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An evaluation of the supply risk for China's strategic metallic mineral resources

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ABSTRACT

An important issue for ensuring a nation's economic security involves evaluating the supply risk of its strategic mineral resources. Considering the impact of strategic emerging industries on the supply risk of China's strategic minerals, this study establishes an indicator system for evaluating such risks. Specifically, using stochastic multi-criteria acceptability analysis for the ELimination Et Choix Traduisant la REalité TRI method, this study systematically evaluates the supply risk of 14 strategic metallic mineral resources in China from 2008 to 2017 and through 2025. The results indicate that: 1) From 2008 to 2017, the supply risk level of molybdenum and rare earth elements were low or low-to-medium, and those of 12 other minerals were high or medium-to-high; 2) For copper, gold, tungsten, molybdenum, antimony, and lithium, the supply risk level increased, and that for nickel decreased, while for iron, tin, chromium, and rare earth elements it irregularly fluctuated; and 3) The supply risk of chromium, molybdenum, lithium, and rare earth elements was influenced by potentially higher risk factors caused by poor substitutability and low recycling rate.

1. Introduction

Global population growth, technological changes, and economic development have resulted in increased demand for minerals, both in terms of quantity and type (Graedel and Reck, 2016; Nassar et al., 2020). Specifically, the transition to clean energy in response to global warming, particularly low-carbon technologies, has triggered a rapidly increasing demand for metallic minerals (Sovacool et al., 2020). For example, if the global temperature increases by 2 °C, it is expected that the demand for metallic minerals for electric vehicle power batteries (e.g. aluminum, cobalt, and iron) will increase more than tenfold (Arrobas et al., 2017). In addition, the new technology revolution has further increased countries' concerns about the scarcity of metallic minerals (Wang et al., 2017). While demand for metallic minerals may continue to grow, the supply of these minerals is affected by unexpected incidents. Labor strikes in South Africa affect the world's supply of platinum-group metals (Yager et al., 2012), and the supply of cobalt is limited by conflicts in the Democratic Republic of the Congo (Hatayama and Tahara, 2017). Moreover, America's tariffs on steel and aluminum imports also restrict the global supply of these metals (Galbraith, 2018). As a result, the gap between supply and demand of metallic minerals is widening. Therefore, to implement preventive measures and protect the development of countries from mineral supply disruption, an assessment of mineral supply risk is critical (Fan et al., 2018; Graedel et al., 2015; Jasiński et al., 2018).

Studies on mineral supply risk assessment mainly consider the influencing factors of supply when setting an indicator system for comprehensive evaluation (Rosenau-Tornow et al., 2009; Schmid, 2019; van den Brink et al., 2020). Common indicators can be divided into four aspects: resources (e.g. reserves, depletion time, and import dependence), market (e.g. demand growth, market concentration, and production cost), technology (e.g. recyclability, substitutability, and companion fraction), and regulation (e.g. world governance index, environmental performance index, and trade barriers; Achzet and Helbig, 2013; Graedel et al., 2012; Jasiński et al., 2018). However, these common indicators for supply risk evaluation exclude economic importance indicators, which are generally used for assessing criticality (Helbig et al., 2016b). The supply of strategic metallic minerals is closely related to economic development; thus, separating economic importance from supply risk evaluation is in conflict with our common understanding that the supply risk of minerals is premised on its economic importance (Knobloch et al., 2018). As such, supply risk evaluation

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needs to include economic importance indicators. At present, the indicators of economic importance are mainly set at the national, industrial (mega-sectoral), and corporate levels, reflecting the impact of minerals on national GDP (Blengini et al., 2017; Jie et al., 2013), value added of industries (mega sector; Blengini et al., 2017; Nassar et al., 2020), and corporate revenues (Duclos et al., 2010; Griffin et al., 2019). Meanwhile, the promotion of strategic emerging industries has become an important scheme for major countries to forge a new round of economic and technological development (SCC, 2010). However, the indicators used in the above-mentioned studies exclude the impact of minerals on strategic emerging industries. Specifically, strategic emerging industries are industries that have a leading role in the overall economic and social development of a country, and they are based on major technological breakthroughs and development needs (MST, 2011). These industries are different from traditional manufacturing industries (Nassar et al., 2020) and industrial mega-sectors (Blengini et al., 2017). Therefore, selecting indicators for strategic emerging industries is important for evaluating mineral supply risk.

In addition, how to aggregate information from indicators is also a significant issue. Evaluating the supply risk for strategic minerals is a multidimensional endeavor that concerns resources, economic, technological, and international aspects. Thus, the multi-criteria decision analysis (MCDA) method is highly suitable for such a comprehensive analysis (Jasiński et al., 2018). MCDA methods for supply risk evaluation primarily include a supply risk matrix and an index (Achzet and Helbig, 2013; Hatayama and Tahara, 2017), and the results are principally in the form of a matrix distribution (Glöser et al., 2015; Knobloch et al., 2018; USDE, 2010) and scores (Beylot and Villeneuve, 2015; Graedel et al., 2012; Zhou et al., 2019) of supply risk. However, the supply risk of minerals may change when affected by higher risk factors. Therefore, robustness of the current estimated supply risk is critical for identifying potentially higher risk factors. Clearly, this robustness cannot be obtained from the matrix distribution or scores of the supply risk of minerals. Furthermore, some indicators' data and methods' parameters are uncertain in the process of supply risk evaluation (Erdmann and Graedel, 2011; Glöser et al., 2015). For example, differences between technically possible recycling and real collection rates lead to inaccurate data (Achzet and Helbig, 2013). The supply risk matrix and index methods must be based on accurate data; they are not good at aggregating uncertain indicator data. To address these two problems, the stochastic multi-criteria acceptability analysis (SMAA-TRI) for the ELimination Et Choix Traduisant la REalité TRI (ELECTRE TRI) method, which extends the ELECTRE TRI method, is applied because it can not only deal with inaccurate data and uncertain parameters, but also visualize the robustness of the results of the ELECTRE TRI method (Merad et al., 2004; Tervonen et al., 2007; Yu, 1992). This method has been effectively applied for assessing nanomaterials, green chemistry, and mineral supply by Tervonen et al. (2009), Cinelli et al. (2017) and Jasiński et al. (2018).

To accelerate the transformation of economic development and become a powerful manufacturing country, China proposed the 'Made in China (2025)' plan. This is an action plan for implementing the 'manufacturing power strategy', which includes innovation, green development, and the integration of informatization and industrialization in manufacturing industries (SCC, 2015). Recently, driven by this strategy, the manufacturing industry has been developing rapidly in China, especially the strategic emerging industries such as the new energy, new materials, and high-end equipment manufacturing industries (SCC, 2015). The proportion of these strategic emerging industries' value added to China's GDP has increased from 4% in 2010 to 8% in 2015 (Zhao, 2016), and it is anticipated to reach 15% in 2020 (SCC, 2016). Considering this trend, strategic emerging industries have been recognized by NBSC (2018b). The development of these industries is based on huge demand for mineral resources (Zhou et al., 2015). In response to this demand, China listed 14 metallic minerals—iron (Fe), chromium (Cr), copper (Cu), aluminum (Al), gold (Au), nickel (Ni), tungsten (W), tin (Sn), molybdenum (Mo), antimony (Sb), cobalt (Co), lithium (Li), rare earth (REE), and zirconium (Zr)—as strategic minerals (MNRC, 2016). Strategic minerals are minerals that are essential for national economic security, defense security, and strategic emerging industries, including scarce minerals that rely massively on imports and dominant minerals that have abundant reserves and can regulate the international market (Chen, 2002; MNRC, 2016). As stimulated by the 'Made in China (2025)' plan and by strategic emerging industries, the supply of strategic metallic minerals has become increasingly tight. Specifically, the demand and import dependence for scarce minerals—such as Fe, Cr, Cu, Al, Ni, Au, Co, Zr, and Li—are on the rise, which may lead to supply interruption (Liu et al., 2016; MES, 2018; Xu et al., 2016). The consumptions of dominant minerals—such as W, Sn, Sb, Mo, and REE—are so large that the superiority quality of minerals has decreased (Chen et al., 2016). These strategic minerals are critical at a national level in China (Achzet and Helbig, 2013; MNRC, 2016), but the associated supply risk is unknown and requires investigation. As such, it is urgent to assess the supply risk of these minerals to ensure security and to pre-plan for the supply of strategic metallic minerals in China.

Faced with this supply issue, scholars have carried out related research in China. Some studies have begun to add indicators of economic importance for mineral supply evaluation in China. For example, Yang et al. (2016) adopted the 'ratio of consumption to gross value of industrial output' in their mineral security evaluation. Zhu (2018) used the concept of 'economic contribution' to measure the contribution of minerals to GDP. Recently, Wang et al. (2018a) and Zhou et al. (2019) noticed the connection between minerals and strategic emerging industries, and they assessed the supply risk of minerals in strategic emerging industries, such as new energy and new energy vehicle industries. However, there are no indicators that reflect the connection between the supply of strategic minerals and strategic emerging industries. Additionally, few studies have focused on certain minerals for evaluation based on researchers' understanding of the importance of mineral resources and the demands of specific industries. For example, Liu et al. (2018) assessed the supply risk of Cr. Zhou et al. (2019) evaluated 12 minerals in the clean energy industry such as Sn, Co, and Cr. Wang et al. (2019a) assessed the supply security of 13 strategic metallic minerals. Nonetheless, these studies did not assess the supply risk of all the 14 metallic minerals included in China's strategic minerals catalogue (i.e. China's strategic metallic minerals). Furthermore, evaluating the supply risk of strategic metallic minerals means implementing preventive measures that can help the economy to develop sustainably in the future (Zhu, 2018). However, most of the above-mentioned studies only focused on the evaluation of the past and did not connect the assessments of the past with the future situation.

Therefore, aside from common indicators, strategic importance indicators are adopted here to measure the strategic emerging industries' impacts on the supply of metallic minerals using a new indicator system. The SMAA-TRI method is used to evaluate 14 strategic metallic minerals and deal with imprecise data on recycling rate and uncertain parameters when applying ELECTRE TRI. The evaluation results are presented in terms of the supply risk probability for each mineral, which provides a more comprehensive view of these minerals' supply status and helps in analyzing potential higher risk factors. Moreover, the criteria in SMAA-TRI, which is based on ELECTRE TRI, are non-compensatory and do not require trade-offs (Jasiński et al., 2018). For this method, the indicators' data can be heterogeneous and do not require standardization (Tervonen et al., 2007). Furthermore, this study connects the results of the supply risk evaluation of metallic minerals from 2008 to 2017 with the future supply situation to infer the supply risk of metallic minerals in 2025, in reference to the literature on metal consumption and China's economic development status.

This study contributes as follows. First, the factors related to strategic emerging industries are considered in the new supply-risk-evaluation indicator system to evaluate China's strategic metallic minerals quantitatively and qualitatively. Second, the SMAA-TRI method is adopted to reflect comprehensively the supply risk (per type of mineral) of 14 metallic minerals in China from 2008 to 2017. Third, this work identifies potential higher risks in the supply of certain minerals based on the possibility of each risk, and the causes of such risks are subsequently revealed. Lastly, the supply risk of China's strategic metallic minerals in 2025 is analyzed and discussed based on the results of the supply risk evaluation from 2008 to 2017.

2. Evaluation indicator system for the supply risk of strategic metallic minerals

2.1. The framework of indicators

A country's supply risk of strategic mineral resources is affected not only by domestically available minerals, but also by technology use, mineral import, and the correlation between the minerals and the economy. The availability of domestic minerals is the basic factor that affects mineral supply, while the correlation between minerals and the economy affects investments in mineral exploitation and supply disruption. The level of technology directly affects the efficiency of mineral mining and utilization. Importing minerals is one of the most important ways for a country to obtain minerals from the international market. Based on these four dimensions, eleven quantitative and qualitative indicators are selected to evaluate the supply risk of China's strategic metallic minerals, considering the indicators' applicability, relevance, data availability, and credibility (Achzet and Helbig, 2013; Jasiński et al., 2018), as shown in Fig. 1. Some other indicators such as press coverage, climate change vulnerability, and mine capacity utilization have weak correlation to the present study, while the data are not available for other indicators such as by-product dependency, company concentration, and trade barriers.

2.2. Description of the indicators

2.2.1. Resource availability

Resource availability reflects a country's capability to maintain a steady supply of minerals. The improvement of this capability can reduce mineral supply risk. This dimension includes three sub-indicators: the proportion of China's reserves to global reserves, the reserve-to-production ratio, and the import dependence.

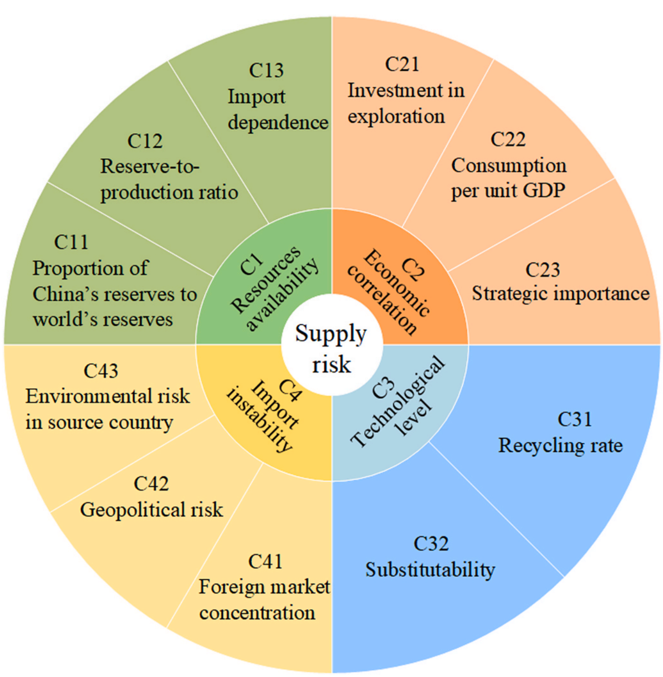

Fig. 1. The supply risk evaluation indicators for strategic metallic minerals.

Specifically, the proportion of China's reserves to global reserves reflects the state of China's mineral reserves in the world (Zhang et al., 2018). China's strategic minerals include scarce minerals and dominant minerals, and this indicator can reflect whether China's mineral reserves have worldwide priority. The reserve-to-production ratio measures the time that existing mineral reserves are available for production under the nation's current mining capacity (Hatayama and Tahara, 2015). It can reflect the supply potential of domestic minerals without external supply (Zhang et al., 2018) and be a useful indicator for evaluating periodic availability of a resource (Schneider et al., 2014). Additionally, the import dependence reflects a country's capability of providing minerals without imports (Achzet and Helbig, 2013). Higher import dependence can lead to greater uncertainty and higher risk from foreign markets, requiring countries to take additional measures when faced with such a situation.

2.2.2. Economic correlation

Economic correlation measures the impact of economic input on mineral supply risk, as well as the contribution of minerals to the economy. The increase of economic input can reduce the supply risk of minerals, and the consequences of supply disruption are related to the contribution of minerals to the economy. Three sub-indicators are included in this dimension: investments in exploration, consumption per unit of GDP, and strategic importance.

More specifically, investment in exploration measures investments (from national finance, enterprises, and institutions) in exploration industries (Niu, 2007). It can help in improving exploration technology and in discovering more mineral reserves. The consumption per unit of GDP reflects the amount of minerals needed per unit of GDP growth (Zhang et al., 2018). Demand for minerals is derived from countries' economic development. The indicator connects demand and economic growth to measure the consumption intensity of minerals. Moreover, strategic importance—specific to China and different from the industry's value added to GDP (Nassar et al., 2020)—reflects the contribution of minerals to GDP in strategic emerging industries. The MNRC (2016) and NBSC (2018b) have recognized China's strategic minerals and strategic emerging industries as part of China's development strategy. This indicator represents the minerals' strategic importance to China's economy.

2.2.3. Technological level

Technological level reflects the function of mineral mining and technology use on easing supply pressure. Improvements in technology can reduce supply risk. Two of its sub-indicators are recycling rate and substitutability.

Recycling rate is the proportion of secondary metal to total supply, and reflects the impact of scrap consumption on mineral supply pressure (Graedel et al., 2011). Metal scrap is also an important supply source, as recycling can compensate for a portion of the primary supply (Zhou et al., 2019). Substitutability refers to the feasibility of a mineral to be replaced without increasing cost and decreasing product performance (Hollins and Faunhofer, 2014). Metal substitution can shift some demand of a metal mineral to another; thus, it can also relieve supply pressure (Helbig et al., 2016a). Therefore, these two indicators are important for evaluating metallic mineral supply risk.

2.2.4. Import instability

Import instability measures the risks caused by foreign markets such as the source countries' politics and export policy. This dimension includes three sub-indicators: foreign market concentration, geopolitical risk, and environmental risks from source countries.

Foreign market concentration is calculated based on data from producing countries. It measures the risk from market monopoly in foreign mineral markets (Achzet and Helbig, 2013). This means that if mineral production is concentrated in a few countries, the mineral supply can be easily disrupted by the political stability and environmental performance of these counties (Brown, 2018; Zhou et al., 2019). Therefore, this study selects geopolitical risk and environmental risk for measuring the import instability of metallic mineral resources.

Geopolitical risk reflects the risk of importing minerals from source countries with poor political governance (Graedel et al., 2012). Political risk may affect a mineral's supply if a country imports from producing countries that have poor governance (EC, 2014; Kaufmann et al., 2011). Environmental risk measures the risk from source countries that suffer from environmental pollution or damage (Wendling et al., 2018). Compared with countries that have high environmental standards, source countries with low environmental standards may have higher accident risk, thereby disrupting mineral supply (Jasiński et al., 2018).

Table 1 presents the calculations of indicator data.

3. Evaluation methods to determine the supply risk of strategic metallic minerals

3.1. The stochastic multi-criteria acceptability analysis -TRI method

The SMAA-TRI method, which is based on the ELECTRE TRI method, assigns a set of alternatives to pre-defined classes based on a series of criteria according to a fuzzy outranking relationship (Yu, 1992). This relationship is determined by alternatives and profiles, and the final class is obtained by the weighted sum of the results based on all criteria (Merad et al., 2004). In this study, the SMAA-TRI method is adopted to evaluate the supply risk of strategic metallic minerals. This method divides the supply risk into four risk classes: low, low-to-medium, medium-to-high, and high risk. It uses the class acceptability index to display the overall supply condition of minerals by demonstrating the probability of each supply risk class, and takes the class with maximum probability as the supply risk class of a mineral (Tervonen et al., 2007). The key parameters are as follows. The weights of indicators (w) denote the importance coefficients and represent the indicators' voting power. The higher the weight is, the more important the indicator is. Class profiles (P_h) are the upper bound of class h and the lower bound of class $h+1$. The indifference thresholds (q) of an indicator define the greatest difference at which an alternative is considered indifferent to a profile. The preference thresholds (p) of an indicator define the smallest difference at which an alternative is preferred to a profile. The cutting level (λ) describes the minimum cumulative weight of indicators that supports the next class. Fig. 2 briefly illustrates the analytical process.

First, the indicator data are entered, and the thresholds and parameters in the SMAA-TRI method are determined. Some indicators (γ) whose values are difficult to obtain are set with a value range. Table 3 and Table 4 describes the parameter settings, such as w,P_h,q,p, and λ.

Second, the *class membership function* ($m_l^h(\gamma,\lambda,T)$) is determined. This is a process of executing ELECTRE TRI to determine whether a mineral can be essentially assigned to a class. The random values for inaccurate data (γ) and λ are taken from their ranges to execute the ELECTRE TRI method by Monte Carlo simulation, together with the deterministic data (s) and parameters $T = \{s, w, P_h, p, q\}$. Subsequently, the class membership function of l mineral on h class can be obtained.

Third, the class acceptability index (π_l^h) can be obtained by integrating the product of the class membership function and the probability density function of inaccurate data, ($f_R(\gamma)$) and ($f_L(\lambda)$), respectively. The class acceptability index is within the range [0, 1] and represents the probability that a mineral can be assigned to a risk class.

Finally, the class with the maximum acceptability index is regarded as the supply risk of a mineral because the class acceptability index can be construed as the probability that a mineral can be assigned to a class.

3.2. Weighting method for the indicators

The weights of indicators play a decisive role in evaluating the supply risk of strategic metallic minerals. To obtain scientific weights, this study adopts a combination of subjective and objective weighting.

The SMAA TRI is a non-compensatory MCDA method (Galo et al., 2018; Tervonen et al., 2007), such that the weighting method cannot allow trade-offs between indicators. Figueira and Roy (2002) improved upon Simos (1990)'s procedure to determine the indicators' weights in

Table 1
Calculation and attributes of indicators for evaluating the supply risk of strategic metallic minerals.

Dimensions	Indicators	Calculations	Attributes
Resource availability	Proportion of China's reserves to global reserves	Mineral reserves in China/Mineral reserves in the world	-
	Reserve-to-production ratio	Mineral reserves/Mineral production	-
	Import dependence	Mineral net imports/Mineral apparent consumption (net imports = imports - exports; apparent consumption = production + net imports)	+
Economic correlation	Investment in exploration	National financial allocation + Local financial allocation + Domestic enterprise funds + Investment from Hong Kong, Macao and Taiwan + Foreign investment + Other investment	-
	Consumption per unit of GDP	Mineral apparent consumption/GDP	+
	Strategic importance	Value added of strategic emerging industries related to a mineral [a]/GDP	+
Technological level	Recycling rate	Tonnage of secondary metal/Tonnage of total supply of a metal	-
	Substitutability	Measured by substitutability index from European Commission's report regardless of the slight discrepancy	+
Import instability	Foreign market concentration	It is acquired by summing the square of the shares of producers' production to the world except the importing country. $HHI(\phi) = \sum_{i=1}^{MP} \phi_i^2$, where MP is the number of mineral-producing countries except the importing country, and ϕ_i is the proportion of a country's mineral production to the world.	+
	Geopolitical risk [b]	Measured by the estimate of "Political Stability and Absence of Violence/Terrorism" (PV) in *Worldwide Governance Indicators*. $R_P = \sum_{j=1}^{ME} (g_i \cdot \eta_i)$, where ME is the number of source country, g_i is the WGI-PV of j country, and η_i is the proportion of the imports from j country to the total imports of China.	+
	Environmental risk [b]	Measured by the Environmental Performance Index (EPI) of Yale University research. $R_e = \sum_{j=1}^{ME} (e_j \cdot \eta_j)$, where e_j is the EPI of country j.	+

Notes:

[a] Value added of strategic emerging industries related to minerals is an estimated value. The value added of sectors in strategic emerging industries is calculated according to Strategic Emerging Industry Classification (2018), National Economic Industry Classification (2017), and 2012 Input-Output Table from National Bureau of Statistic of China (NBSC, 2017, 2018b). The details of calculation can be found in the Supplementary data.

[b] When the value of import dependence is negative, the mineral supply does not rely on imports and is not affected by geopolitical and environmental risks from source countries. Therefore, in this case, the values of the geopolitical risk and environmental risk from source countries are adjusted to 2.5 and 100 respectively from 2008 to 2017 (The maximum values of WGI and EPI are 2.5 and 100 respectively, indicating the most stable politics and the best environmental performance.).

ELECTRE-type methods. The improved procedure considers the importance difference between the first and the last rank and revises the determination of the importance distance between two adjoining ranks (Figueira and Roy, 2002). The weights of the improved Simos' procedure are based on the ordinal indicators' scores and originate from non-compensatory procedures. Thus, this method does not include trade-offs and can give weights the meaning of importance coefficients (Munda, 2012). The improved Simos' procedure for ELECTRE-type methods has been successfully applied to many cases, such as mining area management (ELECTRE TRI; Merad et al., 2004), material selection (ELECTRE III; Shanian et al., 2008), and logistics management (ELECTRE I; Govindan et al., 2019). However, the improved Simos' procedure is a subjective weighting method and is based on decision makers' ranking information, which may lead to arbitrariness of weights and neglect the objectivity of data. Therefore, it is necessary to use an objective weighting method to correct the arbitrariness and make up for this shortcoming.

Shannon (1948)'s entropy weight method is one of the most effective methods for obtaining objective weights when evaluating water quality (Zou et al., 2006), customer satisfaction (Li et al., 2014), and environmental conflict (Delgado and Romero, 2016). The method determines the weights of indicators according to the influence of the indicators' disorder degree on the whole system. When differences among the values of all objects on the same indicator are big, this indicator is considered to contain much information, and its information entropy is considered small; thus, the indicator should be assigned a high weight (Zou et al., 2006). The indicators' data differ among strategic metallic minerals during the study period; therefore, the entropy weight method can effectively acquire objective information from data to eliminate the influence of subjective factors on the weights.

Therefore, this study combines the improved Simos' procedure and the entropy weight method by integrating the weights' 'order' and 'intensity' information (Li et al., 2017). The 'order' information refers to the weight's ranking according to its relative importance in the supply risk assessment system. The 'intensity' information denotes the numerical difference in the weights' values. This method decomposes the information of each weight into order and intensity information, and recombines the information based on the principle of giving priority to the order information of subjective weights and the intensity information of objective weights. The order information of subjective weights enables the combination weights to include background information from experts in mineral supply, while the intensity information of objective weights enables the combination weights to reflect the information brought by objective indicator data. This method combines the advantages of subjective weight and objective weight, which is in line with the purpose of subjective and objective combination weighting. By decomposing and reorganizing the weight information, the interpretability and rationality of each step in the process of combining weights are enhanced (Li et al., 2017; Yu et al., 2019). Such a combination not only considers the background of supply risk assessment and indicator data, but also results in a more scientific indicator weight by avoiding the deficiencies of subjective and objective weighting methods (Zhao et al., 2016). Fig. 3 briefly describes the weighting process.

The improved Simos' procedure for subjective weighting can be summarized in the following steps:

Step 1: Collect ordinal information from experts in mineral supply. We consulted eleven experts in mineral resources research and decision makers in government departments (see Supplementary data). The indicator cards are ranked by these experts in an ascending order of the indicators' importance. If the experts think some indicators are equally important, they can put these indicators in the same rank. The importance distance between any two adjoining ranks is supposed to be ε. When this distance is more than ε, blank cards are necessary to adjust the distance. Inserting η blank cards means that the importance of the indicators at the latter rank is $(\eta+1)\varepsilon$ more than that of the indicators at the former rank.

Step 2: Calculate the ratio z of the most important indicator to the least important one in the ranking.

$$z=\frac{\left(\sum_{t=0}^{c-1}(F-t)\right)d}{\left(\sum_{t=0}^{d-1}(1+t)\right)c} \tag{1}$$

where F is the total number of cards, including blank cards; d is the number of indicators at the first rank; and c is the number of indicators at the last rank.

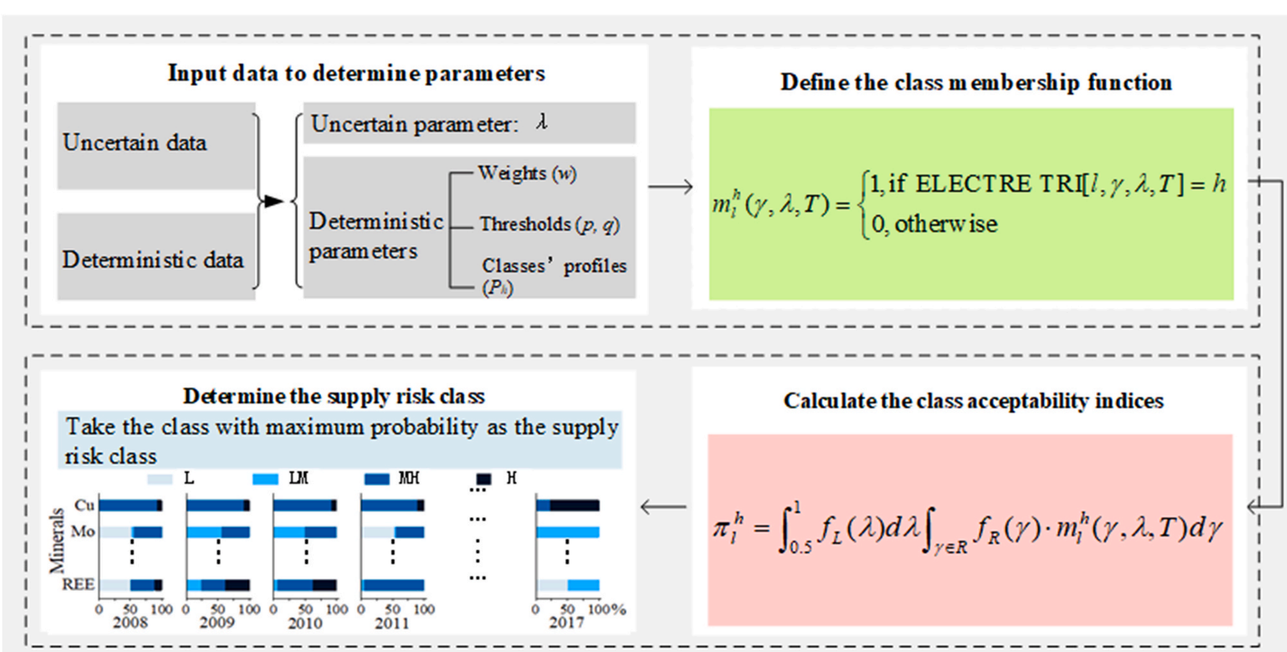

Fig. 2. The SMAA-TRI methodological procedure for evaluating supply risk.

Step 3: Compute the non-normalized weights of each rank, w_r'. Indicators at the same rank have the same non-normalized weight.

$$\begin{cases} b_r = b_r' + 1, \\ b = \sum_{r=1}^{R-1} b_r, \\ \varepsilon = \dfrac{z-1}{b}, \end{cases}$$
$$w_r' = 1 + \varepsilon(b_0 + \ldots + b_{r-1}). \tag{2}$$

where r is the rank of an indicator excluding blank cards and $r = 1, 2, \ldots, R-1$, b_r' is the number of blank cards between rank r and $r+1$, $b_0 = 0$.

Step 4: Normalize the weights of the v-th indicator, $\overline{w}_v$. The non-normalized weight of the v-th indicator can be obtained from w_r' according to the rank of the v-th indicator.

$$\overline{w}_v = \frac{w_v'}{\sum_{v=0}^{v=V} w_v'} \tag{3}$$

where V is the total number of indicators, and the sum of $\overline{w}_v$ is 1. According to Shanian et al. (2008), this study retains four decimals, and the sum of the indicators' weights is 1; thus, rounding off the weight is unnecessary. Moreover, the weights from eleven experts are aggregated by arithmetic average (Zhao, 2017).

In addition, the entropy weight method for objective weighting can be summarized in the following three steps.

Step 1: Normalize the data of indicators according to the correlation between the indicator and the research objective.

$$y_{\alpha\beta} = \frac{x_{\alpha\beta} - \min(x_\alpha)}{\max(x_\alpha) - \min(x_\alpha)} \tag{4}$$

$$y_{\alpha\beta} = \frac{\max(x_\alpha) - x_{\alpha\beta}}{\max(x_\alpha) - \min(x_\alpha)} \tag{5}$$

Step 2: Determine the information entropy of the α-th indicator.

$$E_\alpha = -\frac{1}{\ln n}\sum_{\beta=1}^{n} p_{\alpha\beta}(\ln p_{\alpha\beta}), \alpha = 1, 2, \ldots, m; \beta = 1, 2, \ldots, n \tag{6}$$

where $\rho_{\alpha\beta} = y_{\alpha\beta}/\sum_{\beta=1}^{n} y_{\alpha\beta}$, when$\rho_{\alpha\beta} = 0$; $\lim_{\rho_{\alpha\beta}\to 0}\rho_{\alpha\beta}\ln\rho_{\alpha\beta} = 0$.

Step 3: Compute the weight of the α-th indicator.

$$w_\alpha^* = \frac{1 - E_\alpha}{\sum_{\alpha=1}^{m}(1 - E_\alpha)} \tag{7}$$

Finally, the combination of subjective and objective weights is implemented through the following optimization model, as shown in Fig. 4.

Specifically, the objective function helps get the objective weights' intensity information by minimizing the difference between combined and objective weights. Further, w_v and w_v^* denote the combined and objective weights of the v-th indicator, respectively. $V$is the total number of indicators.

The bounds constraint takes the intersection of the subjective and objective weights' neighborhoods as the range of the combined weights' value, where ub_v and lb_v are the maximum and minimum values of the v-th indicator, respectively. This study takes the absolute value of the difference between the subjective and objective weights as the neighborhood. In short, the larger one between the subjective and objective weight of an indicator is regarded as the upper bound and the smaller one as the lower bound.

The basic constraint ensures that the sum of the combined weights is 1.

The order constraint can help obtain subjective weights' order information by guaranteeing the combined weights' ranking in accordance with the subjective weights, where $u < v$ is the subjective weight's ranking, u and v are the rankings of the bigger and smaller weights, respectively.

4. Data and parameters

4.1. Data sources

Data on the reserves and production of other minerals mainly come from *Mineral Commodity Summaries* (2009–2018), but Cr's and Al's reserves data are from *China Mineral Resources* (2011–2018) and Global Mineral Resources Information Platform (DRC, 2019), respectively, while Cr's production data come from *China Land and Resources Statistical Yearbook* (2009–2018). Import and export data are from the UN Comtrade Database and *China Land and Resources Statistical Yearbook* (2009–2018). Data on investments in exploration are from *China Land and Resources Statistical Yearbook* (2009–2018). The Worldwide Governance Indicators and Environmental Performance Index are published by the Word Bank (WB, 2018) and Yale University (Wendling et al., 2018), respectively. GDP and industry value added data for estimating strategic importance are from China's National Bureau of Statistics, as sourced from NBSC (2017, 2018b). The substitutability index is from the

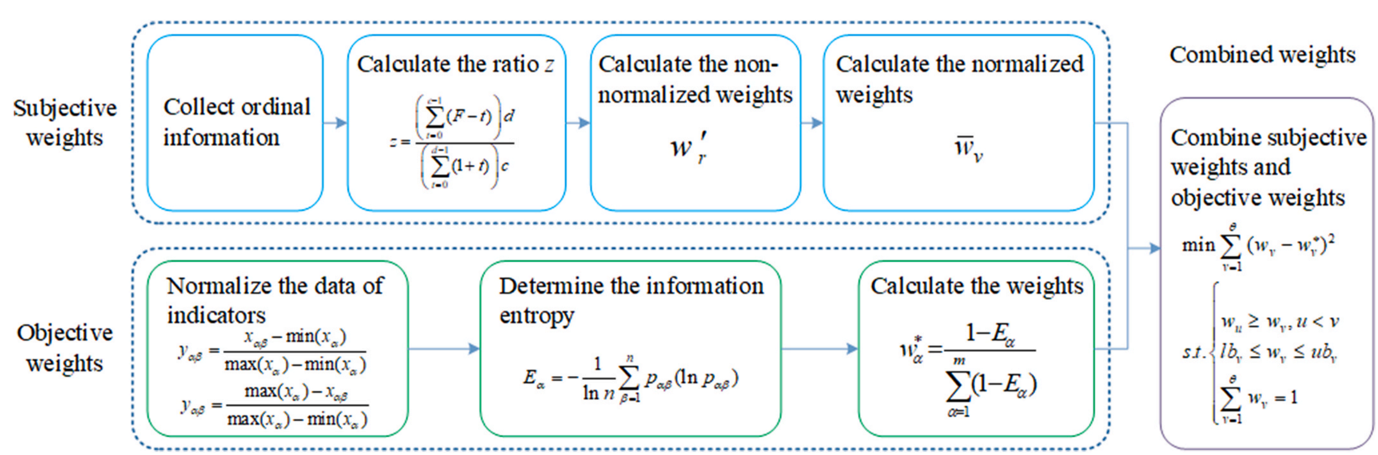

Fig. 3. The combination of subjective and objective weighting.

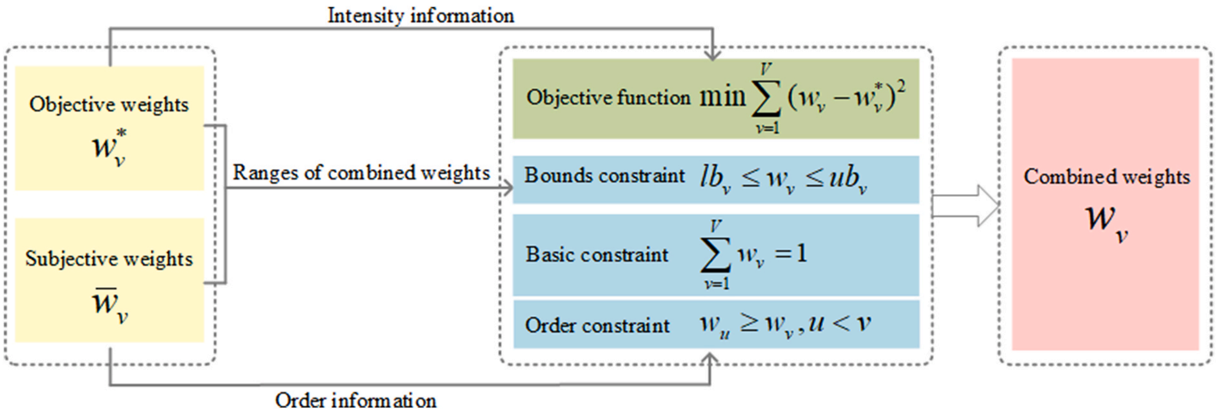

Fig. 4. Optimization model of combined weights.

European Commission (EC, 2010; 2014, and 2017). The range of recycling rates is from the United Nations Environment Programme (Graedel et al., 2011), Asian Metal (AM, 2019), and other literature (Li et al., 2019; Pan et al., 2018; Zhu, 2018). Specifically, Au's import, export, and recycling data are from *Report on Gold Resources 2016* of China Geological Survey (Lin et al., 2016). Details are provided in Supplementary data.

4.2. Weights

The subjective and objective weights are acquired based on the improved Simos' procedure and entropy weight methods, respectively. The combined weights are obtained based on the optimization model according to their order and intensity information.

For example, in the subjective weighting, the ranks provided by the first expert are converted to weights, as shown in Table 2. "*" denotes the blank card. The ranks of indicators are shown in the second column. The ratio $z = 14$ is obtained by applying Eq. (1). The non-normalized weights, $w_r^{'}$, are computed using Eq. (2), and $b = 12$, $\varepsilon = \frac{13}{12}$. Eq. (3) helps in calculating the normalized weights, $\overline{w}_v$.

In the objective weighting, the import dependence can be taken as an example. Its data are normalized by applying Eq. (4), and information entropy, $E_{C13} = 0.9862$, is computed using Eq. (6). Eq. (7) can be used to obtain objective weight, $w_{C13}^* = 0.0183$.

Finally, combined weights are computed using the optimization model. For example, in the objective function, the difference between combined and objective weights of import dependence can be interpreted as $(w_{C13} - 0.0183)^2$. In the bounds constraint, the subjective weight of import dependence is 0.1743, and the objective weight is 0.0183. The value range of this indicator's combined weight can be set to $[0.0183, 0.1743]$. In the basic constraint, the sum of these eleven indicators' weights is 1. In the order constraint, eleven indicators are ranked according to their subjective weights as C13, C42, C22, C21, C12, C23, C41, C43, C11, C31, and C32. Therefore, the constraint can be set to $w_{C13} \ge w_{C42}$

$$\ge w_{C22} \ge w_{C21} \ge w_{C12} \ge w_{C23} \ge w_{C41} \ge w_{C43} \ge w_{C11} \ge w_{C31} \ge w_{C32}$$

.

The subjective, objective and combined weights are noted in Table 3. The Supplementary data displays the ranking from experts using the improved Simos' procedure and notes the values of entropy in the entropy weight method.

4.3. The profiles of the classes and indicator thresholds

The profiles of the classes and indicator thresholds are set according to the indicator data and existing literature. Further, the indicator data are allocated to four classes—low (L), low-to-medium (LM), medium-to-high (MH), and high (H) risk—as illustrated in Table 4. The indifference (q) and preference thresholds (p) measure the profiles' uncertainty. The relationship of q and p is set according to Jasiński et al. (2018), and $p = 2 \times q$.

5. Results and analysis

5.1. Overall supply risk level

The class acceptability index of the supply risk from 2008 to 2017 is obtained based on Section 3, as illustrated in Fig. 5 (Detailed indices are shown in Supplementary data). The index represents the probability that the supply risk is assigned to a certain class. The acceptability index for each supply risk class ranges between 0% and 100%. The sum of each mineral's acceptability is 100% in all four classes.

Cr, Cu, Co, and Zr are exposed to high supply risk. Cr, Cu, Co, and Zr reserves are scarce, and their supply primarily depends on imports. Each of the four minerals accounts for less than 4% of the global reserves, and their import dependence is more than 85% (MNRC, 2018; USGS, 2019). Specifically, the proportion of China's Co reserves to global reserves is only 1%, with import dependence of more than 97%. Additionally, the demand for Cr, Cu, and Zr has increased sharply in recent years due to the vigorous development of strategic emerging industries in China, such as the high-end equipment manufacturing, new energy vehicle, and electronic equipment and component industries. For example, the consumption of Zr has increased from 0.65 million tons in 2008 to 1.11 million tons in 2017 (MLRC, 2009; MNRC, 2018). As a result, the gap between supply and demand for these three minerals has intensified. Furthermore, Co's foreign supply is affected by the source countries' political stability and environmental performance. The foreign market concentration of Co is more than 38% (MNRC, 2018), which implies that China's Co import is concentrated in a few countries. Its foreign supply is also affected by the producing countries' political instability and low

Table 2
Converting the ranks into weights.

Rank r	Indicators in the rank r	b_r	Non-normalized weights $w_r^{'}$	Normalized weights $\overline{w}_v$
1	C31	1	1	0.0146
2	C11 C32	1	2.08	0.0305
3	C42	1	3.17	0.0463
4	C41	1	4.25	0.0621
5	C23	1	5.33	0.0780
6	C12	1	6.42	0.0938
7	C21*	2	7.50	0.1096
8	C22**	3	9.67	0.1413
9	C23	1	12.92	0.1888
10	C13	–	14.00	0.2046

Table 3
Weights of indicators for evaluating the supply risk of strategic metallic minerals.

Indicators	Subjective weights	Objective weights	Combined weights
Proportion of China's reserves to global reserves	0.0542	0.0321	0.0542
Reserve-to-production ratio	0.0923	0.0069	0.0833
Import dependence	0.1743	0.0183	0.1624
Investment in exploration	0.0968	0.0170	0.0833
Consumption per unit of GDP	0.1339	0.6354	0.1624
Strategic importance	0.0878	0.0301	0.0833
Recycling rate	0.0317	0.0256	0.0317
Substitutability	0.0313	0.0373	0.0317
Foreign market concentration	0.0731	0.1201	0.0833
Geopolitical risk	0.1624	0.0359	0.1624
Environmental risk	0.0622	0.0413	0.0622

environmental performance. The geopolitical and environmental risks are -2.28 and 42.27, respectively (WB, 2018; Wendling et al., 2018).

Eight minerals are exposed to medium-to-high risk, namely, Fe, Al, Au, Ni, W, Sn, Sb, and Li. China is the largest consumer of Fe, and its consumption of Fe has always been large (Zhu, 2018). However, China's Fe reserves were about 21 billion tons in 2016 and have not increased dramatically in the past (USGS, 2019). Considering China's extensive use of Fe, its economy will be seriously affected once the supply of Fe is disrupted. Furthermore, the applications of Al in electrical appliances, heat dissipation materials, and aviation also make China's consumption of Al large. Domestic reserves can meet the demand for Al for about 30 years, while import dependence for Al has reached as high as 60% in recent years (MNRC, 2018; USGS, 2019). Although Au is the least consumed mineral among these 14 metallic minerals, it cannot satisfy China's demand, with the proportion of its Au reserves to global reserves at less than 4% and its import dependence at more than 60% (Lin et al., 2016). The supply of Ni is influenced by its source countries. The import dependence for Ni has increased to 99% (MNRC, 2018). Further, the Philippines as a primary source country for Ni has a worldwide governance indicator, which denotes political stability and the absence of violence or terrorism (WGI-PV), valued at approximately -1 (WB, 2018). Thus, the Philippines' turbulent political situation is likely to lead to a supply interruption. Meanwhile, China has a large reserve of Li, at approximately 20% of the global reserves (USGS, 2019), but it cannot supply Li with its low-grade and backward mining technology (AM, 2020). Hence, import dependence for Li has reached as high as 60% (MNRC, 2018). In addition, W, Sn, and Sb have been dominant minerals in China because of their large reserves in the past. However, with heavy mining each year, the three minerals may face resource depletion or dependence on import in the future. According to the reserve-to-production ratio, the depletion time for W, Sn, and Sb are about 27, 12, and 5 years, respectively (USGS, 2019). Meanwhile, import dependence for Sn and Sb has increased to 80% and 40%, respectively (MNRC, 2018; USGS, 2019).

Mo is mainly exposed to low-to-medium supply risk. The supply of Mo is better than those of minerals that are at high or medium-to-high risk level. Mo is one of the dominant minerals of China, and its supply depends on domestic reserves. The reserves of Mo can satisfy China's demand for about 64 years (USGS, 2019).

Meanwhile, REE's supply risk level is low. Compared with other mineral resources, REE are plentiful in China. Its reserves and production rank first worldwide. Therefore, domestic supply can meet the demand. Import dependence for REE is negative, which indicates net exports, and its supply is less affected by the international market (MNRC, 2018; USGS, 2019).

5.2. Changes in supply risk class

Fig. 6 illustrates the changes in the supply risk class of strategic metallic minerals from 2008 to 2017.

The supply risk of Cu, W, Au, and Li increased during the ten-year study period. Rising demand for Cu has pushed its supply risk level from medium-to-high to high. Cu is widely used in traditional industries such as power, metallurgy, and transportation, and it also plays an important role in emerging industries such as new information technology and new materials. This has led to a gradual increase in the mined amount of Cu. Cu's depletion time decreased from 31 years to 15 years, and the import dependence for Cu increased from 85% to 91% (USGS, 2010, 2019). Poor substitutability and decline in the source countries' environmental performance has changed W's supply risk level from low-to-medium to medium-to-high. Furthermore, countries with low environmental standards can face the risk of supply disruptions more easily than those with higher environmental standards (Jasiński et al., 2018), while improving environmental performance can effectively reduce the possibility of supply interruptions caused by environmental damage. The environmental performance index (EPI) of Russia—a major exporters of W to China—decreased from 83.8 to 53.4 (Wendling et al., 2018). The substitutability index of W also changed to 0.9, which has increased the substitution cost of W in alloy and electronic industries (EC, 2017). Increased demand for Au and Li in China has raised their supply risk level from low-to-medium to medium-to-high. Aside from its monetary functions and jewelry applications, Au is widely used in electronics and aerospace industries, which has increased import dependence for Au from 15% in 2008 to 67% in 2017 (Lin et al., 2016). Li's consumption has increased in strategic emerging industries such as the new energy, new materials, and high-end equipment manufacturing industries. Meanwhile, because of low grade and mineral mining limitations, Li, which previously had net exports, has become 60% import dependent (AM, 2020; MLRC, 2013).

Ni's supply risk decreased from 2008 to 2017. The supply risk level of Ni has dropped from high to medium-to-high. Large increases in Ni's reserves and reduced demand have mitigated its supply risk. Ni's reserves rose from 1.1 million tons in 2008 to 2.9 million tons in 2017 (USGS, 2010, 2019). Simultaneously, the consumption intensity and total consumption of Ni have shown a decreasing trend since 2013. The consumption per unit of GDP for Ni fell from 120 tons to 46 tons in 2017, while total consumption fell from 71.39 million tons to 35.13 million tons in 2017 (MLRC, 2013; NBSC, 2018a).

The supply risk of Al, Co, Zr, and Sb did not change significantly between 2008 and 2017. China's total consumptions of Al, Co, and Zr are on the rise as the economy continues to grow. However, increasing exploration investments have raised these minerals' reserves and supplies (MNRC, 2018; USGS, 2019). Therefore, no obvious changes have appeared in the import dependence and consumption intensity for these minerals (MNRC, 2018). Meanwhile, the international market for these minerals has been stable. As a result, the supply risk of Al, Co, and Zr has not change significantly. Sb reserves have decreased between 2008 and 2017, but this change was basically consistent with the change in its consumption during this period (MNRC, 2018; USGS, 2019). Hence, its supply risk also did not change significantly.

Changes in demand have led to irregular fluctuations in the supply risk of Fe, Cr, Sn, Mo, and REE. Moreover, the demand for Fe, Sn, and

Table 4
The profiles of the classes and indicator thresholds for evaluating the supply risk of strategic metallic minerals.

Indicators	Classes' Profiles				q	p	Basis for Parameters
	L	LM	MH	H			
Proportion of China's reserves to global reserves	>0.25	0.15–0.25	0.05–0.15	<0.05	0.025	0.05	As this paper's profiles are 0.05 bigger than those in Yang et al. (2016), the profiles' uncertain value is 0.05.
Reserve-to-production ratio	>75	50–75	25–50	<25	2.5	5	On the basis of studies by Hatayama and Tahara (2015), Schneider et al. (2014) and Liu et al. (2018), the difference among these studies' profiles is 5.
Import dependence	<0.25	0.25–0.5	0.5–0.75	>0.75	0.025	0.05	The values of import dependence range between zero and one, and four equal points of this interval are used as profiles. However, the difference is approximately 0.05, compared to results from Zhu (2018) and Liu et al. (2018).
Investment in exploration	>60119.92	15910.25–60119.92	4558.48–15910.25	<4558.48	–	–	The exploration investments substantially vary for each mineral. Thus, an ascending numerical sort of the value of investment from 2008 to 2017 is used, and the quartiles are used as profiles.
Consumption per unit of GDP	<50	50–100	100–150	>150	–	–	The indicator values are mostly between 0 and 200, and four equal points of this interval are used as profiles.
Strategic importance	<0.025	0.025–0.05	0.05–0.075	>0.075	–	–	The indicator values are mostly between 0 and 0.1, and four equal points of this interval are used as profiles.
Recycling rate	>0.5	0.25–0.5	0.1–0.25	<0.1	0.025	0.05	According to research by UNEP (Graedel et al., 2011), and compared to Yang et al. (2016) and Liu et al. (2018), the difference is 0.05.
Substitutability	<0.25	0.25–0.5	0.5–0.75	>0.75	–	–	The indicator values are mostly between 0 and 1, and four equal points of this interval are used as profiles (EC, 2014).
Foreign market concentration	<0.15	0.15–0.2	0.2–0.25	>0.25	0.025	0.05	The profiles are moderately restrictive, representing a compromise between the EU and US Merger Guidelines (Brown, 2018). The difference is approximately 0.05.
Geopolitical risk	>1	0–1	-1–0	<-1	0.1	0.2	They are set according to Jasiński et al. (2018) and the average standard error of the WGI-PV value from the World Bank. The average standard error is 0.2 (Kaufmann et al., 2011).
Environmental risk	>79	69.5–79	57.5–69.5	<57.5	4.3	8.6	This is set according to Jasiński et al. (2018), and the average change across 180 countries is 8.6 (Wendling et al., 2018).
$\lambda \in [0.65–0.85]$							This is according to literature related to the SMAA-TRI method (Merad et al., 2004; Tervonen et al., 2009).

REE can change sporadically as a result of the influence of national policies or corporate decisions, which affect the supply risk. For example, Fe consumption per 100 million yuan reached about 3800 tons between 2011 and 2014, but it fell to 1927 tons in 2015 (MLRC, 2016; NBSC, 2018a). This made Fe's supply risk high in 2011–2014 and medium-to-high in other years. Changes in EPI values have led to fluctuations in the supply risk of Cr and Mo. For example, the EPI values in South Africa, a major source of Cr, fell to 34.6 in 2012 and rose to 70.5 in

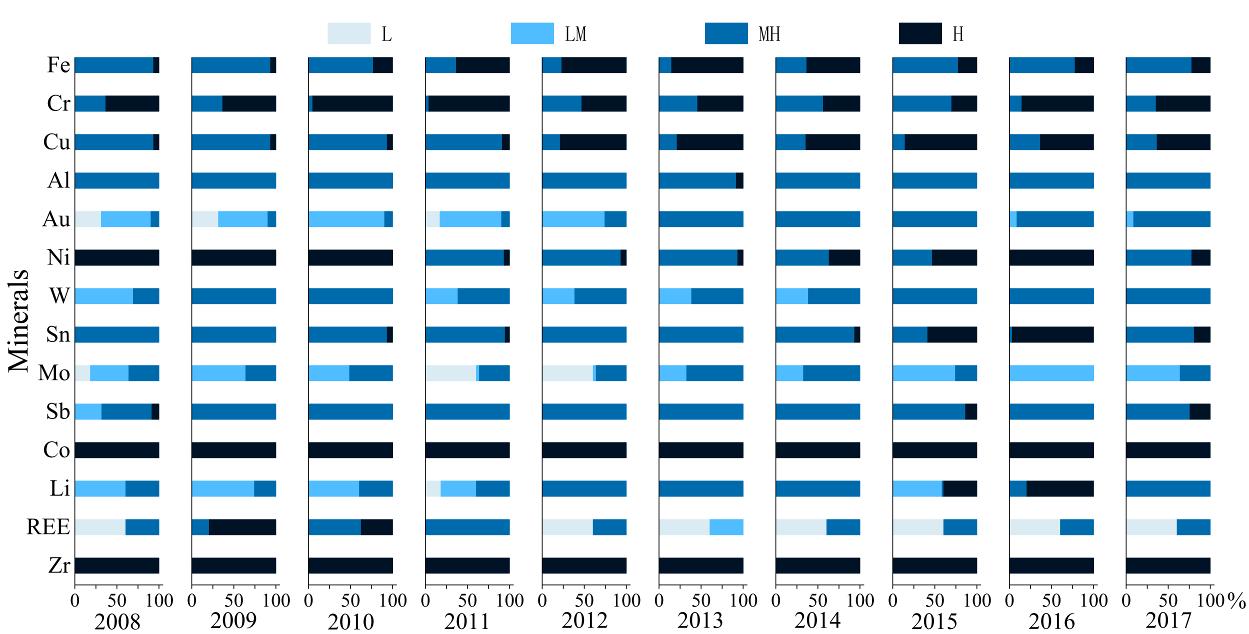

Fig. 5. Class acceptability index for the supply risk of strategic metallic minerals (2008–2017).

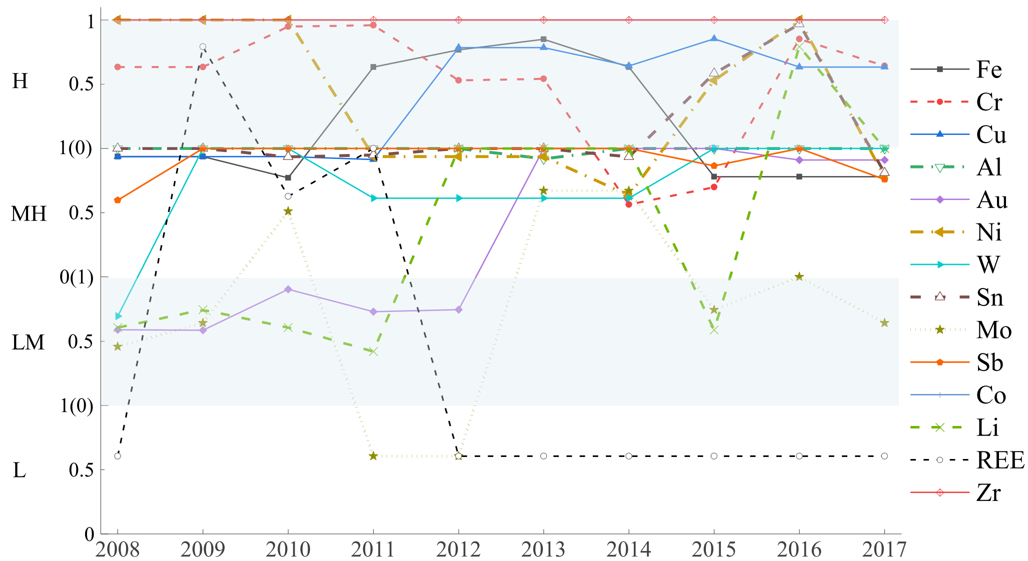

Fig. 6. Changes in strategic metallic minerals' supply risk class (2008–2017). Notes: Each value point is the class acceptability index of the risk class with the maximum probability. The acceptability index's ranges of the four supply risk classes on the Y-axis are [0, 1]. The supply risk increases from bottom to top: low risk (L), low-to-medium risk (LH), medium-to-high risk (MH), high risk (H).

2016 (Wendling et al., 2018).

5.3. Potential supply risk identification

The supply risk's class acceptability index can indicate potential risks in the current supply status. This index also represents the probability that a mineral is assigned to a specific class. Compared with the acceptability index of the current risk class, when a mineral's higher risk class reaches a specific value (e.g. the probability of the higher risk class reaches 30%), this mineral will have a potential risk. The potential risk indicates that some factors are increasing this mineral's supply risk.

Six minerals—Cr, Ni, W, Mo, Li, and REE—have demonstrated different potential risks under their current supply status. For example, Fig. 5 illustrates Cr's class acceptability index for the medium-to-high risk class in 2014 at 56.37%, while that of the high-risk class is at 43.61%. This indicates that the supply risk for Cr is driven by some factors that change its supply risk level from medium-to-high to high; in other words, a potential risk exists. The poor substitutability and low recycling rates of Cr, Ni, W, Mo, Li, and REE are responsible for these elements' potential risks in different years. Substitution and recycling of minerals can mitigate supply risk without a significant increase in their reserves. However, the substitutability indices of these minerals are above 0.6, especially for Cr and Mo, whose substitutability indices in 2017 are greater than 0.9 (EC, 2017). This indicates that the substitution of these minerals will either require a high cost or lead to a degradation of product performance (Hollins and Faunhofer, 2014). Moreover, the recycling of Li and REE accounts for only 1% of their total supply and cannot effectively mitigate their supply risk (Graedel et al., 2011; Jasiński et al., 2018).

The supply risk level of the other minerals is either high or a higher risk status for them is less probable; thus, they exhibit relatively stable supply risk.

6. Analysis of the supply risk of strategic metallic minerals in 2025

The 'Made in China (2025)' plan is one of the main driving factors of the current demand for strategic metallic minerals. Based on the results of the supply risk assessment from 2008 to 2017, this paper discusses changes in the supply risk trend of strategic metallic minerals in China from 2018 to 2025.

With large demand, China's strategic metallic minerals are expected to be in short supply for a long period (Li et al., 2019). Moreover, as the global economy transforms, mineral imports will continue to be affected by geopolitical risks and the policy and environmental issues of the producing countries (SCC, 2017). Additionally, overseas investment and cooperation in mineral exploration cannot alleviate the supply pressure effectively due to low economic efficiency (MIIT, 2016b). As a result, China's foreign supply of metallic minerals cannot increase sharply in a short time. Each country's supply of minerals is from both home and abroad. Therefore, the following supply risk analysis of strategic metallic minerals based on the evaluation results from 2008 to 2017 only focuses on the domestic gap between supply and demand.

The supply risk level of Cu, Co, and Zr is expected to remain high, and that of Al is anticipated to remain medium-to-high. According to the assessment from 2008 to 2017, Cu, Co, and Zr have been basically at a high supply risk level. Although China's economic growth has slowed down, demand for Cu is anticipated to continue growing at a low speed (MIIT, 2016b). The development of alloy materials and precise casting industries has further increased the demand for Co and Zr (Tan et al., 2015; Wang et al., 2019b). The supply risk of Cu, Co, and Zr is expected to remain high, with China having 3% of the global reserves (USGS, 2019), as demand continues to rise and domestic supply not increasing markedly. Consumption per unit of GDP for Al is expected to continue at a low growth rate of about 0.03% before 2025 (Zhang, 2018). Therefore, it is anticipated that Al's supply risk will remain at a medium-to-high level before 2025.

The supply risk of Au, Cr, Ni, W, Sn, Sb, and Li is expected to increase from the current level of medium-to-high to high. According to the supply risk assessment from 2008 to 2017, these seven minerals are at a medium-to-high supply risk level. Under China's supply-side structural reform, the demand for gold jewelry seems to maintain a low growth rate (Yuan et al., 2018). However, Au's supply may decrease in the next 30 years (Yuan et al., 2018), which is likely to raise Au's supply risk level to high. With the vigorous development of strategic emerging industries such as new energy, new materials, energy conservation, and environmental protection in China, the demands for Cr, Ni, W, Sn, Sb, and Li has been increasing rapidly (MIIT, 2016b). The application of Ni and Li in battery materials has stimulated the demand for Ni and Li (Yuan et al., 2018). Key developments in high-quality alloy materials have increased the consumption of Cr and Sn. The demand for Cr is anticipated to reach about 19 million tons in 2023 (Pan et al., 2018), while the consumption of Sn may increase by 2% annually (Wang et al., 2018b). The development of vacuum electronic devices and high-end alloy materials is expected to increase consumption of W by 5% annually (Zhang, 2017). The application of Sb in flame retardant and battery industries is expected to lead to a peak consumption of Sb in 2025 (Luo et al., 2017). While the demand has been increasing, the domestic supply of these minerals has not improved significantly, and even shows a declining trend. For example, Li's reserves decreased from 3.2 million tons to one million tons in 2018 (USGS, 2019). Therefore, the increasingly prominent gap between supply and demand is likely to raise the supply risk to high.

The supply risk of Mo is anticipated to rise from the current low-to-medium level to at least medium-to-high, while REE's supply risk level may rise from low to low-to-medium. With the development of high-end alloy materials and vacuum electronic devices, the annual growth rate of Mo's demand is expected to reach about 8% (Zhou et al., 2018). Although Mo reserves have increased, they still cannot meet the rapidly growing demand and thus, foreign supply is necessary. Import dependence for Mo has increased from 0% to 13% (MNRC, 2018; USGS, 2019). Therefore, its supply risk level is likely to increase from low-to-medium to at least medium-to-high. With the development of strategic emerging industries, the output of major rare earth functional materials, such as rare earth magnetic and catalytic materials, has increased by over 15% annually (MIIT, 2016c), which may put more pressure on its supply. Therefore, although China's reserves and output of REE are the largest worldwide, the future supply risk level of REE is likely to rise from low to low-to-medium.

The supply risk level of Fe is anticipated to decrease from medium-to-high to low. Fe's supply risk fluctuated from 2008 to 2017. Demand for Fe is likely to continue to decline due to the overcapacity of steel and China's economic transformation (MIIT, 2016a). Moreover, the use of scrap steel is also continuously being promoted. It is estimated that the scrap ratio may increase from 10.66% in 2015 to 20% in 2025, which can relieve the supply pressure effectively (Zhu, 2018). Hence, it is anticipated that the risk of Fe's supply will decrease.

7. Conclusions and policy recommendations

7.1. Conclusions

The SMAA-TRI method revealed eleven indictors on resource availability, economic correlation, technological level, and import instability. These indicators were chosen to evaluate the supply risks of 14 strategic metallic minerals. The evaluation results lead to the following conclusions:

a) The supply risk of 14 strategic metallic minerals in China has been generally high between 2008 and 2017. While the supply risk levels of Mo and REE have been low or low-to-medium, the other 12 minerals have exhibited high or medium-to-high supply risk levels. The high supply risk of these 12 minerals results from a high dependence on imports, caused by high demand and insufficient domestic supply;

b) The supply risk of Cu, Au, W, and Li has increased between 2008 and 2017, while that of Ni has decreased. The development of strategic emerging industries has increased the demand for Cu, Au, and Li. Changes in mineral substitutability and the source countries' environmental performance are responsible for the increasing supply risk of W. The increasing reserves and decreasing demands for Ni has reduced its supply risk. Meanwhile, demand fluctuations are the primary reason for the changes in the supply risk of Fe, Sn, and REE, and the supply risk fluctuations of Cr and Mo are caused by changes in the source countries' environmental performance;

c) The supply risk of six minerals—Cr, Ni, W, Mo, Li, and REE—have been affected by potential higher risk factors, primarily due to their poor substitutability and low recycling rate, which have failed to alleviate supply pressures; and

d) The supply risk of seven strategic metallic minerals—Au, Cr, Ni, W, Sn, Sb, and Li—is expected to increase to high levels from 2018 to 2025, while the supply risk of Fe is anticipated to decrease. With no marked improvement in supply, the supply risks for Au, Cr, Ni, W, Sn, Sb, and Li are likely to rise to high levels, and the supply risk of Mo may rise to a medium-to-high level. The supply risk levels of Cu, Co, and Zr are expected to remain high, and that of Al is anticipated to remain at medium-to-high. Steel's overcapacity and economic transformation in China are expected to reduce the demand for Fe, while the use of scrap steel may effectively ease the supply pressure on Fe, causing its supply risk to decrease. Lastly, the supply risk of REE is expected to increase because of the growing output of major rare earth functional materials.

7.2. Policy recommendations

This study's evaluation results for the supply risk of China's strategic metallic minerals from 2008 to 2017 lead to the following policy recommendations for decreasing supply risk and ensuring supply security.

a) Strengthen the exploration of 12 minerals—Fe, Cr, Cu, Al, Au, Ni, W, Sn, Sb, Co, Li, and Zr—and expand their import channels. Compared with some minerals with abundant reserves, such as Mo and REE, import dependence for ten minerals—Fe, Cr, Cu, Al, Au, Ni, Sn, Co, Li, and Zr—is more than 55%. Further, W and Sb are primarily supplied domestically but can only be mined for less than 30 years. Therefore, some measures should be taken to reduce the supply risk of these minerals. Attracting all types of investments—including national finance, enterprise, public, and foreign investments—can strengthen mineral exploration. Moreover, encouraging mineral enterprises to invest in foreign sources in the context of international cooperation, for instance, through China's Belt and Road initiative, can help diversify the source of these minerals.

b) Establish strategic reserves for Fe, Cr, Cu, Al, Au, Ni, W, Sn, Mo, Sb, Co, Li, REE, and Zr. According to the evaluation results, changes in the supply risk of these 14 minerals have resulted from demand fluctuations and policy and enterprise decisions in the process of economic development. Strategic reserves can be established to fill the supply and demand gap of scarce minerals (such as Fe, Sn, and Cr) in a timely manner and prevent minerals such as REE from reducing their dominance due to large exports.

c) Improve the technology levels for substitution and recycling of Cr, Ni, W, Mo, Li, and REE. At present, the substitution of Cr, Ni, W, and Mo may lead to high cost or degrade the associated products' performance. Meanwhile, the recycling rates for Li and REE metals are minimal. The government can introduce incentives to promote technological innovation and motivate enterprises to invest in scientific research. Such investments can help improve substitution and recycling of these metallic minerals.

d) Improve the utilization efficiency and cooperation for the recovery of metallic minerals. Demand growth from the development of strategic emerging industries will put most of China's minerals supply at high risk in the future. With no improvement in domestic supply, improving mineral utilization efficiency and cooperation for recovery of these minerals can ease supply pressures. On the one hand, improving the utilization efficiency of low-grade minerals can make full use of China's large amounts of low-grade metallic minerals. On the other hand, because metals is often forged as alloys, promoting the coordinated development of metal recovery can improve the recycling rates of alloy metals.

Author Statement

Shiwei Yu: Conceptualization, Methodology, Validation, Analysis, Writing-original draft, Writing-review & editing. Haoran Duan:

Methodology, Validation, Computing, Writing-original draft. Jinhua Cheng: Project administration, Writing-review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2020.101891.

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Further reading

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