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Assessing supply risks for non-fossil mineral resources via multi-criteria decision analysis

Dominik Jasiński[a,*,1], Marco Cinelli[a,b,2], Luis C. Dias[c], James Meredith[d], Kerry Kirwan[a]

[a] Warwick Manufacturing Group, University of Warwick, Coventry CV4 7AL, UK
[b] Institute of Advanced Study, Millburn House, University of Warwick Science Park, Coventry CV4 7HS, UK
[c] INESC Coimbra, CeBER and Faculty of Economics, University of Coimbra, Av. Dias da Silva 165, 3004-512 Coimbra, Portugal
[d] Department of Mechanical Engineering, University of Sheffield, S1 3JD, UK

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ABSTRACT

Criticality assessments of raw materials are inherently based on multiple criteria, which justifies the use of multi-criteria decision analysis (MCDA) to aid the interpretation of the data by providing a comprehensive evaluation. A structured and transparent selection procedure is firstly introduced in this paper to choose eight supply risk assessment criteria to evaluate the security of supply for thirty-one raw materials used in automotive manufacturing. A synergic combination of MCDA methods is then proposed for the classification of raw materials in risk classes according to the supply risk criteria. Risk classes are recommended following from a robustness analysis based on stochastic and optimisation MCDA methods where risk levels assigned to the raw materials are firstly visualised on a relative frequency basis. The sorting of the raw materials is also refined by narrowing down the best and worst plausible classes when justifiable constraints on criteria weights are accounted for in the modeling. For example, the robustness analysis suggests that rare earth elements and tellurium have a high eventuality of supply chain disruption, closely followed by indium, germanium and boron. Conversely, the results suggest that the risk of supply disruption for iron, copper, zinc and aluminium is mostly medium-low or low. The proposed step-wise decision support approach can be used as a complementary tool to the existing life cycle assessment methods for a more comprehensive assessment of the short-term availability of natural resources.

1. Introduction

An uninterrupted supply of raw materials, free from disturbances and bottlenecks that may lead to volatility in commodity pricing and markets, is a requirement for sustainable economic development. Erdmann and Graedel (2011) Sectors that rely heavily on raw materials (e.g. construction, manufacturing, and transport) are extremely vulnerable to any physical shortage or increasing prices of these materials. Schneider et al. (2014) As such, the need for a systematic quantification and assessment of the risks and impacts related to the increasing depletion of natural resources is currently more important than ever (Rørbech et al., 2014).

The methods applied to assessment of the potential consequences associated with resource use frequently come from life cycle assessment (LCA) literature (Rørbech et al., 2014; Klinglmair et al., 2014). However, existing LCA models focus exclusively on the mid- to long-term geologic and economic finiteness of resources. They ignore other technological, geopolitical, regulatory and social risk factors (e.g. wars, market imbalances, governmental interventions or restrictions to mining due to environmental degradation) that may lead to supply disruptions and increasing commodity prices in the short term (Erdmann and Graedel, 2011; Schneider et al., 2014; Drielsma et al., 2016). Consideration of these additional risk factors in the evaluation of resource depletion impacts has recently emerged as a new research field

Abbreviations: MCDA, multi-criteria decision analysis; ELECTRE, ELimination and Choice Expressing Reality; SMAA-TRI, Stochastic Multicriteria Acceptability Analysis for ELECTRE TRI; IRIS, Interactive Robustness analysis and parameters' Inference for multicriteria Sorting problems; CAI, Class Acceptability Indices; C_i, Risk class *i*; g_j, Criterion *i*; w_i, Weight of criterion *i*; Pr_h, Class profile *h*; a_i, Alternative i; c a_i, Pr_h, Concordance index for considering alternative i at least as good as class profile h; λ, Lambda = minimum cumulative weight of the criteria to grant a classification; ‡, Cases where the coalition of six criteria is sufficient to grant the classification IRIS; *, Cases where fewer than six criteria trigger the classification with IRIS

* Corresponding author.
E-mail address: d.jasinski@warwick.ac.uk (D. Jasiński).
[1] Current address: Exergy Ltd, Design Hub, Coventry Technology Park, CV1 2TT, UK.
[2] Current address: Future Resilient Systems (FRS), Swiss Federal Institute of Technology (ETH) Zurich, Singapore-ETH Centre (SEC), Singapore.

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and is known as 'minerals criticality assessment' (Drielsma et al., 2016; Helbig et al., 2016). The European Commission (EC) classes a raw material as critical when it faces high risks with regard to access to it, e.g. high supply risk or high environmental risks, and it is of high economic importance. EC (2010) Material criticality is determined by plotting the likelihood of supply disruption (the supply risk) against the vulnerability due to supply disruption, which can be interpreted as a measure of the economic importance of a raw material with consideration of potential direct substitution (Glöser et al., 2015).

Despite relevant contributions from, for example, the US National Research Council (Eggert et al., 2008), Yale University (Graedel et al., 2012; Nassar et al., 2012) and EC (EC, 2010, 2014, 2017; Chapman et al., 2013), minerals criticality assessment remains a new area of research with no widely agreed methodology developed to date (Glöser et al., 2015; Achzet and Helbig, 2013). The observed criticality studies differ with respect to (1) system under study (e.g. economy, country, company or technology), (2) criticality dimensions, (3) the choice of assessment criteria and indicators, (4) indicators weightings and aggregation method, (5) criticality assessment method (e.g. criticality index, criticality matrix or 3-dimensional vectors), (6) the reliance on quantitative data from third parties or expert judgement; and, (7) the degree to which the assessments are forward looking (or not) (Erdmann and Graedel, 2011; Achzet and Helbig, 2013).

While the choice of criticality dimensions, assessment criteria and weightings is subjective and associated with individual judgement, a consistent aggregation of criticality indicators into meaningful indices requires clear-cut methodological requirements (Böhringer and Jochem, 2007; Merad et al., 2004).

Criticality assessments are inherently based on multiple criteria, which calls for the use of multi-criteria decision analysis (MCDA) to provide a comprehensive evaluation. This evaluation can be provided in the form of a ranking, scoring or classification of raw materials by accounting for the evaluation criteria in an integrated manner.

MCDA is a process whose scope is to support decision makers (DMs) in structuring, understanding and solving a problem so that an informed decision can be recommended (Roy, 1996). It is emerging as a valuable strategy to carry out complex assessments due to its ability to effectively handle different types of information, include stakeholders' values and provide a transparent interpretation of the results (Cinelli et al., 2014; Balteiro-Dias et al., 2017). It has been widely used to support sustainability-related decision making (Diaz-Balteiro et al., 2017; Dias et al., 2015) and case studies have also emerged to evaluate criticality of raw materials (Schneider et al., 2014; Nassar et al., 2012; Bauer et al., 2011). The most used MCDA method in this area is the weighted sum approach (Erdmann and Graedel, 2011; Achzet and Helbig, 2013).

To date, the effect of uncertainties in data sets and variations in criteria weights have not been adequately addressed and the literature suggests that more research should be conducted to fill these research gaps and provide examples of robust assessments (Erdmann and Graedel, 2011; Glöser et al., 2015; Achzet and Helbig, 2013). This article is a response to this call by presenting the use of ELimination and Choice Expressing Reality (ELECTRE)-based methods to provide a classification system for the supply risk of raw materials, one of dimensions that determine a material's criticality (together with environmental implications and vulnerability to supply restriction) (Graedel et al., 2012). ELECTRE methods exhibit appealing advantages in comparison with other methods, such as weighted sum (Figueira et al., 2016): the weights of the criteria represent their "voting power" and are independent of their measurement scales, they are non-compensatory (they do not require trade-off rates), they allow performing sophisticated modeling through indifference, preference and veto thresholds and can accommodate any criteria without the need for any transformation.

In this paper we propose two novel contributions:

1. The development of an approach to assess the supply risk of raw materials;
2. The proposal of a synergistic use of MCDA methods to assign a risk class to each material by means of the integrated use of methods for ELECTRE-TRI based on algorithms for stochastic analysis (i.e. SMAA-TRI, Stochastic Multicriteria Acceptability Analysis for ELECTRE TRI) (Tervonen and Lahdelma, 2007) and optimisation (i.e. IRIS, Interactive Robustness analysis and parameters' Inference for multicriteria Sorting problems) (Dias et al., 2002).

To the best of the authors' knowledge, this is the first study of its kind to propose a classification system for raw materials criticality based on a synergistic use of classification methods, or based on driving robust conclusions from a set of weighting vectors.

The methodology adopted to select the evaluation criteria and indicators is presented in Section 2 together with the identification strategy of relevant MCDA methods. Section 3 presents the supply risk matrix and the robust classifications of the materials in risk levels. The results are presented in Section 4 demonstrating how the approach proposed in this paper can enhance the decision support potential of individual supply risk criteria and transparently inform DMs.

2. Materials and methods

2.1. Sample minerals and evaluation criteria

Sample minerals selected for this study are metals and metalloids used in automotive manufacturing. The automotive context in this paper derives from the fact that this research received support from a major British car manufacturer. Thirty-one minerals were selected based on the analysis of materials used to manufacture a diesel-hybrid vehicle, the most complex car in the company's range. The evaluation criteria selected in this study focus exclusively on supply risks (likelihood of supply disruption) associated with increased depletion of raw materials.

General guidelines to aid the assessment criteria selection process were proposed in the literature (Akadiri and Olomolaiye, 2012) and practically applied in the context of sustainable development. Akadiri et al. (2013); Cinelli et al., 2016; Jasiński et al., 2016 These guidelines are largely in line with the recommendations of the Organisation for Economic Co-operation and Development (OECD) and the European Commission Joint Research Centre (EC-JRC) for the construction and use of composite indicators. OECD (2008) The assessment criteria selected should be transparent (the selection process should be clear and understandable), comprehensive (i.e. they should measure each element of a multidimensional concept), applicable across a range of alternative options to ensure comparability and practical in the sense of the tools, time and resources available for analysis (Akadiri and Olomolaiye, 2012; Akadiri et al., 2013; Cinelli et al., 2016; Jasiński et al., 2016)

Following this set of guidelines, the supply risk assessment criteria were first identified based on the review of existing raw materials criticality studies (see Table S1 in Supplementary information for a summary). These criteria were then organised into six main areas of concern (geological, technological, economic, geopolitical, regulatory and social) (Graedel et al., 2012) to form a theoretical framework for the comprehensive supply risk assessment. Finally, all criteria were assessed against four attributes to evaluate whether a specific criterion is suitable to be used in the overall supply risk evaluation (OECD, 2008). These attributes were:

- **applicability** (the degree to which an indicator allows comparability of alternative options);
- **relevance** (the degree to which an indicator covers and contributes to the required topic and concept);
- **accessibility of the data** (the degree to which the data can be

Table 1
The initial framework of the supply risk composite index.

Supply risk components	Supply risk criteria	Potential source of data	Attributes sought			
			Applicability	Relevance	Accessibility	Credibility
Geological risk	Reserve availability	US Geological Survey (USGS) (USGS)	√	X	√	√
	Mine capacity utilisation	Various sources	X	X	X	X
Technological risk	Co-production	Yale University (Nassar et al., 2015)	√	√	√	√
	Recyclability	United Nations Environmental Programme (UNEP) (Graedel et al., 2011), Oakdene Hollins and Fraunhofer ISI (Chapman et al., 2013)	√	√	√	√
	Market substitutability	Oakdene Hollins and Fraunhofer ISI (Chapman et al., 2013)	√	√	√	√
Economic	Demand growth	Oakdene Hollins and Fraunhofer ISI (Chapman et al., 2013)	√	X	√	√
	Historical price volatility	USGS (USGS)	√	√	√	√
	Market balance	Various sources	X	√	X	X
	Minerals production cost	Various sources	X	√	X	X
	Investment in mining	Various sources	X	√	X	X
	Stock keeping	Various sources	X	√	X	X
Geopolitical	Global supply concentration	USGS for country concentration (USGS), no data for company concentration	√	√	√	√
	Governance stability	The World Bank (The World Bank, 2016)	√	√	√	√
	Import dependence	Local geological surveys or statistical agencies	X	√	X	√
	Climate change vulnerability	German Advisory Council on Climate Change (WBGU and Climate change, 2007)	X	X	√	√
Regulatory	Environmental standards	Yale University (Hsu et al., 2016)	√	√	√	√
	Attractiveness of a country for exploration of resources (Policy Potential Index)	The Fraser Institute (Jackson and Green, 2015)	X	√	√	√
	Trade barriers	Various sources	X	√	X	X
Social	Subeconomic stability	United Nations Development Programme (UNDP) (Jahan et al., 2015)	√	√	√	√
	Press coverage – number of articles published	Various sources	X	X	X	X

accessed for use); and

- **credibility of the data** (whether the data originate from or were produced by authoritative and credible institutions).

Table 1 compares all criteria against these four attributes, with an X indicating a negative assessment and √ indicating a positive assessment of a criterion. Only those criteria which were assessed positively against all four attributes were considered in the construction of the supply risk composite index. The remaining criteria are either still immature, lacking in credible data or are not relevant in the context of what is being measured. For example, the geological availability measure is considered credible and is used by eleven criticality assessment studies but was dismissed by the EC as an inadequate indicator of raw materials criticality. The timescales associated with geological availability were deemed to be too long to have any relevant impact on the materials criticality assessment. EC (2014)

The demand growth indicator was not used in this work for similar reasons. Many critical materials will experience a supply surplus in the near future despite a high growth in demand for them (Chapman et al., 2013). However, this may change in the long run as rising demand leads to the supply of these resources becoming increasingly depleted. Hence, beyond the scope of this work, a combination of long-term forecasts of the raw materials' likely demand and supply conditions and geological assessment should extend the criticality analysis to provide a forward-looking view of the future availability of raw materials and the threat of them becoming scarce (Chapman etal., 2013; EC, 2014).

Policy Potential Index (PPI) is a promising indicator that measures the policy attractiveness of a country to exploration investments and thus the potential for expanding minerals production in the future; however, the lack of data for all countries prevents it from being applied to all minerals (Chapman et al., 2013). Import dependency suffers similar limitation as the PPI indicator. Although data are generally available for the major metals from trade ministries or via databases (e.g. the United Nations Commodity Trade Statistics Database), for scarcer metals, such information is not widely available in public databases (Graedel et al., 2012), making comparability of alternative options and minerals difficult. There are also supply risk criteria that have not been previously considered in any criticality assessment study but which offer potential for use in the future. For instance, the Extractive Industries Transparency Initiative (EITI) is a potential measure of revenue transparency and accountability in the extractive sector, while Registration, Evaluation, Authorisation and Restriction of Chemicals (REACH) legislation can identify raw materials whose use in the future may be banned or restricted due to the carcinogenic, mutagenic or toxic substances that may be derived from them (Chapman et al., 2013). It should be noted that with the availability of more data, there would be no restriction to including these criteria to expand the supply risk assessment proposed in this article.

2.2. Supply risk indicators and discriminatory performance levels

Assessment criteria are measured via indicators (Foxon et al., 2002), which, for this study, were determined for the eight selected criteria of recyclability, substitutability, co-production, historical price volatility, country concentration of production, governance stability, environmental standards and subeconomic stability. Furthermore, ranges were defined to denote the supply risk levels for each indicator and thus the overall risk for a mineral. Schneider et al. (2014); Glöser et al. (2015) Both the supply risk indicators and their accompanying ranges were determined based on best practice and recommendations from authoritative institutions and are summarised in Tables S2 and S3 in Supplementary information.

According to Table S3, classifications based on a single indicator use profiles to define intervals associated with risk levels. The most common case is to define four risk levels, ranging from high, high-medium medium-low to low risk. These four risk levels are also used in the multi-criteria classification models developed in this work, requiring to set ranges defining four classes on each remaining indicator (Table S4 in Supplementary information). No reliable discriminatory ranges were found for the environmental standards indicator. To cope with this limitation, a four-point scale was built based on the percentiles of the distribution of the indicator across all countries (OECD, 2008). Based on this approach, the countries with the highest EPI (above the 75th percentile) received a low risk-class profile, those with an EPI between the 50th and 75th percentiles have a medium-low risk-class profile, an EPI between the 25th and 50th percentiles gives a high-medium risk-class profile and a country with an EPI below the 25th percentile received a high risk-class profile.

2.3. Classification of minerals into supply risk classes

The identification of the overall supply risk of the minerals is difficult when looking at the performance on each criterion independently (see Fig. 3). In fact, for each mineral, some criteria score well (or poorly) whereas some others do not and consequently it is not possible to define whether they can be assigned a high, medium-high, medium-low or low risk class.

In order to solve this challenge, MCDA methods were applied in this research as they can account for the performance of the minerals simultaneously and provide an integrated supply risk evaluation. The procedure for the selection of the MCDA methods and the respective outputs is presented in Fig. 1. It included two phases which are briefly presented below.

2.3.1. Phase 1 of the decision aiding process

Evaluation criteria are identified in a justifiable and traceable manner as described in Section 2.1, but their relative importance is not set in the relevant literature (unless assumptions are made as explained in Phase 2 below). Consequently, the MCDA method needs to be able to handle missing information on the weights of the criteria.

As described in Section 2.2, ranges of performance for allotment to a certain class were determined for each indicator, which implies the introduction of threshold values (i.e. profiles) distinguishing classes of performance (see Table S4).

Regarding the desired capability of the method, a robust classification to preference-ordered classes that takes into account the uncertainty in the input information has been a recurrent call in the literature (Glöser et al., 2015; Achzet and Helbig, 2013).

As a consequence of these modeling needs, the most suitable MCDA method to emerge was SMAA-TRI (Tervonen et al., 2009a), which has already been used in decision-making problems with similar characteristics (Tervonen et al., 2009b; Cinelli et al., 2017). It is an approach based on an algorithm called ELECTRE TRI that allows for the assignement of raw material to risk class on a percentage basis resulting from 10,000 Monte-Carlo simulations of random criteria weights. Details on the SMAA-TRI working procedure can be found in Tervonen et al. (2009c) and (Tervonen, 2014).

2.3.2. Phase 2 of decision aiding process

The second modeling phase modified the preference information by adding constraints on the weights of the criteria. By accounting for the fact that an institution as authoritative as the EU decided to consider four (i.e. recyclability, substitutability, country concentration, governance stability) out of the eight criteria in their framework. EC (2014) Consequently, the four criteria selected by the EU can be seen as having a higher importance than the others and thus higher weight, leading to the weights constraints w_1, w_2, w_5, $w_6 > w_3$, w_4, w_7, w_8 (see upper-right part of Fig. 1).

The selection of the relevant MCDA method was refined by considering that DM can deem a certain minimum number of criteria (in this case 75%) as sufficient to grant a class, without requiring all the criteria to be in favour for it or a better one (Domingues et al., 2015). What is more, knowing the weights of the criteria that lead to a class represented another requirement for the identification of the method, as it can add transparency to the decision recommendation.

This modeling context resulted in the selection of IRIS as a suitable

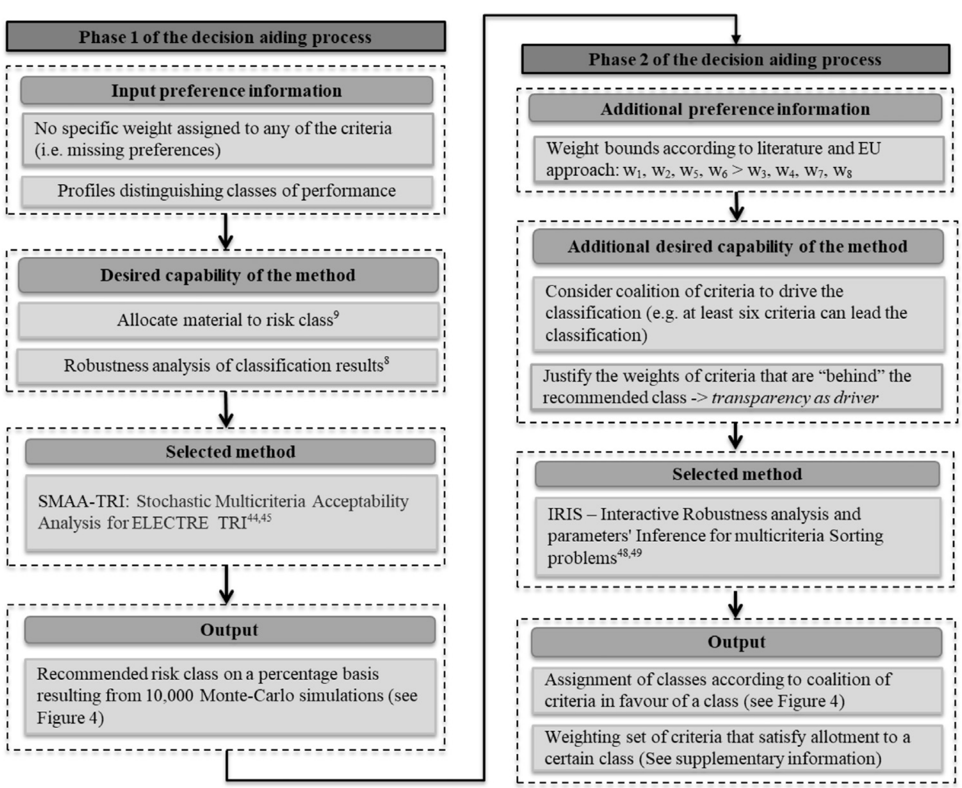

Fig. 1. The methodological procedure for the classification of minerals into supply risk classes.

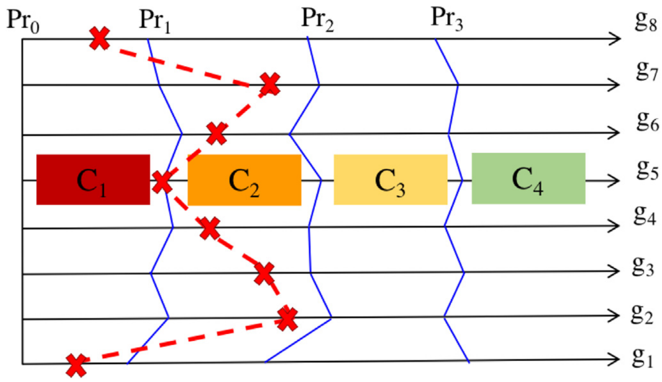

Fig. 2. Example of raw materials scoring in simplified ELECTE-TRI model (C_1 = high risk, C_2 = high-medium risk, C_2 = medium-low risk, and C_4 = low risk are a set of risk classes; Pr_h are risk class profiles; g_j are the criteria used in the classification; the direction of the arrows represents improved performance).

MCDA method (Dias and Mousseau, 2003). IRIS uses an optimisation-based algorithm to provide a range of risk classes together with the values of the criteria weights that drive each classification. IRIS operates with the ELECTRE TRI method as SMAA-TRI. Details on its working procedure can be found in Dias et al. (2002) and Dias and Mousseau (2003).

2.3.3. How does the classification algorithm work?

The models developed in this case study operate with an algorithm named ELECTRE-TRI (Roy, 1991), which sorts the raw materials into risk classes (C_i). This method compares the score for each criterion (g_j) with respect to class profiles (Pr_h), which distinguish between a high (C_1), high-medium (C_2), medium-low (C_3) and low (C_4) risk class (see Fig. 2). Every C_i is defined by two profiles, a lower bound and an upper bound. For example, in the case of C_1 in Fig. 1, Pr_0 is the lower bound profile and Pr_1 is the upper bound profile.

The performance of each criterion for every material is compared with the Pr_h from the worst to the best to evaluate whether such performance is at least as good as the profile (in MCDA terms the verb *outrank* is used). For each criterion in which the raw material equals or overcomes the Pr_h, the respective weight of the criterion is added to a index named concordance ($c(a_i, Pr_h)$). A threshold value denoted λ is used to drive the classification. Starting with $h = 1$, if $c(a_i, Pr_h)$ (which can be also expressed as the cumulative weight of the criteria that equal or overcome the Pr_h) does not reach λ, the minimum cumulative weight of the criteria to grant a better classification, the raw material is allotted to class C_h (C_1 in Fig. 2). If $c(a_i, Pr_h)$ reaches or exceeds λ, the mineral can be assigned to a better class and it is compared with the next profile Pr_{h+1}. The process goes on until we reach a profile Pr_h such that $c(a_i, Pr_h)$ is lower than λ or when we reach the best class.

For instance, in Fig. 2, criteria scores for g_2 to g_7 are at least as good as Pr_1, the upper profile of C_1. The sum of the weights of these agreeing criteria is $w_2 + w_3 + \ldots + w_7$. In case where $w_2 + w_3 + \ldots + w_7 < \lambda$ then the material belongs to class C_1, meaning that the criteria in support of C_2 are not enough to grant such class. In the opposite case, where $w_2 + w_3 + \ldots + w_7 \geq \lambda$, the raw material can be classified to C_2. As it clearly appears from this simple example, the classification procedure of ELECTRE-TRI is driven by the weight of the criteria that are in support of each C_i.

In order to account for the hesitation of DMs in face of uncertainty or imprecision in the values of the criteria and profiles, indifference and preference thresholds (Diaz-Balteiro et al., 2017) were used, which could be extrapolated from the available relevant literature (see Table S4 in Supplementary information). These account for the fact that the difference in performance between each criterion g_j and Pr_h can be considered insignificant if these performances are very close to each other. In practical terms, a criterion value slightly worse than Pr_h might still warrant the support (or the partial support) of that criterion to the hypothesis that the raw material outranks Pr_h.

Criteria / Risk level profiles	g_1 = Recyclability	g_2 = Substitutability	g_3 = Co-production	g_4 = Historical price volatility	g_5 = Country concentration	g_6 = Governance stability	g_7 = Environmental standards	g_8 = Subeconomic stability
	Recycled content	Substitutability index	% of global primary production obtained as a companion	Standard deviation of changes in prices	Herfindahl Hirschman-Index	World Governance Index	Environmental Performance Index	Human Development Index
C_1 = High risk	$g_1 \leq 10\%$	$g_2 = 1.0$ (not substitutable)	$g_3 > 75\%$	$g_4 > 0.40$	$g_5 > 2500$ (very high concentration)	$g_6 < -1.0$	$g_7 < 57.5$	$g_8 < 0.550$
C_2 = High-Medium risk	$10\% < g_1 < 25\%$	$0.7 \leq g_2 < 1$ (hardly substitutable at high cost or loss of performance)	$51\% < g_3 \leq 75\%$	$0.28 < g_4 \leq 0.40$	$2000 < g_5 \leq 2500$ (highly concentrated)	$-1.0 \leq g_6 < 0$	$57.5 \leq g_7 < 69.6$	$0.550 \leq g_8 < 0.700$
C_3 = Medium-Low risk	$25\% \leq g_1 \leq 50\%$	$0.3 < g_2 < 0.7$ (substitutable at low cost but with loss of performance)	$25\% \leq g_3 \leq 50\%$	$0.16 \leq g_4 \leq 0.28$	$1500 \leq g_5 \leq 2000$ (moderately concentrated)	$0 \leq g_6 \leq 1.0$	$69.6 \leq g_7 \leq 79$	$0.700 \leq g_8 \leq 0.800$
C_4 = Low risk	$g_1 > 50\%$	$g_2 \leq 0.3$ (easily substitutable at low cost, no loss of performance)	$g_3 < 25\%$	$g_4 < 0.16$	$g_5 < 1500$ (unconcentrated)	$g_6 > 1.0$	$g_7 > 79$	$g_8 > 0.800$
Criterion preference*	↑	↓	↓	↓	↓	↑	↑	↑
Lithium (Li)	1%	0.7	52%	0.144	4818	1.111	82.94	0.871
Aluminum (Al)	35%	0.7	0%	0.185	2327	0.072	71.84	0.777
Copper (Cu)	29%	0.7	9%	0.184	1332	0.407	75.17	0.788
Magnesium (Mg)	33%	0.7	<5%	0.221	8096	-0.391	66.37	0.736
Gold (Au)	30%	1.0	14%	0.154	621	0.051	72.20	0.742
Niobium (Nb)	22%	0.7	2%	0.179	8021	0.015	79.57	0.772
Nickel (Ni)	35%	0.7	2%	0.325	1458	0.068	69.32	0.700
Chromium (Cr)	19%	0.5	2%	0.144	2682	0.034	69.50	0.706
Beryllium (Be)	17%	1.0	11%	0.133	8491	1.111	82.76	0.896
Silicon (Si)	0%	0.7	0%	0.224	4846	-0.211	70.25	0.756
Iron (Fe)	40%	0.7	<1%	0.142	2112	0.253	74.61	0.788
Lead (Pb)	52%	0.7	10%	0.272	3097	0.003	71.19	0.762
Silver (Ag)	27%	1.0	71%	0.259	986	0.108	77.61	0.770
Rare Earth Elements (REEs)	<1%	0.7	100%	0.728	7595	-0.307	66.69	0.739
Titanium (Ti)	52%	0.7	0%	0.446	958	0.256	69.48	0.735
Zinc (Zn)	22%	0.7	10%	0.211	1758	0.109	71.97	0.765
Molybdenium (Mo)	33%	1.0	46%	0.337	2324	0.327	74.40	0.801
Platinum Group Metals (PGMs)	37%	1.0	35%	0.427	3387	-0.002	75.70	0.730
Vanadium (V)	0%	0.3	82%	0.355	3702	-0.364	70.91	0.733
Antimony (Sb)	18%	0.5	80%	0.270	6285	-0.380	67.69	0.734
Tantalum (Ta)	18%	0.7	28%	0.301	3167	-0.364	53.58	0.532
Tin (Sn)	22%	0.3	3%	0.296	2034	-0.271	59.74	0.616
Gallium (Ga)	37%	0.7	100%	0.213	6236	-0.233	68.19	0.754
Indium (In)	37%	1.0	100%	0.257	3374	0.259	70.88	0.805
Cobalt (Co)	32%	0.7	85%	0.358	2824	-0.548	67.46	0.638
Tellurium (Te)	0%	0.3	100%	0.501	4070	0.622	82.23	0.860
Graphite	0%	0.5	0%	0.203	4876	-0.373	63.41	0.695
Germanium (Ge)	42%	1.0	100%	0.214	4935	0.021	70.15	0.776
Tungsten (W)	46%	0.5	5%	0.180	6736	-0.327	68.02	0.730
Manganese (Mn)	37%	1.0	3%	0.506	1621	0.136	71.12	0.731
Boron (B)	0	1.0	0%	0.194	5097	0.034	70.55	0.774

Fig. 3. Supply risk matrix indicating the ranges of criteria values discerning between the allotment to each class and values for the selected sample materials (g_j = criterion; C_i = risk classes; *: the arrow 'up' signifies that the greater the value on the list of possible values, the better it is, and the arrow 'down' indicates the opposite).

3. Results and discussion

3.1. Supply risk matrix and values

The supply risk matrix containing the eight supply risk assessment criteria and the risk-level profiles determined for each criterion is presented in Fig. 3. A 'high' risk profile (red colour) indicates that a raw material performs extremely poorly in the corresponding (column) criterion and there is thus an increased risk of a supply disruption for this material. This dependence works conversely if a mineral is classified as being in a 'low' risk profile (green colour).

Thirty-one metals and metalloids used in automotive manufacturing were assessed against the supply risk matrix, with each mineral assigned a risk category according to its performance on each supply risk criterion (indicator). Fig. 3 summarises the results for all thirty-one minerals and mineral groups by indicating the performance as well as the resultant risk category within each supply risk assessment criterion. In order to obtain a single HHI, WGI, EPI and HDI score for a particular mineral, the scores for each country were weight-averaged by the annual mining production of that country. This is in line with the approach proposed by Yale University and the EC (Graedel et al., 2012; EC, 2014). The underlying data behind the reported performance and production volumes for all raw materials were submitted in the form of an Excel file in Supplementary information.

The results in Fig. 3 demonstrate that apart from, for example, REEs, Ta and Cu, there is large variability in the distribution of risk-level profiles across minerals. This complicates matters if the aim is to assign a single risk-level profile to a mineral based on all eight assessment criteria. The next section demonstrates the possibility of obtaining robust classifications of the materials in their risk-level profiles based on a synergistic use of SMAA-TRI and IRIS classification methods.

3.2. Supply risk classes via SMAA-TRI and IRIS

The results of the risk class allocations of the raw materials are shown in Fig. 4, illustrating the synergistic contribution of the SMAA-TRI and IRIS methods. The classes are colour-coded from left to right and ordered from the highest risk, C_1, to the lowest risk, C_4. This easily allows DMs to distinguish between the most and least critical materials. Each material is characterised with the share of classifications (CAI – Class Acceptability Indices) based on SMAA-TRI, which can range between 0% and 100% for each risk class (C_i). For different raw material and class combinations, these percentages indicate the proportion of the simulations (using randomly values for the weights and random values for the threshold λ) that place a given raw material in a given class. For each row in Fig. 4, the overall sum of the CAI for the corresponding raw material's potential classifications is always 100%. For instance, the first row of Fig. 4, indicates that REE is in class C_1 for approximately 75% of the simulations and in C_2 for approximately 25% of the simulations (the exact values are provided in the Supplementary information, Excel sheets). CAI can be more concentrated on one C_i, such as in the case of Co and Cr, whose CAI are 99% C_2 and 85% C_3, respectively. In other cases, CAI can be more widespread among the classes. An example is Li, with 19% C_1, 55% C_2, 17% C_3 and 9% C_4. These differences in classifications are due to the combined effect of scoring of the raw materials on the eight criteria, their relation to the Pr_h and thresholds and the use of a range for λ. (for a detailed explanation of how SMAA-TRI leads to the specific CAI percentages displayed in Fig. 4 see Supporting information Section S1) The more widespread the CAI are, the more the risk classification of the material depends on fixing the criteria weights and λ (subjectively, by a DM).

The SMAA-TRI results clearly show the distinction between those materials for which the classification is more robust than others, meaning that the uncertain modeling parameters (i.e. weights and λ value) have a lower effect on the variability of the sorting. Classifications that show more than 50% of the CAI for one class can be considered more robust than other classifications where this does not arise. This occurs for 26 out of 31 materials (i.e. REE, Te, In, Ge, B, Mn, Graphite, V, Li, Co, Si, Mg, Sb, Ta, Ag, Pb, Au, Ti, W, Fe, Sn, Ni, Cr, Cu, Al, Zn). Let us note that the models do not aim at advancing one single deterministic classification based on a single run of the input data. Rather, we consider a wide range of possible combinations of weights and preferences of the DM (through λ values between 0.65 and 0.85) for assignment to a certain class, leading to a probabilistic outcome. Consequently, the DM can clearly see some potential classifications which are more robust than another ones and make a more informed choice, knowing that the evaluation is robust according to multiple models settings.

Furthermore, there are materials where the usefulness of a frequency-based visualisation of the results is even more apparent, and this occurs where a high percentage (e.g. ≥ 80%) of the Monte Carlo iterations support a certain class. In this regard, a nominal indication of a recommended class (e.g. possible classes are C_1 and C_2) can be misleading as a risk-averse DM might be inclined to select the worst from among the possible classes. However, when a high proportion of the CAI recommends a better class (e.g. 10% C_1 and 90% C_2), the DM may accept this sorting, understanding that the combined effect of the uncertain information can only in limited instances support the worst classification of the raw material. This is the case for Co (C_2 for 99% of CAI), Ta (C_2 for 83% of CAI), Au (C_3 for 83% of CAI), Cr (C_3 for 85% of CAI) and Zn (C_3 for 85% of CAI).

As presented in Section 2.3, Phase 2 of the decision aiding procedure refines the modeling. Firstly, information on the weights of the criteria can be introduced based on the work of the EU, leading to the constraint $w_1, w_2, w_5, w_6 > w_3, w_4, w_7, w_8$. In addition, it is possible to assume that DMs might accept three quarters of the criteria to be sufficient to justify a classification and would also like to know the actual weights assigned to the criteria. These modeling settings can be implemented with IRIS software and the results are shown in Fig. 4 with the ‡ and * symbols. Symbol ‡ indicates the worst possible class if a DM accepts that a coalition of six criteria is sufficient to grant the classification (meaning that 75% of the criteria place the raw material in that class, or better). Symbol *, when present, indicates the cases where fewer than six criteria are able to trigger a better classification, while still respecting the constrain that $w_1, w_2, w_5, w_6 > w_3, w_4, w_7, w_8$.

For each raw material, different values for the criteria weights might lead to the same classification. For any given material-class pair that might occur, IRIS yields a representative combination of weights that leads to classify that raw material in that class. This combination is chosen, among other possible ones, by selecting the one that is farther away from violating any of the constraints. The specific weights that IRIS model calculates for each possible material classification are reported in the Supplementary information, Excel sheets.

This setting leads to a more definitive differentiation of the materials because the available variability of the models parameters was restrained. It can be seen that the classification becomes more detailed: the number of possible recommended classes decrease between one and three when compared with the SMAA-TRI results. This step-wise approach can be used as a means to drive the decision-making process towards a more thought-through procedure.

For example, based on SMAA-TRI, there is a 15% and 30% chance of Nb being allocated to C_1 and C_2 respectively, a 47% chance of it being allocated to C_3 and only a 8% chance of it going to C_4. Hence, it can be assumed that there is a large probability of Nb being allocated to either class C_1, C_2 or C_3 if weights are missing (i.e. SMAA-TRI results). However, by imposing certain constraints on the results (i.e. weights and criteria coalition), C_3 is a class with at least 75% of the criteria in its favour (i.e. IRIS results), which could be considered sufficiently robust by a DM to perform an informed choice.

As far as the IRIS sortings are concerned, the high risk class (C_1) is assigned when there are less than six criteria supporting a better class, and their combined weight is (for some of the accepted weight vectors)

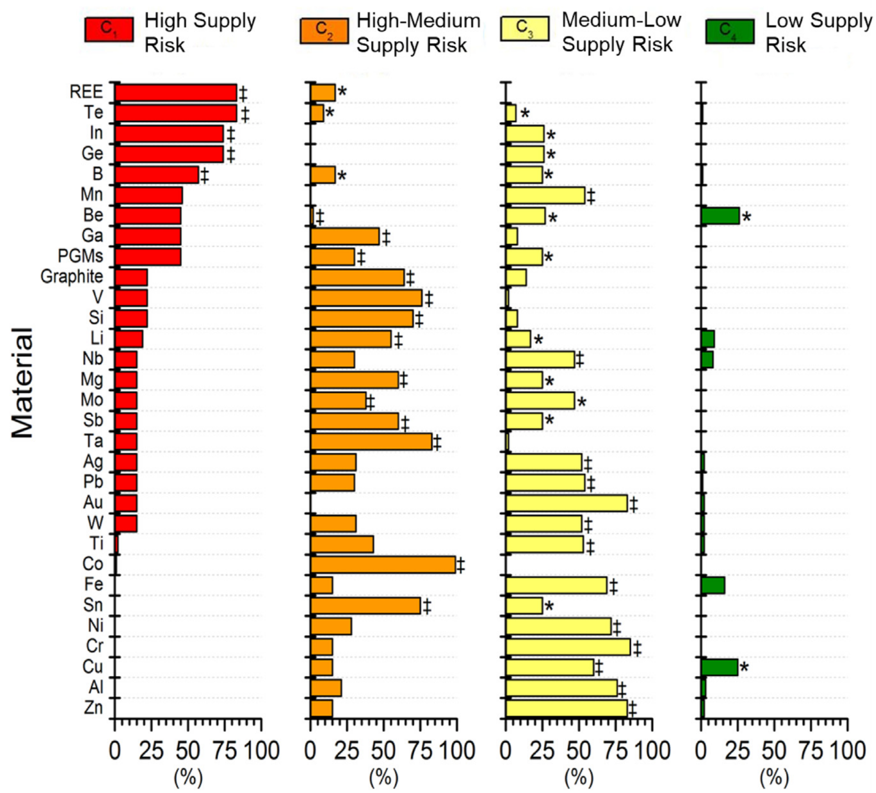

Fig. 4. Supply risk classification of thirty-one raw materials via SMAA-TRI (share of CAI % for each class) and IRIS (‡ = IRIS sorting with at least six criteria supporting the classification; * = IRIS sorting in cases where fewer than six criteria trigger the classification).

insufficient to reach the λ. In cases where this happens (i.e. for REE, Te, In, Ge, B), then C_1 is recommended.

The high-medium risk class, C_2, is assigned when there are at least six criteria that support the classification. For example, C_2 is assigned for Be, PGMs and Li since there are at least six criteria that have a cumulative weight $\geq \lambda$ and that are at least as good as Pr_1. In some cases, there can be multiple potential classifications provided by IRIS where the weight vectors of the criteria are such that fewer than six criteria have enough combined weight to support the sorting and thus a lower risk classification is recommended, such as in the case of REE (C_2), Be (C_3 and C_4), PGMs (C_3) and Li (C_3) (raw materials with * in Fig. 4).

Further considerations emerge with materials where there is an even spread of CAI involving up to all of the available classes, such as in the case of Li, Nb and Ti. This happens because (i) such materials have criteria that score in each class, (ii) a wide variability of weight vectors is accepted and (iii) λ ranges between 0.65 and 0.85. This modeling setting thus allows various combinations of weight vectors of the criteria that can (or not) have a sufficient cumulative weight to overcome λ in the SMAA-TRI simulations. It is especially in such cases that IRIS sortings can help with the interpretation of the results. Knowing that at least six criteria are in support of a certain classification and overcome λ enriches the decision-supporting potential, proposing at least C_2 for Li, C_3 for Nb and C_3 for Ti.

A potential issue of concern is what we defined as "class discontinuity", which is shown in the case of Au, which can be assigned to C_1 and C_3 but not C_2 or In, which can be assigned to C_1 and C_3 but non C_2. Other materials that suffer from this uncertainty are Ge and Mn. This phenomenon is due to the lack of criteria whose score is in the "jumped" class and thus support the assignment to it. In the case of Au for example, g_2 supports assignment to C_1. Under certain weight vectors g_2 receives such high weight (34% from IRIS software) that the remaining coalition of criteria cannot overcome the λ and consequently the highest risk level (C_1) is assigned (see also Fig. 2). This means that in cases where the DM is willing to accept that g_2 has such high weight (thus high importance) then this is a plausible classification, otherwise only the better classe (i.e. C3) would be relevant to consider. ELECTRE-TRI is a non-compensatory method, hence if there are no criteria that support a certain class, then such class is never considered as a possible allotment, independently from the performance on the other criteria.

3.3. Comparison of the results with the EC criticality study

Minerals criticality assessment exercises are system-specific, and hence not necessarily comparable with other studies (Drielsma et al., 2016; Glöser et al., 2015). For example, the EC criticality assessment (EC, 2014) relates to materials that are relevant to the European industry, while this study focuses on metals and metalloids used in automotive manufacturing. Furthermore, the EC evaluates raw materials in line with the classical definition of minerals criticality by considering both the risk with regard to access to a material as well as its economic importance. This study focuses exclusively on supply risks associated with increased depletion of raw materials, although there are no restrictions to extend the analysis to other criticality dimensions. Despite these limitations, some comparison between both studies is possible if one looks at the supply risk dimension only.

The results obtained through a synergetic use of SMAA-TRI and IRIS are largely aligned with the EU's risk profiles of raw materials, with minor exceptions. For example, the supply risk of Te is considered by the EU as relatively low, while this study considers this material as high risk. This may be because the EU put a strong emphasis on substitutability, which largely drives their results (Chapman et al., 2013) Te is easily substitutable (risk class C_4); however, it performs low in other criteria (e.g. co-production and historical price volatility), not considered by the EU in their study. Hence, the weights allocated to the substitutability criterion, or the weights coalition with other criteria (such as environmental standards and subeconomic stability), were not enough to overcome λ and thus recommend the risk class profile better than C_1 (Te) and C_2 (V). These sortings could change if, for example, a higher weight would be assigned to substitutability than to other criteria, or λ would be lowered to 0.5.

The advantage of the combinatorial use of SMAA-TRI and IRIS is that it allows to investigate the possible changes in results by accounting for the uncertainty of input parameters, in this case the weights of assessment criteria. Other MCDA methods either use equal weighting or need specific weight values (not available in this study), while SMAA-TRI and IRIS can operate without or with limited information about the weights of input parameters (assessment criteria).

4. Conclusions

The novel approach proposed in this article to assess the supply risk of raw materials is structured upon a conjoint use of MCDA classification methods; in this case, SMAA-TRI and IRIS. It does not aim to provide a certain class sorting for the raw materials; instead, it can be seen as a strategy to guide the decision process, highlighting the emergence of robust conclusions according to multiple and justifiable sets of constraints that can be imposed by the DMs on the MCDA methods. For example, the robustness analysis, considering criteria weight constraints, determined that the rare earth elements and indium have a high eventuality of supply chain disruption. Conversely, the risk of supply disruption for copper, zinc and aluminium is largely medium-low or low. The proposed step-wise decision support approach can be used as a complementary tool to the existing life cycle assessment methods for a more detailed and comprehensive assessment of the short-term availability of natural resources. Even though the methodology has been applied to thirty-one materials, it is also applicable to additional ones. Furthermore, more assessment criteria can be incorporated in the future (e.g. Policy Potential Index or global supply concentration at the company level), once they will comply with data quality and availability. Finally, the current results concern the present situation and do not consider the future evolution of the raw materials market. Hence, future work may involve building the long-term scenarios for each mineral with the consideration of geological availability and finiteness of minerals.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.resourpol.2018.04.011.

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