitability of underground space, as projected by the model proposed in this paper.

The Netica version 5.18 software is utilized to validate the Bayesian network model. Fig. 11 illustrates the inference model for the same evaluation unit with different input parameters and displays the states of

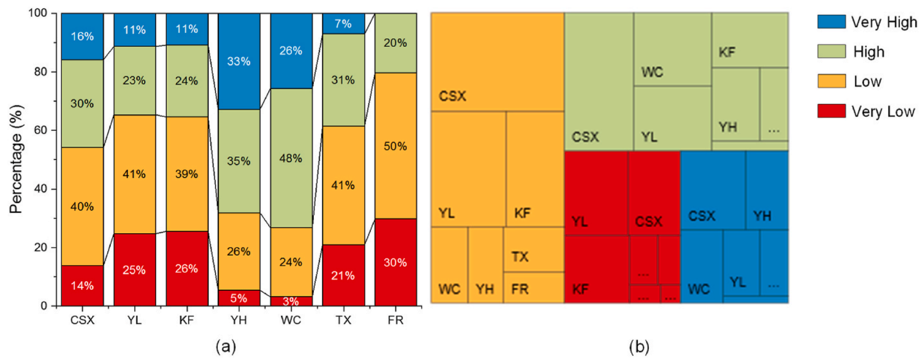

Fig. 10. Suitability of each district.

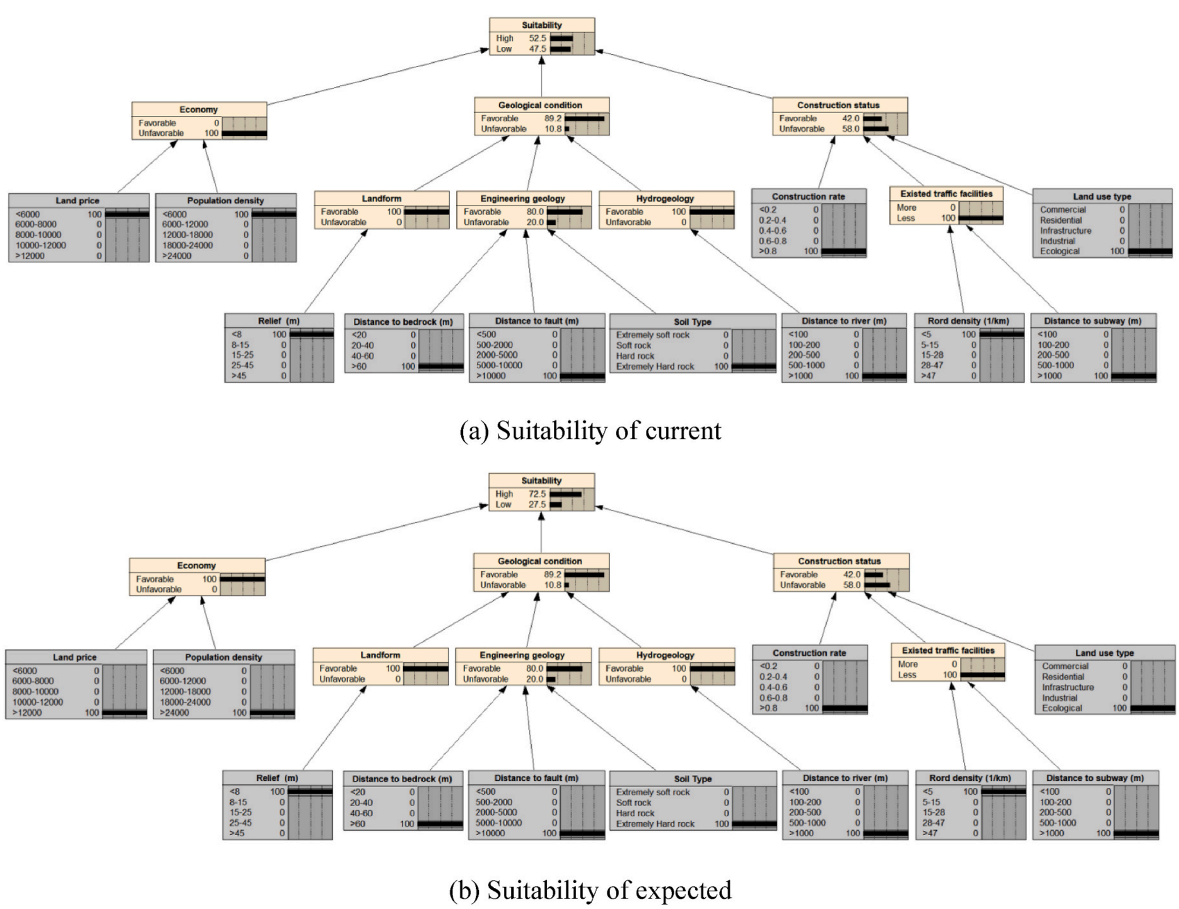

Fig. 11. The impact of socio-economic value on suitability.

the nodes. The nodes ($X_1 \sim X_8$) have two states, while the nodes ($S_1 \sim S_{12}$) have four or five. The nodes with entered parameters are shaded in grey. Fig. 11a presents the current evaluation results of the evaluation unit. According to the model, the land price of the evaluation unit is less than 6000 yuan/m^2, and the population density is less than 6000 persons/km^2. The states of the remaining nodes are obtained from Fig. 11a. At this point, the Favorable state of X_2 is 0, while the High state of node X_1 is 52.5%. Fig. 11b depicts the future development of the evaluation unit. In this model, the land price exceeds 12000 yuan/m^2, and the population density increases to 24000 persons/km^2. Simultaneously, the High states of the node suitability increase by 20%, resulting in a final value of 72.5%.

4.2. Potential application in metro line planning

This section evaluates the potential application of the model in metro line planning. Our analysis indicates that socio-economic value, geological conditions, and construction status primarily determine the suitability of urban underground space. By the General Territorial Space Plan of Changsha City (Changsha Natural Resources and Planning Bureau, 2021), metro Lines 9 and 10 are planned for construction in the future. Therefore, this section examines the suitability of these two metro lines. Fig. 12 illustrates the location of Lines 9 and 10 in Changsha, with Line 9 spanning 40 km from north to south and Line 10 spanning 55 km from west to east.

Fig. 12a illustrates that the starting and ending sections of Line 9 and Line 10 exhibit unfavorable suitability of underground space regarding socio-economic value. Conversely, the middle section, where the two lines intersect, demonstrates a more favorable suitability of underground space. This is attributed to urban centers having higher land prices and more population density. Fig. 12b shows the favorable suitability of underground space to geological conditions. Notably, some Very Low sections in the proposed Line 9 and Line 10 are situated close to the river and active fault. Fig. 12c presents the favorable suitability of underground space based on the construction status. As observed from the figure, several sections with Very Low suitability exist, particularly in Line 9.

Fig. 13 displays the geological adaptability profiles of two metro lines, with the horizontal coordinates representing the mileage and the vertical coordinates indicating the geological adaptability values, categorized into four levels: Very Low, Low, High, and Very High. It is evident from the graph that the geological conditions of Line 9 differ significantly from those of Line 10, with Line 9 exhibiting poorer geology overall. Specifically, section (points a to b) of Line 9, which constitutes 12.3% of the entire line, is classified as Very Low due to its passage through a fault zone. In contrast, over 60% of sections of Line 10 are assessed as High or Very High. Despite this, some parts of Line 10 have unfavorable geological conditions, with the lowest geological adaptability value being 0.12.

In this section, we attempt the potential application of the Bayesian network model in metro planning. Furthermore, we use the forward inference for the future when some condition changes. For example, we analyze the impact of socio-economic value changes on the development potential of urban underground spaces. When the states go from unfavorable to favorable, the High states of the node suitability increase by 20%.

However, there are also some limitations in this work. Firstly, this approach heavily relies on expert knowledge. The advantage of utilizing a qualitative method to determine the conditional probability tables (CPTs) in the proposed Bayesian network model lies in its ability to leverage expert knowledge effectively. This provides a comprehensive and experiential understanding of ambiguous and uncertain concepts, such as the concept of the suitability of underground spaces. Nevertheless, this dependence on subjective information may impose limitations and potentially introduce biases associated with individual perspectives. Secondly, this work considers the entire area below the

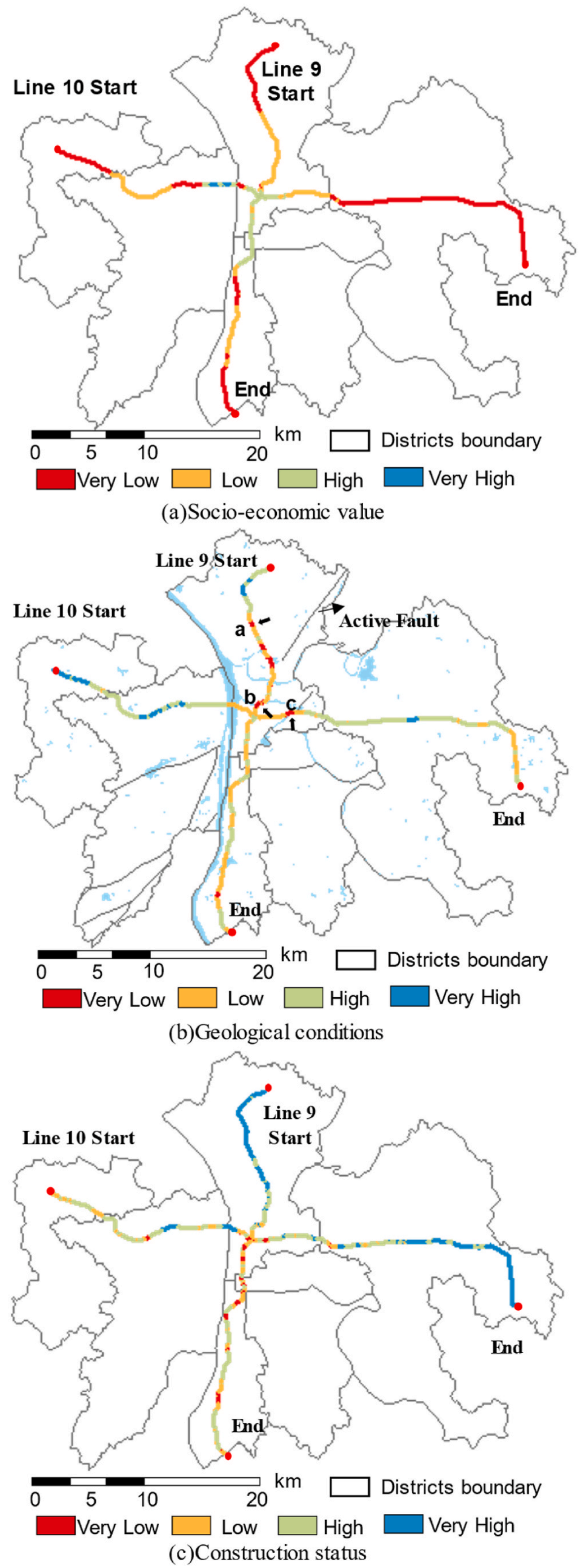

Fig. 12. Favorable for underground exploitation of factors.

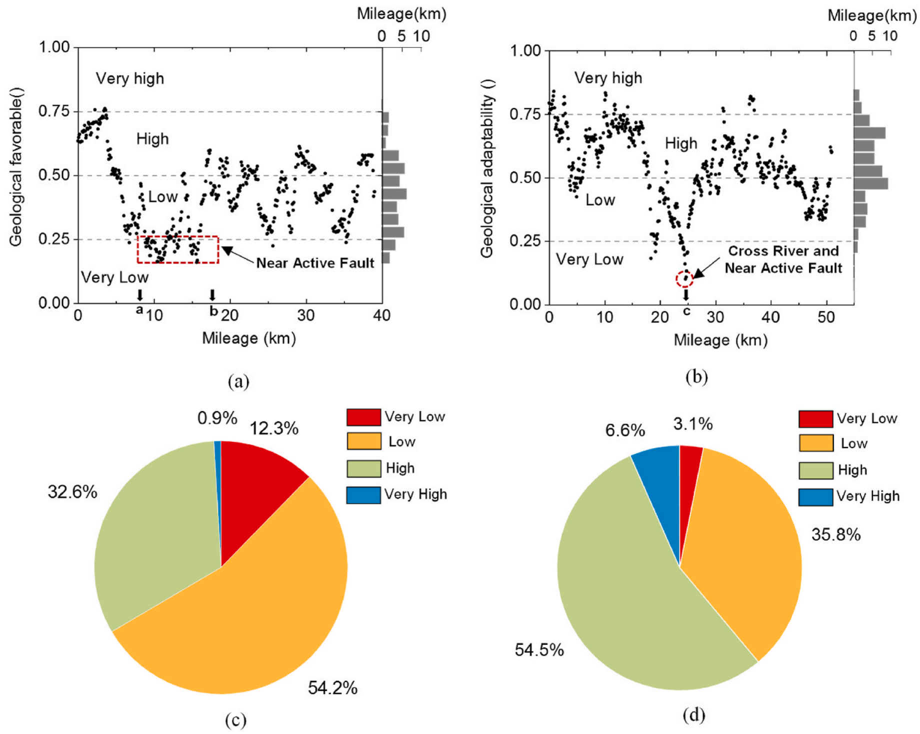

Fig. 13. (a) Geological favorable for planned Line9; (b) Geological favorable for planned Line10; (c) Statistics of Line9; (d) Statistics of Line10.

surface within a 50-m range as the whole evaluation zone for development potential without accounting for differences at various depths. Therefore, further research can be carried out for different depths, such as shallow, middle, and deep layers. Although there are some limitations, this work tries to evaluate urban underground space resources using the Bayesian network model, which offers fresh perspectives for urban underground space planning.

5. Concluding remarks

This paper investigates the practical application of the Bayesian network model in evaluating the potential for utilizing urban underground space. The study offers an in-depth analysis of the structure, parameter selection, and inference validation of the Bayesian network model, placing significant emphasis on scrutinizing the validity and rationality of this approach. The principal findings of the study are as follows.

1) The Bayesian network model can be used to assess the suitability of underground space, as it can handle complex and uncertain data. Therefore, it is expected to be an auxiliary tool for urban underground space planning.
2) The case study of Changsha demonstrates that the Bayesian network model can provide insights into the potential for exploiting underground space at the sub-district level. The results reveal that certain sub-districts, such as Changshaxian, have a high suitability potential, while others have a lower potential, presenting an inverted Y distribution.
3) Bayesian inference analysis shows that the potential for exploiting underground space increases as the socio-economic value of an area increases. The suitability potential is 52.5% when the socio-economic value is unfavorable, while it increases by 20% to a final value of 72.5% when it is favorable.
4) The study evaluates two planned metro lines and finds that Line 10 is more favorable for suitability than Line 9 from geological conditions. Specifically, 12.3% of Line 9's are evaluated as Very Low, while over 60% of Line 10's are evaluated as High or Very High.

Overall, this study explores the applicability of the Bayesian network model in assessing the suitability of underground space, providing important implications for urban planners and policymakers in making informed decisions about the development and use of underground space.

Funding

This research was supported by National Key Research and Development Program of China (2019YFB1705201); Science and Technology Infrastructure Program of Guizhou Province (2020-4Y047); Opening Fund of Key Laboratory of Geohazard Prevention of Hilly Mountains, Ministry of Natural Resources (KLGHZ202104); National Natural Science Foundation of China (52090082); Youth Science and Technology Innovation Talent Project of Hunan Province (2021RC3043); Transportation Science and Technology Development and Innovation Project of Hunan Province (202303-2).

CRediT authorship contribution statement

Zhiwen Xu: Methodology, Software, Visualization, Data curation, Formal analysis. **Suhua Zhou:** Methodology, Software, Supervision, Formal analysis, Funding acquisition, Project administration, Writing – review & editing. **Chao Zhang:** Conceptualization, Methodology, Supervision, Funding acquisition. **Minghui Yang:** Writing – review & editing, Funding acquisition. **Mingyi Jiang:** Writing – original draft, Visualization, Investigation.

Declaration of competing interest

The authors declare that no conflict of interests existed in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

All financial supports were greatly acknowledged.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.138135.

References

Bobylev, N., 2009. Mainstreaming sustainable development into a city's Master plan: a case of Urban Underground Space use. Land Use Pol. 26 (4), 1128–1137. https://doi.org/10.1016/j.landusepol.2009.02.003.

Changsha Natural Resources and Planning Bureau, 2021. General Territorial Space Plan of Changsha City (2021-2035) (Draft for Public Opinion).

Chen, B., Xu, B., Gong, P., 2021. Mapping essential urban land use categories (EULUC) using geospatial big data: progress, challenges, and opportunities. Big Earth Data 5 (3), 410–441. https://doi.org/10.1080/20964471.2021.1939243.

Doyle, M.R., 2016. From hydro/geology to the streetscape: evaluating urban underground resource potential. Tunn. Undergr. Space Technol. 55, 83–95. https://doi.org/10.1016/j.tust.2016.01.021.

Duan, Y., Xie, Z., Zhao, F., Zeng, H., Lin, M., Chen, H., Zuo, X., He, J., Hou, Z., 2021. Suitability of underground space development in plateau cities based on geological environment analysis: case study in kunming, China. J. Urban Plann. Dev. 147 (2) https://doi.org/10.1061/(asce)up.1943-5444.0000687.

Frisk, E.L., Volchko, Y., Sandström, O.T., Söderqvist, T., Ericsson, L.O., Mossmark, F., Lindhe, A., Blom, G., Lång, L.O., Carlsson, C., Norrman, J., 2022. The geosystem services concept – what is it and can it support subsurface planning? Ecosyst. Serv. 58 (November) https://doi.org/10.1016/j.ecoser.2022.101493.

Hanea, A.M., Kurowicka, D., Cooke, R.M., Ababei, D.A., 2010. Mining and visualising ordinal data with non-parametric continuous BBNs. Comput. Stat. Data Anal. 54 (3), 668–687. https://doi.org/10.1016/j.csda.2008.09.032.

Hosseini, S., Barker, K., 2016. Modeling infrastructure resilience using Bayesian networks: a case study of inland waterway ports. Comput. Ind. Eng. 93, 252–266. https://doi.org/10.1016/j.cie.2016.01.007.

Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., Goethals, P.L.M., 2013. A review of Bayesian belief networks in ecosystem service modelling. Environ. Model. Software 46, 1–11. https://doi.org/10.1016/j.envsoft.2013.03.011.

Li, H.Q., Parriaux, A., Thalmann, P., Li, X.Z., 2013. An integrated planning concept for the emerging underground urbanism: deep City Method Part 1 concept, process and application. Tunn. Undergr. Space Technol. 38, 559–568. https://doi.org/10.1016/j.tust.2013.04.010.

Li, X.Z., Li, C., Parriaux, A., Wu, W., Li, H.Q., Sun, L., Liu, C., 2016. Multiple resources and their sustainable development in Urban Underground Space. Tunn. Undergr. Space Technol. 55, 59–66. https://doi.org/10.1016/j.tust.2016.02.003.

Li, Z., Openshaw, S., 1993. A natural principle for the objective generalization of digital maps. Cartogr. Geogr. Inf. Syst. 20 (Issue 1), 19–29. https://doi.org/10.1559/152304093782616779.

Lu, Z., Wu, L., Zhuang, X., Rabczuk, T., 2016. Quantitative assessment of engineering geological suitability for multilayer Urban Underground Space. Tunn. Undergr. Space Technol. 59, 65–76. https://doi.org/10.1016/j.tust.2016.06.003.

Lyu, H.M., Shen, S.L., Zhou, A., Yang, J., 2020. Risk assessment of mega-city infrastructures related to land subsidence using improved trapezoidal FAHP. Sci. Total Environ. 717, 135310 https://doi.org/10.1016/j.scitotenv.2019.135310.

Makana, L.O., Jefferson, I., Hunt, D.V.L., Rogers, C.D.F., 2016. Assessment of the future resilience of sustainable urban sub-surface environments. Tunn. Undergr. Space Technol. 55, 21–31. https://doi.org/10.1016/j.tust.2015.11.016.

Marcot, B.G., Penman, T.D., 2019. Advances in Bayesian network modelling: integration of modelling technologies. Environ. Model. Software 111, 386–393. https://doi.org/10.1016/j.envsoft.2018.09.016. September 2018.

National standards of the People's Republic of China, 2015. Standard for engineering classification of rock masses (GB/T50218—2014). National standards of the People's Republic of China, pp. 5–6 (In Chinese).

National standards of the People's Republic of China, 2019. The Standard for Urban Underground Space Planning (GB/T 51358-2019). National standards of the People's Republic of China, pp. 33–36 (In Chinese).

Peng, J., Peng, F.L., 2018. A GIS-based evaluation method of underground space resources for urban spatial planning: Part 1 methodology. Tunn. Undergr. Space Technol. 74, 82–95. https://doi.org/10.1016/j.tust.2018.01.002. October 2017.

Peng, F. Le, Qiao, Y.K., Sabri, S., Atazadeh, B., Rajabifard, A., 2021. A collaborative approach for urban underground space development toward sustainable development goals: critical dimensions and future directions. Front. Struct. Civ. Eng. 15 (1), 20–45. https://doi.org/10.1007/s11709-021-0716-x. Higher Education Press Limited Company.

Qiao, Y.K., Peng, F. Le, Luan, Y.P., Wu, X.L., 2022a. Rethinking underground land value and pricing: a sustainability perspective. Tunn. Undergr. Space Technol. 127 (January), 104573 https://doi.org/10.1016/j.tust.2022.104573.

Qiao, Y.K., Peng, F. Le, Wu, X.L., Luan, Y.P., 2022b. Visualization and spatial analysis of socio-environmental externalities of urban underground space use: Part 2 negative externalities. Tunn. Undergr. Space Technol. 121, 104326 https://doi.org/10.1016/j.tust.2021.104326. November 2021.

Qian, Q.H., 2016. Present state, problems and development trends of urban underground space in China. Tunn. Undergr. Space Technol. 55, 280–289. https://doi.org/10.1016/j.tust.2015.11.007.

Saaty, T.L., 1994. To make a decision : the analytic. Interfaces 24 (6), 19–43.

Tan, F., Wang, J., Jiao, Y.Y., Ma, B., He, L., 2021. Suitability evaluation of underground space based on finite interval cloud model and genetic algorithm combination weighting. Tunn. Undergr. Space Technol. 108, 103743 https://doi.org/10.1016/j.tust.2020.103743. December 2019.

Tang, J., Heinimann, H., Han, K., Luo, H., Zhong, B., 2020. Evaluating resilience in urban transportation systems for sustainability: a systems-based Bayesian network model. Transport. Res. C Emerg. Technol. 121, 102840 https://doi.org/10.1016/j.trc.2020.102840. October.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Model. 203 (3–4), 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033.

Vahidnia, M.H., Alesheikh, A.A., Alimohammadi, A., 2009. Hospital site selection using fuzzy AHP and its derivatives. J. Environ. Manag. 90 (10), 3048–3056. https://doi.org/10.1016/j.jenvman.2009.04.010.

Van Ree, C.C.D.F., van Beukering, P.J.H., 2016. Geosystem services: a concept in support of sustainable development of the subsurface. Ecosyst. Serv. 20, 30–36. https://doi.org/10.1016/j.ecoser.2016.06.004.

Wu, X., Xu, L., Zhong, L., 2020. Key indicators of 15-minute life circle in the standard for urban residential area planning and desi. Planners, 51778422, 33–40.

Xi, Y., Li, X., Zhu, H., Zhang, W., Zhao, S., Xu, W., 2022. Three-dimensional high-precision assessment of mountainous urban underground space resources: a case study in Chongqing, China. Tunn. Undergr. Space Technol. 123 https://doi.org/10.1016/j.tust.2022.104439.

Yan, F., Shangguan, W., Zhang, J., Hu, B., 2020. Depth-to-bedrock map of China at a spatial resolution of 100 meters. Sci. Data 7 (1), 1–13. https://doi.org/10.1038/s41597-019-0345-6.

Zhao, P., Li, X., Zhang, W., Xiong, Z., Xu, W., Dai, J., Deng, L., 2022. System dynamics: a new approach for the evaluation of urban underground resource integrated development. Tunn. Undergr. Space Technol. 119, 104213 https://doi.org/10.1016/j.tust.2021.104213. September 2020.

Zhou, D., Li, X., Wang, Q., Wang, R., Wang, T., Gu, Q., Xin, Y., 2019. GIS-based urban underground space resources evaluation toward three-dimensional land planning: a case study in Nantong, China. Tunn. Undergr. Space Technol. 84, 1–10. https://doi.org/10.1016/j.tust.2018.10.017. April 2018.