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RESEARCH AND ANALYSIS

Toward a dynamic evaluation of mineral criticality

Introducing the framework of criticality systems

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Abstract

A new methodology to quantify minerals' criticalities is proposed—the criticality systems of minerals. In this methodology, four types of *agents*—mineral suppliers, consumers, regulators of the market, and others, such as the communities near mining operations—interact with each other through three types of *indicators*: *constraints*, such as the political stability in the mining regions, the mineral's substitutability and economic importance; *agents' interactions*, such as buyer–seller bargaining; and *interactive variables*, such as the demand, supply, and price. When the criticality systems of two mineral groups are constructed, analyses that compare the *indicators* of these criticality systems can determine which group is more critical than the other. This methodology allows evaluation of criticality in a dynamic and systemic manner.

KEYWORDS

complex systems, dynamic systems, industrial ecology, mineral criticality, statistical learning, supply risk

1 | INTRODUCTION

Non-fuel mineral resources and metals (referred to as minerals) play an indispensable role in society. For example, the production of a computer microprocessor requires more than 60 minerals (DOE, 2010a). Therefore, the restriction of their supplies is of broad concern (Achzet & Helbig, 2013; Ali et al., 2017; BGS, 2012; Erdmann & Graedel, 2011; Jin, Kim, & Guillaume, 2016). Hence, a *criticality assessment* is required to identify those minerals that are both highly important and prone to supply disruptions.

Arguably, the earliest criticality assessment methodology is the U.S. National Research Council *Criticality Matrix* (NRC, 2008), which is a *static-indicator-based* methodology, meaning that it evaluates the criticality of minerals at a time instant using static indicators. The criticality matrix has two dimensions: the supply risk and the economic importance. This framework has become the basis for many influential studies (Achzet & Helbig, 2013; BGS, 2012; BGS, 2015; Coulomb, Dietz, Godunova, & Nielsen, 2015; DOE, 2010a, 2010b; Duclos, Otto, & Konitzer, 2010; EU, 2010; EU, 2014; NRC, 2008; Graedel et al., 2012; Graedel, Harper, Nassar, Nuss, & Reck, 2015; Nuss, Harper, Nassar, Reck, & Graedel, 2014; Rosenau-Tornow, Buchholz, Riemann, & Wagner, 2009; Skirrow et al., 2013). One of them used the *Criticality Space* (Graedel et al., 2012, 2015), which is also a static-indicator-based methodology. Unlike the Criticality Matrix, it proposes a three-dimensional assessment—the supply risk, the vulnerability of the end users to supply restrictions, and the cradle-to-gate environmental implications. For each of these dimensions, quantitative indicators are selected to evaluate different aspects, for example, the National Economic Importance (NEI) is calculated and used to reflect the economic aspect of a national-level mineral end user's vulnerability to supply restriction. In contrast, the Criticality Matrix uses a qualitative assessment.

Static-indicator-based methodologies have limitations: First, they do not account for time-dependencies (Knoeri, Wäger, Stamp, Althaus, & Weil, 2013); furthermore, the relationships between the indicators used and the dynamics of minerals' market systems and industrial ecology have not been statistically validated (Frenzel, Kullik, Reuter, & Gutzmer, 2017). Knoeri et al. (2013) suggested to address the time-dependency issue by proposing a conceptual framework using material flow analysis techniques to model the circulation of a mineral in its life cycle, and an agent-based model to simulate the interactions between the substitution decisions of minerals and their material flow systems. However, no follow-up studies are published. Sprecher et al. (2015) used resilience theory to dynamically evaluate neodymium's supply risk, focusing only on the supply chain. The findings demonstrated that resilience is dependent on three factors: *resistance*, or the ability of a system to function within an acceptable range of performance during disturbance; *rapidity*, or the ability to quickly recover after disturbance; and *flexibility*, or the substitutability of a system. Mancheri et al. (2018) used a similar methodology to analyze tantalum. However, this methodology also has some limitations: it solely focuses on the supply-side criticality ignoring the minerals' importance and the end users' vulnerability; and it did not demonstrate how to compare the resistance, rapidity, and flexibility of two minerals quantitatively, which is fundamental for differentiating the degrees of criticality. Smith and Eggert (2016) chose a different avenue of research in the criticality field compared to others. Their methodology focused on the multifaceted nature of mineral substitution and the impact of which on criticality assessment. While it promotes understandings about substitutions in the context of criticality, other criticality aspects were not considered. In addition, none of these studies (Knoeri et al., 2013; Mancheri et al., 2018; Smith & Eggert, 2016; Sprecher et al., 2015) statistically validated the relationship between the indicators used and the dynamics of the mineral's market system and industrial ecology.

Due to these limitations, a more comprehensive methodology is needed. In this article, we introduce the *Criticality System*, a framework in which four types of *agents*—mineral suppliers, consumers, regulators of the market, and others, such as the communities near mining operations—interact with each other through three types of *indicators*, which represent essential constituents of the industrial ecology and market systems of minerals: *constraints*, which reflect the limiting factors to the agents, for example, the depletion time and the substitutability of a mineral; *agents' interactions*, which reflect their behaviors, for example, the bargaining between mineral suppliers and consumers; and *interactive variables*, which reflect the gatherable observations resulting from the agents' interactions, for example, the demand, supply, and price of a mineral. The criticality system is *complex*, meaning that the agents and the indicators are highly interconnected; therefore, changes in one of them will lead to *cascading effects*.

When the criticality systems of two groups—the *commonly known more-critical* minerals, such as rare earth elements (REEs) and platinum (Pt) and the *commonly known less-critical* minerals, such as iron ore and copper—are constructed, it is possible to compare these two groups' criticality systems to look for differences. Guided by their commonly known criticality statuses, these differences will lead us to the patterns and trends that differentiate more-critical minerals from less-critical minerals. On the other hand, if the criticality statuses of two mineral groups are less obvious or less commonly known, it is also possible to compare their criticality systems, looking for hidden structures that separate them.

The criticality system is based on the criticality space (Graedel et al., 2012, 2015) and the industrial market structure analysis (Ross, 1990; Scherer, 1996). The former shows that the constraints of a critical mineral are different from that of a non-critical one; the latter shows that the agents' interactions and the interactive variables are very different between critical and non-critical industries. We combine these two concepts to create the criticality-system framework. The criticality system has the following advantages: the ability to explicitly demonstrate the impact of the indicators on the dynamics of the mineral's market system and industrial ecology; and the ability to evaluate criticality over time (the dynamic perspective) rather than at one point in time (the "snapshot" perspective).

2 | THE METHODOLOGY: AN OVERVIEW OF THE CRITICALITY SYSTEM

2.1 | The methodology in general

Let us visualize the criticality system in detail. Figure 1 illustrates the indicators, the agents, directions of the impact, and the *feedback loops*. The criticality system is designed to reflect possible chains of events, such as changes of the constraint affect the behaviors and interactions among the agents, which further affect the interactive variables; through feedback, the affected interactive variables influence the entire system with some delay. For example, the reduction of a mineral reserve's depletion time could shift the bargaining power from the consumers to the suppliers, leading to a reduction of supply and an increase in price. These changes propagate through the entire system, resulting in more exploration and mining activities, which replenish the mineral reserves. As a result, the depletion time in the future will increase.

Unfortunately, the agents' interactions, such as buyer–seller bargaining, are usually *unobservable*, as they tend to be privileged information. Therefore, we focus on assessing the remaining indicators (i.e., the constraints and the interactive variables summarized in Tables 1 and 2 of the main article and Table S1-1 in supporting information S1 available on the Journal's website), as they are likely to be the causes (i.e., the constraints) or the effects (i.e., the interactive variables) of the agents' interactions. To do so, we collect time-series datasets and measure their correlations. Of interest are the correlations between the constraints and the interactive variables (Figure 2), which we call *constraint–variable correlations*; and those among the interactive variables, which we call *mutual-variable correlations*.

Finally, our approach compares groups of minerals, looking for different patterns and trends in their indicators over time, which reflect the criticality of each group. In the following sections, we provide details on the techniques required for this comparative analysis, and how the results help us to identify a more-critical mineral group from a less-critical one.

2.2 | Data requirement

A list of the indicators is available in Tables 1, 2, and S1-1. Most of the datasets required to quantify these indicators over multiple time periods are publicly available and can be obtained from a single source. For example, the annual policy potential index (PPI) of the countries worldwide is

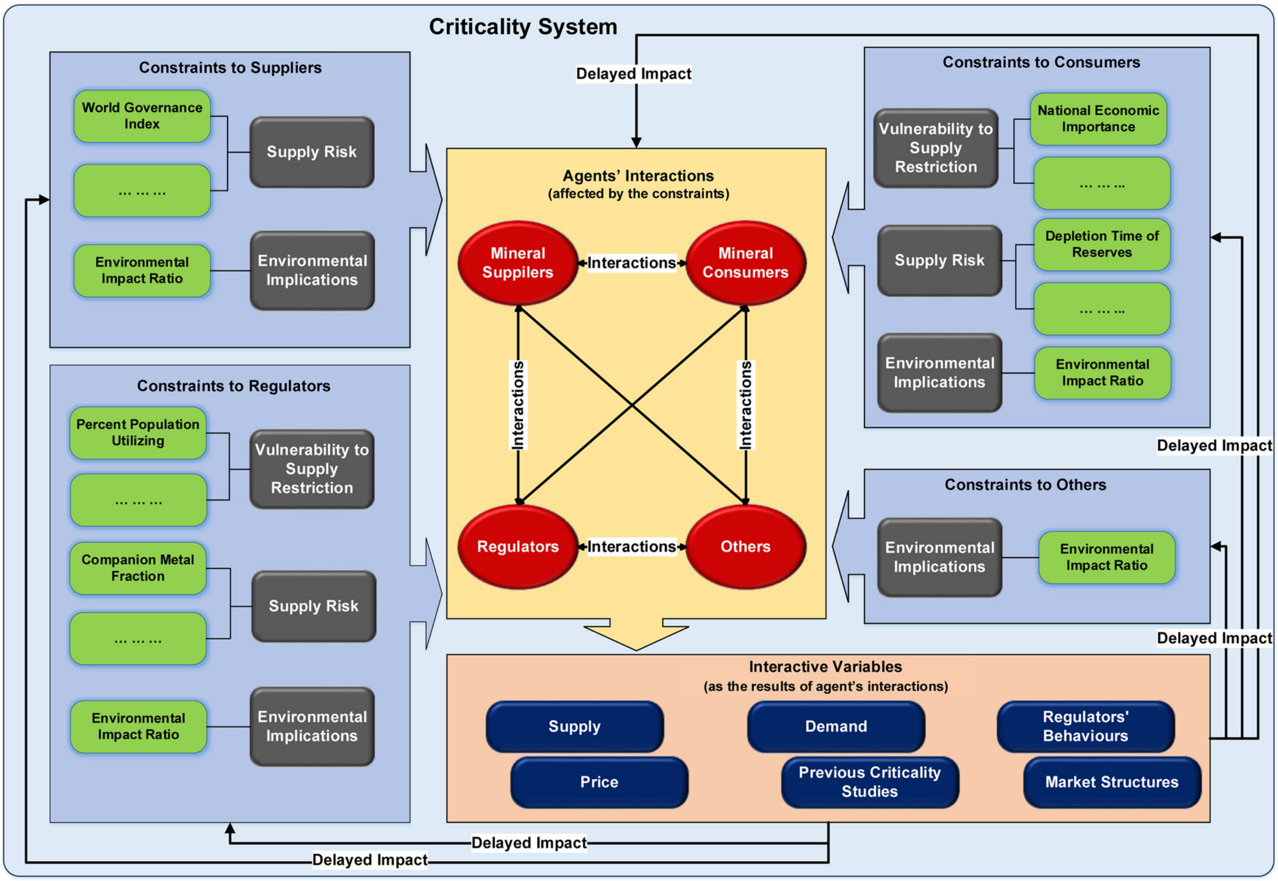

FIGURE 1 A detailed illustration of the feedback loops among the elements in the criticality system

published by the Fraser Institute every year (McMahon & Cervantes, 2011), while minerals' prices are available from commodity markets, such as the London Metal Exchange. Some data must be collected from multiple sources. For example, the data required to calculate the NEI need to be sourced from more than one governmental agency, such as the U.S. Bureau of Economic Analysis and USGS. Finally, other data must be purchased from an industry firm in order to obtain the required high resolution. For example, the annual world copper-mine productions of different countries can be purchased from the International Copper Study Group.

Data availability is important. Indicators summarized in Tables 1, 2, and S1-1 are selected to reflect various aspects of a mineral's supply risk, the end users' vulnerability to supply restriction, and the market dynamics, all of which are important. If certain required datasets are unavailable, the ability to assess the respective aspects is lost, which may affect the overall assessment result.

2.3 | The impact of different user preferences

Tables 1, 2, and S1-1 list a significant number of indicators, the weight of which on the criticality assessment may differ depending on perspectives. Thus, some indicators may be preferred over others. For instance, between two indicators, the former would be preferred over the latter if (a) the former has a stronger correlation to the mineral's price fluctuations than the latter, and (b) price fluctuation is a major concern to the end user.

2.4 | Statistical learning techniques required

The analyses of the indicators and their correlations overtime (as will be discussed in detail later) focus on identifying trends and their statistical significance. We use two techniques for this purpose: ordinary least square (OLS) regression and robust linear regression with Huber weights. OLS provides statistics, such as the gradient standard error and its p-value, which allow us to assess the trend's reliability. On the other hand, robust linear regression can adjust for the existence of extreme outliers and high leverage points that would distort the value of the trend. We suggest the following procedure to carry out the analysis:

TABLE 1 A summary of the constraints selected to reflect supply risk, vulnerability, and environmental implications. The analyses of these constraints' impact on the agents at a time instant. The calculations of these constraints are explained in Table S1-1 in Supporting Information S1 on the Web

Constraints (Supply risk)	Description of the constraints	Implications of the constraints
Depletion time of reserves ($DT_{transformed}$)	The depletion time provides an adequate approximation of the availability of the mineral in Earth's upper crust (Graedel et al., 2011, 2012).	A high score of $DT_{transformed}$ calculated according to Equations (S1)–(S3) represents a short depletion time of a mineral, which indicates the supply risk associated with geological availability of the mineral is high.
Companion metal fraction (CMF)	CMF measures the degree of dependence on the mineral's production to the production of a "host" mineral (Graedel et al., 2012).	A high CMF of a mineral indicates the supply risk associated with the production of the mineral's host mineral is high.
Transformed and weighted policy potential index (TPPI & WPPI)	The transformed PPI score of a country assesses the impact on mining activities and exploration investments in this country due to the uncertainty associated with the governmental and non-governmental barriers (McMahon & Cervantes, 2011). The weighted PPI score for a particular mineral is calculated by summation of the Transformed PPI scores for all jurisdictions weight-averaged by their annual mining production of the mineral. (Graedel et al., 2012).	A high transformed PPI score of a mineral-producing country indicates a high supply risk of the minerals supplied from this country due to a high level of the governmental and non-governmental barriers of the country A high weight PPI suggests a high supply risk of the mineral associated with the high level of the overall governmental and non-governmental barriers in all jurisdictions worldwide where this mineral is produced.
Transformed and weighted human development index (THDI & WHDI)	The transformed HDI score of a country provides an assessment of the level of social progress of a country (UN, 1990–2015). An economy that is based on a higher level of social development is generally less tolerant to intrusive mining activities. The weighted HDI score for a particular mineral is calculated by summation of the transformed HDI scores of all jurisdictions weight-averaged by their annual mining production of the mineral. (Graedel et al., 2012).	A high transformed HDI score of a mineral-producing country indicates a high supply risk of the mineral supplied from this country due to a high level of social development which does not tolerate the intrusive mining activities very well. The high weight HDIs suggest a high supply risk of the mineral associated with the conflicts of the social values in all jurisdictions around the world where this mineral is produced.
Transformed and weighted WGI: political stability and absence of violence (TWGI-PV & WWGI-PV)	The transformed WGI-PV score of a country measures the uncertainty associated with the political and social stabilities of the country (Kaufmann, Kraay, & Mastruzzi, 2011). The weighted WGI-PV score for a particular mineral is calculated by summation of the WGI-PV scores of all jurisdictions worldwide weight-averaged by their annual mining production of the mineral. (Graedel et al., 2012).	A high transformed WGI-PV score of a mineral-exporting country indicates a high supply risk of the mineral supplied from this country due to the instability of the political and social environment in this country Due to the transformation of the original WGI-PV score according to Table S1-2 in Supporting Information S1 on the Web, the high Weight WGI-PVs suggests a high supply risk of the mineral associated with the overall instability of the political and social environments in all jurisdictions where this mineral is produced.
National economic importance (NEI)	NEI measures the importance of a mineral to a country by evaluating the value of the mineral utilized as the percentage of the country's GDP (Graedel et al., 2012).	A high NEI of a mineral to a mineral-consuming country indicates the country is vulnerable to supply restriction from the aspect of the impact on the economy.
Percent population utilizing (PPU)	PPU measures the magnitude and the scope of the impact on the population in a mineral-consuming country when the supply of the mineral is limited (Graedel et al., 2012).	A high PPU of a mineral to a mineral-consuming country indicates the country is vulnerable to supply restriction from the aspect of the percentages of the population utilization of the mineral.
Substitute performance (SP)	SP measures how well the substitutes of a mineral perform as compared to the original mineral (Graedel et al., 2012).	A high SP score calculated according to Equation (S5) of a mineral to a mineral-consuming country indicates the country is vulnerable to supply restriction due to inadequate substitutes' performance of the mineral.
Substitute availability (SA)	SA measures the availability of the substitutes of a mineral, and it is estimated using all the assessment criteria listed in the supply risk dimension of Yale's criticality space (Graedel et al., 2012).	A high SA score obtained, according to Table S1-2 in Supporting Information S1 on the Web, of a mineral to a mineral-consuming country indicates the country is vulnerable to supply restriction due to inadequate substitutes' availability of the mineral.
Net import reliance (NIR)	NIR evaluates a country's reliance on the import of a mineral (Graedel et al., 2012).	A high NIR of a mineral to a mineral-consuming country indicates the country is vulnerable to supply restriction due to the country's reliance on the importation of the mineral
Transformed global innovation index (TGII)	TGII index estimates how innovated a country is (Graedel et al., 2012).	A high TGII calculated according to Equation (S8) of a mineral-importing country indicates the country is vulnerable to supply restriction due to inabilities of the country to innovate. A low GGI, to some degrees, compensates the supply restriction by innovations.
Environmental implication (EI)	EI evaluates the damage to human health and ecosystems using the ReCiPe endpoint method and the ecoinvent data (Frischknecht et al., 2005; Goedkoop et al., 2009; Graedel et al., 2012).	A high EI of a mineral during its production phase indicates that the mineral is more "environmentally expensive" to produce; a high EI of a mineral during its utilization phase could make the mineral more "environmentally expensive" to be used.

Note. Full forms of all abbreviations including $DT_{transformed}$, CMF, TPPI, WPPI, TWGI-PV, WWGI-PV, THDI, WHDI, NEI, PPU, SP, SA, NIR, TGII, and EI are in the table next to the abbreviations.

TABLE 2 Descriptions and calculation of the interactive variables

Interactive variables	Description	Equations
Demand (D)	The data about the annual demand for a mineral need to be at a country level, that is, how much a country consumed the mineral in a given year. It is preferable that the level of details of the data is more refined, for example, how much each sector in each country consumed the mineral in a given year. Past trends and volatilities can be learned using statistical learning.	
Supply (S)	The data about the annual supply of a mineral need to be at a country level, that is, how much a country supplied the mineral at a given year. It is preferable that more details can be obtained, for example, how much each major mining company in each mineral-supplying country supplied the mineral in a given year.	
Price (P)	The data need to be averaged for each year, need to be adjusted for inflation, and need to be at a global scale. Past trends of price can be learned using statistical learning. Past volatilities can be calculated by Equation (1), where P_t is the price of the mineral at the period t, $\bar{P}_T$ is the average of the mineral's prices throughout the period from 0 to T, T is the total length of all periods, and V_T is the price volatility indicator (Frischknecht et al., 2005; Goedkoop et al., 2009).	$V_T = \frac{\sqrt{\frac{\sum_{t=0}^{t=T}(P_t - \bar{P}_T)^2}{T-0}}}{\bar{P}_T}$ (1)
Market structure (CR4)	We consider both the concentration of the mineral's global supply and the concentration of the consumption at a corporate level. Two indicators need to be calculated: the CR4 of the global demand; the CR4 of the global supply; they are calculated according to Equations (2) and (3), respectively (Ross, 1990). If the resolution of the data does not support the corporate-level CR4 indexes, the national-level CR4 indexes are also acceptable, which require the datasets of the annual production and consumption of the largest four nations, respectively.	$CR4_{Global\ supply} = \frac{\text{The production of the largest four companies in globe}}{\text{Global production of the mineral}}$ (2) $CR4_{Global\ consumption} = \frac{\text{The consumption of the largest four companies in globe}}{\text{Global consumption of the mineral}}$ (3)
Regulator's behaviors (GI)	Equation (4) is formulated to quantify the scale of government interventions (GI), GI^t_{Country} is the government intervention scale of a country at a given year denoted by t, $\overline{\overline{m}}^t_S$ is the number of times the government increased or decreased the taxes and subsidies to the suppliers or consumers of a mineral in the country in the year t standardized according to Equation (5), $\overline{\overline{m}}^t_p$ is the number of times the government implemented price control regulations of a mineral in the year t standardized according to Equation (6), $\overline{\overline{m}}^t_A$ is the number of times the high court of the country ruled the antitrust law cases against the suppliers or consumers of a mineral in the year t standardized according to Equation (7), $\overline{\overline{m}}^t_I$ is the number of times the country filed charges against other countries to the World Trade Organization of a country due to the trade issues concerning a mineral in the year t standardized according to Equation (8), $\overline{\overline{m}}^t_R$ is the number of times the federal research institute of the country conducted the research of the productions, applications of a mineral in the year t standardized according to Equation (9), I_S, I_P, I_A, I_I, I_R are coefficients which can be chosen freely by users to adjust the relative importance of $\overline{\overline{m}}^t_S, \overline{\overline{m}}^t_p, \overline{\overline{m}}^t_A, \overline{\overline{m}}^t_I, \overline{\overline{m}}^t_R$, they lie in an interval between 0 and 1. The initial values of all Is are set to 1 to reflect their equal importance to the equation. We assume that the total number of period recorded is n.	$GI^t_{Country} = \frac{((\overline{\overline{m}}^t_S \times I_S) + (\overline{\overline{m}}^t_p \times I_P) + (\overline{\overline{m}}^t_A \times I_A) + (\overline{\overline{m}}^t_I \times I_I) + (\overline{\overline{m}}^t_R \times I_R))}{5}$ (4) $\overline{\overline{m}}^t_S = \frac{m^t_S - (\frac{\sum_{t=0}^{t=n} m^t_S}{n})}{\sqrt{\sum_{t=0}^{t=n}(m^t_S - \sum_{t=0}^{t=n} m^t_T)^2/n}}$ (5) $\overline{\overline{m}}^t_p = \frac{m^t_p - (\frac{\sum_{t=0}^{t=n} m^t_p}{n})}{\sqrt{\sum_{t=0}^{t=n}(m^t_P - \sum_{t=0}^{t=n} m^t_P)^2/n}}$ (6) $\overline{\overline{m}}^t_A = \frac{m^t_A - (\frac{\sum_{t=0}^{t=n} m^t_A}{n})}{\sqrt{\sum_{t=0}^{t=n}(m^t_A - \sum_{t=0}^{t=n} m^t_A)^2/n}}$ (7) $\overline{\overline{m}}^t_I = \frac{m^t_I - (\frac{\sum_{t=0}^{t=n} m^t_I}{n})}{\sqrt{\sum_{t=0}^{t=n}(m^t_I - \sum_{t=0}^{t=n} m^t_I)^2/n}}$ (8) $\overline{\overline{m}}^t_R = \frac{m^t_R - (\frac{\sum_{t=0}^{t=n} m^t_R}{n})}{\sqrt{\sum_{t=0}^{t=n}(m^t_R - \sum_{t=0}^{t=n} m^t_R)^2/n}}$ (9)
Previous criticality scores (PCS)	The PCS gathered is normalized according to Equation (10). Equation (11) is designed to provide the average score of the criticality of a mineral in year t, PCS^t_i is the normalized criticality score of the study i in year t, I_i is the coefficient which can be chosen freely by users to adjust the relative importance of the study i, they lie in an interval between 0 and 1, and n is the number of studies reordered in year t.	$PCS_i = \frac{\text{Score of the mineral evaluated of study } i}{\text{Max. score of study } i - \text{Min. score of study } i}$ (10) $PCS^t_{Average} = (\sum_i^n (PCS^t_i \times I_i))/n$ (11)

Note. Full forms of all abbreviations including D, S, P, GI, and PCS are in the table next to the abbreviations.

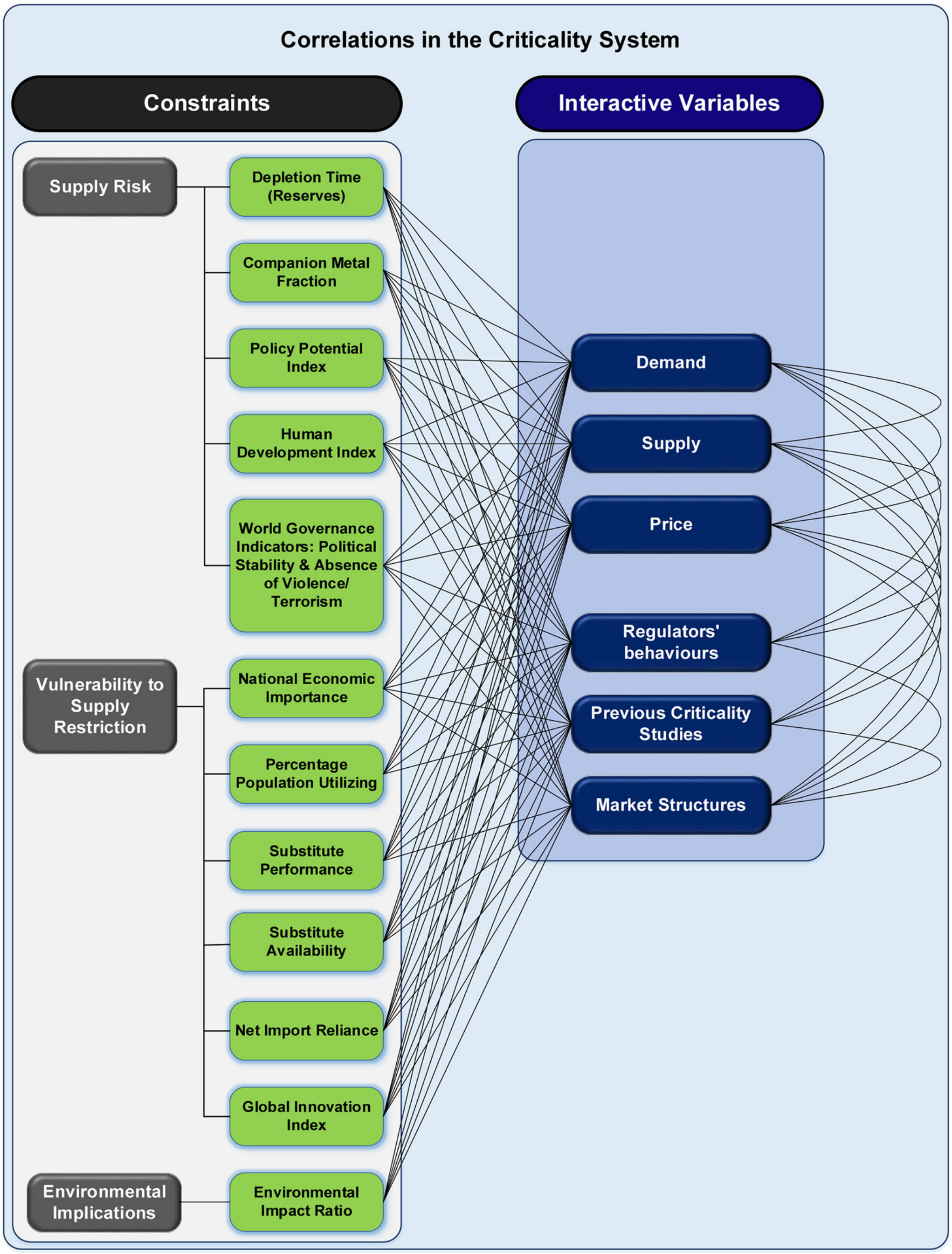

FIGURE 2 The correlations between the constraints and the interactive variables of the criticality system (the constraint–variable correlations) and the correlations among the interactive variable (the mutual-variable correlations) of the criticality system

1. Determine the linear relationship between two indicators using OLS (or use OLS to determine the linear trend of an indicator by setting its time-series data as the response variable and the corresponding time series as the feature variable), verifying that the *p*-value and the adjusted R-squared value indicate statistical significance. If there is no significance, record the results, and no further analysis is required.
2. If the OLS analysis shows significance, carry out Robust regression and compare the gradient and standard error to those of OLS. If different, we suggest keeping the results from robust regression, as there is evidence of the existence of extreme outliers or high leverage.

We limit ourselves to linear regression techniques due to limits on data availability. These techniques assume a normal distribution of the residuals. If more data are available, other non-linear techniques would be more appropriate. However, their discussion is outside the scope of this article.

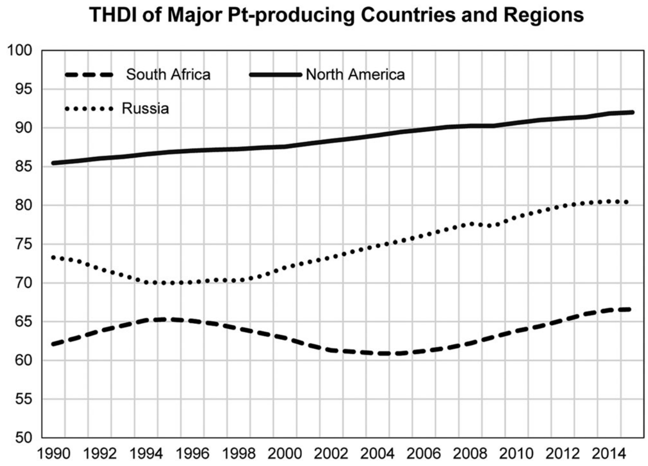

FIGURE 3 THDIs (UN 1990–2015) of South Africa, Russia, and North America from 2001 to 2015
Note. THDI is the abbreviation for transformed human development index. Data used to create this figure are available in Supporting Information S2 on the Web.

3 | DISCUSSIONS: STRUCTURES OF THE CRITICALITY SYSTEM AND CRITICALITY EVALUATIONS

3.1 | The constraints

As discussed, the constraints reflect the external factors and impacts on the agents' behaviors and interactions. We selected 12 constraints from the indicators used in the criticality space (Graedel et al., 2012), most of which are indexes or public information available from credible sources. Five focus on the supply risk, seven focus on the end users' vulnerabilities, and one focuses on cradle-to-gate environmental implications of minerals. Table 1 presents the definitions for each constraint and explains the implications of a given value at a point in time. Sections 1.1–1.3 of the Supporting Information S1 present our rationale for selecting these constraints. Table S1-1 presents the calculations required to obtain their values. Changes in the constraints over time are usually recorded yearly, although higher resolutions are possible if data are available. The analysis of focuses on (a) the constraints' values at the most recent time instant, which provide insights into the current status of the supply risk and vulnerability they represent, and (b) the *direction*, *gradient*, and *volatility* of their trends, which provide insights into the evolution of the constraints over time.

Platinum has been frequently considered as a critical mineral (BGS, 2012; DOE, 2010a; EU, 2010; EU, 2014; Sverdrup & Ragnarsdottir, 2016). Therefore, as an example of the constraint analysis, we analyze a constraint in platinum's criticality system reflecting the supply risk associated with conflicts of different social values—the analysis of the transformed human development indexes (THDIs) of South Africa and Russia, which are the largest and the second-largest platinum-producing countries, respectively. The THDIs of South Africa and Russia in 2015 were 66.6 and 80.4, suggesting that the supply risk of platinum associated with the intolerance to intrusive developments of mining industries in Russia was higher than that of South Africa. On the other hand, the analysis of the THDIs of South Africa and Russia from 1990 to 2015 show that (a) a wave-like pattern of South Africa's THDIs during this period (Figure 3), (b) a clear and linear trend of growth of Russia's THDIs which has an OLS gradient of 0.435 and a small p-value of 2.14×10^{-10} (Figure 3). These indicate that (a) the supply risk of platinum associated with the intolerance to the intrusive development of mining industries in South Africa oscillated without a clear trend of improvement, (b) the supply risk of the same aspect in Russia, on the other hand, showed a clear linear trend of increase.

3.2 | The interactive variables

The interactive variables are the manifestations of the agents' interactions taking place in the criticality system. We focus on six interactive variables: the demand, supply, price, regulators' behavior, previous criticality scores, and market structure. The detailed descriptions and calculation procedures of these interactive variables are shown in Table 2. Like the constraints, changes in the interactive variables over time are usually recorded annually. Higher resolutions are possible if more data are available. The analysis of the interactive variables focuses on (a) the interactive variables' values at the most recent time instant, which provide insights into the current status of the market, and (b) the direction, gradient, and volatility of the trends, which provide insights into the market dynamics.

The demand, supply, and price are of direct relevance to the mineral consumers. In general, a critical mineral is likely to exhibit (a) a strong growth of the demand, (b) a rise of the price, and (c) a high level of price volatility over time, which correspond to the following: (a) the consumer's dependency on the mineral was growing at a fast pace, (b) the increase in the supply could not catch up with the increase in the demand, and (c) an inconsistent supply of the mineral subjected to sudden and unexpected fluctuations.

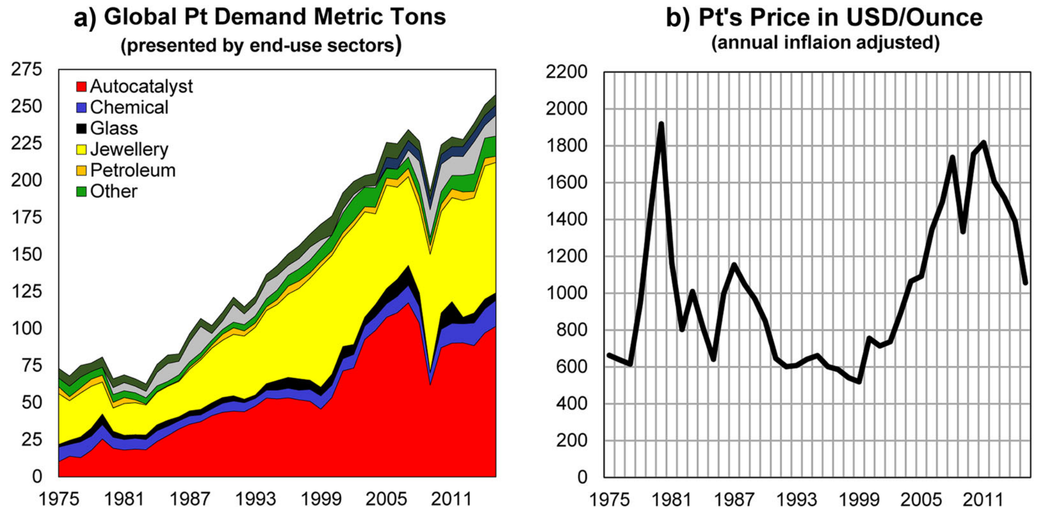

FIGURE 4 (a) The demand for platinum worldwide from 1975 to 2015 presented in terms of different end-use sectors, (b) platinum's yearly price adjusted for the United States' inflation
Note. Pt is the abbreviation for platinum; USD is the abbreviation for the U.S. Dollars. Data used to create this figure are available in Supporting Information S2.

It is commonly accepted that the supply concentration is an aspect of criticality (EU, 2014; Graedel et al., 2012; Mudd, 2012; NRC, 2008). In our methodology, both the supply concentration and the concentration of consumption are being considered using the CR4 scores calculated according to Equations (2) and (3) in Table 2 due to the following reasons: In the global market, if a handful of consumers consume a large share of the total consumption, it is likely that these consumers will have enough market power to push the market away from competition, making the market dynamics more unpredictable and the mineral more critical to other consumers.

When a mineral is critical to a country, the regulator in that country is likely to act aggressively. Therefore, we developed a model that quantifies the level of aggressiveness of a regulator according to Equations (4)–(9) in Table 2. We also built a model to analyze the criticality scores from the previous reports, studies, and publications conducted by government agencies, independent organizations, and academic institutions, which provide insights of the criticality from the respective independent from the market.

To demonstrate the analysis of the interactive variables, we again use platinum as an example. During the period from 1975 to 2015, the annual demand for platinum worldwide shown in Figure 4 (Matthey, 1975–2015; USGS, 2005) has a linear growth trend with an OLS gradient of 0.678, a p-value of smaller than 2.00×10^{-16}, and an adjusted R-squared value of 0.89, indicating that the demand was steadily growing at a rate of approximately 0.678 tonnes/year during this period. The inflation-adjusted price shown in Figure 4 (Matthey, 1975–2015; USGS, 1975–2015b), on the other hand, fluctuated violently while growing during this period, showing an OLS gradient of 13.581 and a p-value of 8.90×10^{-3}. These observations coincide with our descriptions about the critical mineral's demand–supply dynamics at the beginning of this section (i.e., strong growth of the demand, a rise of the price, and a high level of price volatility).

3.3 | The constraint–variable correlations

3.3.1 | Further modeling

To manage the level of complexity, additional assumptions and further modeling are needed before we discuss the constraint–variable correlations. The demand–supply–price interaction (DSPI) model illustrated by Figure 5 is created, in which the following assumptions are made:

- the constraints in one period will only affect the interactive variables the in the same period;
- some interactive variables in one period (the demand and the supply) will interact with each other under a certain environment (the market structure) to generate the rest of the interactive variables in the same period (the price and the regulators' behaviors);
- the interactive variables in one period will affect the interactive variables in the next period, and potentially even the interactive variables in the periods after. This is referred to as *the latent effect* hereafter.

These assumptions can be relaxed to allow more complex interactions. The latent effect in the DSPI model is designed to simulate the delayed impact of one variable to others in the minerals market, for example, the increase of mineral supply is usually slower to respond the increase of the demand.

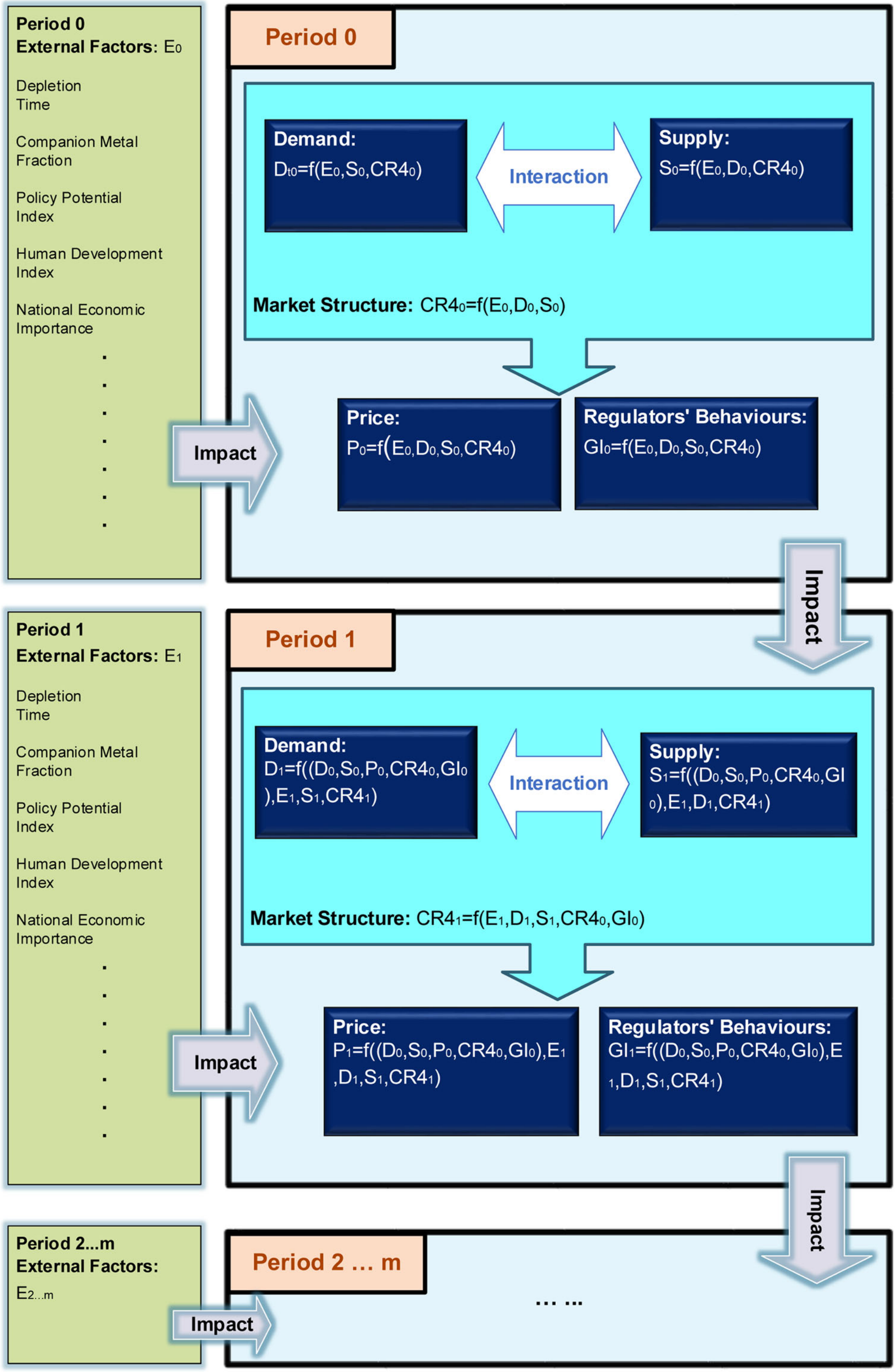

FIGURE 5 The demand–supply–price interaction (DSPI) model

Note. D is the abbreviation for demand, S is the abbreviation for supply, P is the abbreviation for price, E is the abbreviation for external factors, GI is the abbreviation for government behaviors.

3.3.2 | The analysis of the constraint–variable correlations

According to the DSPI model in Figure 3, Equations (12)–(16) are formulated to illustrate how the interactive variables of a mineral in period *t* are affected by the constraints of the mineral in the same period:

$$D_t = f_{DE}\left(E_t\right) \tag{12}$$

$$S_t = f_{SE}\left(E_t\right) \tag{13}$$

$$CR4_t = f_{CRE}\left(E_t\right) \tag{14}$$

$$P_t = f_{PE}\left(E_t\right) \tag{15}$$

$$GI_t = f_{GIE}\left(E_t\right) \tag{16}$$

$$E_t = \{DT_t, CMF_t, WPPI_t, WHDI_t, WWGI - PV_t, TPPI_t, THDI_t, TWGI - PV_t, PS_t, NEI_t, PPU_t, SP_t, SA_t, EIR_t, NIR_t, GII_t\} \tag{17}$$

where D_t, S_t, $CR4_t$, P_t, and GI_t are the demand, supply, market structure, price, government behaviors of a mineral, at period t, respectively; f_{DE}, f_{SE}, f_{CRE}, f_{PE}, and f_{GIE}, are the unknown correlations between the constraints and the interactive variables; E_t is the set containing the constraints; DT_t, CMF_t, PPI_t, HDI_t, PS_t, NEI_t, PPU_t, SP_t, SA_t, EIR_t, NIR_t, and GII_t, are the constraints according to Table 1 of the main article and Table S1-1 from Supporting Information S1 on the Web for period t, respectively.

Tables S1-2 to S1-7 in Supporting Information S1 on the Web summarized the analyses of the constraint–variable correlations. Here, we discuss a case study about platinum (referred to as case study 1 hereafter) to demonstrate the importance of the constraint–variable correlations to the criticality assessment, in which the following relationships were revealed by analyzing the datasets of (a) the demand and supply of platinum, and (b) the social–political environments of major platinum-producing counties during the past decades (Brown et al., 2012–2016; Kaufmann, Kraay, & Mastruzzi, 2011; Matthey, 1975–2015; UN, 1990–2015; USGS, 1975–2015a):

- the increase of the platinum's annual supply is positively associated with the decrease of THDI of South Africa with strong statistical significance;
- the increase of the platinum's annual supply does not appear to be associated with the rise of the transformed policy potential index (TPPI; discussed in Table S1-2) of South Africa with strong statistical significance;
- the increase of the annual demand for platinum in the European Union is positively associated with the increase of platinum's annual supply from South Africa with strong statistical significance;
- the increase of the annual demand for platinum in the European Union does not appear to be associated with platinum's annual supply from Russia with strong statistical significance;

Thus, we conclude that

- the demand for platinum in the European Union is more dependent on the supply from South Africa than on the supply from Russia, which indicates that the European Union will experience more direct and serve impact should the supply from South Africa be restricted, and therefore is more vulnerable to the supply restriction from South Africa than to the supply restriction from Russia.
- the demand for platinum in the European Union is more vulnerable to the supply risk associated with the intolerance to the intrusive developments of mining industries in South Africa (represented by South Africa's THDI) than to the supply risk associated with governmental and non-governmental barriers to mining activities in South Africa (represented by South Africa's TPPI).

3.4 | The mutual-variable correlations

According to the DSIP model in Figure 3, Equations (18)–(22) were formulated to show how the interactive variables at period t are (a) associated with other interactive variables at period t and period $t-1$, (b) are associated with the constraints at period t.

$$D_t = f_D\left(E_t, S_t, CR4_t, D_{t-1}, S_{t-1}, CR4_{t-1}, P_{t-1}, GI_{t-1}\right) \tag{18}$$

$$S_t = f_S\left(E_t, D_t, CR4_t, D_{t-1}, S_{t-1}, CR4_{t-1}, P_{t-1}, GI_{t-1}\right) \tag{19}$$

$$CR4_t = f_{CR}\left(E_t, D_t, S_t, D_{t-1}, S_{t-1}, CR4_{t-1}, P_{t-1}, GI_{t-1}\right) \tag{20}$$

$$P_t = f_P\left(E_t, D_t, S_t, CR4_t, \mathrm{GI}_t, D_{t-1}, S_{t-1}, CR4_{t-1}, P_{t-1}, GI_{t-1}\right) \tag{21}$$

$$\mathrm{GI}_t = f_{GI}\left(E_t, D_t, S_t, CR4_t, P_t, D_{t-1}, S_{t-1}, CR4_{t-1}, P_{t-1}, GI_{t-1}\right) \tag{22}$$

where D_t, S_t, $CR4_t$, P_t, and GI_t are the interactive variables, that is, the demand, supply, market structure, price, government behaviors in period t, respectively; D_{t-1}, S_{t-1}, $CR4_{t-1}$, P_{t-1}, and GI_{t-1} are the interactive variables in period $t-1$, respectively; f_D, f_S, f_{CR}, f_P, and f_{GI}, are the unknown correlations; E_t is the set contains the constraints at period t according to Table 1 of the main article and Table S1-1 from Supporting Information S1 on the Web.

According to Equations (18)–(22), the mutual-variable correlations can be further divided into two categories: the *within-period correlations* and the *interperiod correlations*. For instance, the relationship between the demand in period t (D_t) and the price in the same period (P_t) is a within-period correlation; the correlation between the demand in period $t-1$ (D_{t-1}) and the price in the period t (P_t) is an interperiod correlation.

3.4.1 | The within-period correlation

Tables S1-8 to S1-12 in Supporting Information S1 on the Web show the analyses of the within-period correlations. To demonstrate the importance of the within-period correlations to the criticality assessment, we discuss another case study (referred to as case study 2 hereafter) using platinum as an example. Using the datasets used in case study 1, the multiple linear regression of platinum's annual supply from South Africa onto platinum's annual demand from the European Union, Japan, and North America during the period from 1975 to 2015 (Matthey, 1975–2015; USGS, 1975–2015a) showed that the increase of the annual supply of platinum from South Africa (unit in metric tons) is associated with the increase of the annual demand for platinum (unit in metric tons) in the European Union with strong statistical significance. An OLS gradient of 0.62 and a p-value of 8.40×10^{-5} were found for this multiple linear regression. Whereas such a strong relationship is not present between (a) the supply from South Africa and the demand in Japan, and (b) the supply from South Africa and the demand in North America. Thus, we conclude that the impact on the European Union, should the supply of platinum in South Africa fluctuate, will be more direct and severer than the impact on North America and Japan.

3.4.2 | The interperiod correlations

For the interperiod correlations, we focused on the interperiod demand–price correlation, as it is highly representative of the market dynamics. From Equation (21), it is not hard to show the following relations:

$$(P_t - P_{t-1}) = f_{DP1}\left(D_t - D_{t-1}\right) \tag{23}$$

$$(P_t - P_{t-2}) = f_{DP2}\left(D_t - D_{t-2}\right) \tag{24}$$

$$(P_t - P_{t-3}) = f_{DP3}\left(D_t - D_{t-3}\right) \tag{25}$$

$$(P_t - P_{t-4}) = f_{DP4}\left(D_t - D_{t-4}\right) \tag{26}$$

Where $P_t, P_{t-1}, P_{t-2}, P_{t-3}, P_{t-4}$ are the price at time t, one period before t, two periods before t, etc. $D_t, D_{t-1}, D_{t-2}, D_{t-3}, D_{t-4}$ are the demand at the time t, the period before t, two periods before t, etc. If the unit for each period over m periods is a year, Equation (12) investigates the correlation between the rate of change of price (ΔP_{t-1}) and the rate of change of demand (ΔD_{t-1}) between 2 consecutive years; Equation (13), 3 consecutive years; so on and so forth. The reason for including Equation (14)–(15) rather than including Equation (12) alone is that the former captures the latent correlations between the rate of change of the price and the rate of change of the demand over more than 2 consecutive years.

When the demand for a product is increasing while the supply is experiencing difficulties to keep up with the demand, the price rises, and vice versa. In light of this, if a strong and positive relationship with a steep gradient exists between the ΔP_{t-1} of a mineral and the ΔD_{t-1}, the mineral is likely to be in high risk of supply restrictions. Other interperiod correlations like, for example, how does the rate of change of the price of a mineral correlate to the rate of change of the market structures of the mineral; how does the rate of change of the price of a mineral correlate to the rate of change of the supply of the mineral from a major mineral exporting country, all can be analyzed in a similar manner.

3.5 | The criticality-evaluation steps

To separate the "more-critical" minerals from the "less-critical" minerals, we propose a four-step method.

Step one: Constructing the criticality systems of the minerals of interest.

The user (e.g., a hypothetical country θ) needs to construct the criticality systems corresponding to the minerals of interest (e.g., the criticality systems of the hypothetical minerals of interest A, B, C, D, E, and F).

Step two: Constructing the criticality vectors.

The user needs to compare the indicators of these criticality systems. The indicators of different criticality system subjected to comparison need to reflect the same aspect of the supply risk or the vulnerability from the perspective of the user. For example, the user could compare a constraint such as the NEI of mineral A to those of minerals A, B, C, D, E, and F.

During the comparison, it is important to compare not only the static values of these indicators at the most recent time instant (e.g., the NEIs of minerals A, B, C, and D to country θ in the year 2015) but also (a) the average values during a specific period, presenting "a summary over time" of these indicators (e.g., the average values of the NEIs of minerals A, B, C, D, E, and F to country θ during the period from 1975 to 2015), (b) the results of the linear trend analyses using both OLS regression and robust linear regression with Huber weights, allowing the comparative analysis of the evolutions of one indicator in different minerals' criticality systems over time (e.g., the OLS gradients and the robust gradients of the linear trend analyses of the NEIs of minerals A, B, C, D, E, and F during the period from 1975 to 2015).

Table S1-13 in the Supporting Information S1 on the Web summarizes the comparisons needed to be made when the user (country θ) is trying to compare the criticalities of minerals A and B (due to the limitation of space, minerals C and D are not shown here; the user can add as many minerals as deemed necessary). Specifically, the user (country θ) needs to compare the *value vectors* of the interesting minerals (value vectors A and B are highlighted in deep red and blue, respectively, in Table S1-13) in order to separate the "more-critical minerals" from the "less-critical minerals". In Table S1-13, each row of mineral A's and B's value vectors can be interpreted as a dimension of the criticality to country θ. For example, the row 25 of Table S1-13 provides the information about the linear trends of the NEIs of mineral A and mineral B to country θ during the period from 1975 to 2015, which demonstrates how fast the NEIs of mineral A and mineral B changes. We have designed the vector so that the bigger the value in each row of the vector, the more critical the corresponding dimension is to the user.

Step three: Classification analysis or clustering analysis of the value vectors.

When the criticality statuses of the interesting minerals are obvious, classification algorithms such as support vector machines can be used to analyze their value vectors. This requires labeling of all minerals of interest before evaluation. For instance, minerals such as REEs and Pt are commonly referred to as more critical, and thus their value vectors need to be labeled as 1; less-critical minerals such as iron ore can be labeled as 0. Guided by the labels, the separation of value vectors using classification algorithms leads to the differentiation of more-critical minerals from less-critical minerals, which can be used for future criticality evaluations of minerals with unknown criticality statuses. This is referred to as *the supervised approach*.

When the criticality statuses of the interesting minerals are less obvious, based on their value vectors, both K-means clustering and hierarchical clustering algorithms can be used to separate the minerals into different clusters. The mineral being clustered into the cluster that has the highest average value of all dimensions (i.e., the highest average value of all rows of the value vector) is determined to be "more critical", and vice versa. This is referred to as *the unsupervised approach*.

K-means clustering algorithm is a simple yet elegant algorithm. However, it requires the user to predetermine the number of clusters, and then the algorithm separates the value vectors into the number of non-overlapping clusters bond by the predetermination. The predetermination could be challenging due to the fact that the value vector in any criticality system is high dimensional, which makes the user difficult to intuitively preselect the number of clusters. In contrast, if the value vector is two-dimensional or three-dimensional, the user can first visualize the value vector and predetermine the number of clusters. Thus, we recommend hierarchical clustering algorithm, which completely avoids the issue of the predetermination of clusters. Furthermore, in most programming environments (R Language for example), a tree-based visualization is available for the result of the hierarchical clustering, which makes the result more interoperable.

Step four: Further analysis of those "more critical" mineral.

When the user pinpointed those "more critical" minerals via clustering algorithms or classification algorithms, further analyses focusing on the constraint–variable correlations and the mutual-variable correlations are possible. For example, if mineral A is determined to be more critical, statistical relationship among the PPUs of mineral A to country θ and the price can be analyzed and will help to determine how the fluctuations in price affect the percentages of population utilization of mineral A in the country θ. In addition, these observations can be further compared among different minerals from the country θ's perspective.

4 | CONCLUSIONS

In this article, we introduced a new concept—the criticality systems of minerals. We also introduced a new criticality-assessment methodology—comparing the criticality systems of minerals and looking for patterns and trends that differentiate critical minerals from non-critical minerals via the supervised and unsupervised approaches. The "outer layer" of the criticality system encompasses three types of indicators: the constraints, the agents' interactions, and the interactive variables, all of which focus around the "kernel" of the system—four groups of agents: the consumers, the suppliers, the regulators, and others. All these indicators and agents are intrinsically linked and constantly interact with each other.

We approach the evaluation of mineral criticality via four steps: (a) gather the indicators of a target mineral, (b) formulate its criticality system, (c) compare its criticality vector to those of other minerals, (d) classifying criticality according to the comparisons made via clustering algorithms or classification algorithms, and (e) further analyses via examining and comparing the constraint–variable correlations and the mutual-variable correlations.

The criticality system is designed to be able to empirically demonstrate the statistical relationships between the dynamics of the mineral's market system and industrial ecology and the indicators used, to analyze the interactive and dynamic nature of mineral criticality, to be comparative in nature so that the evaluations of multiple minerals are possible.

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CONFLICT OF INTEREST

The authors have no conflict to declare.

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