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Ore Grade Decrease As Life Cycle Impact Indicator for Metal Scarcity: The Case of Copper

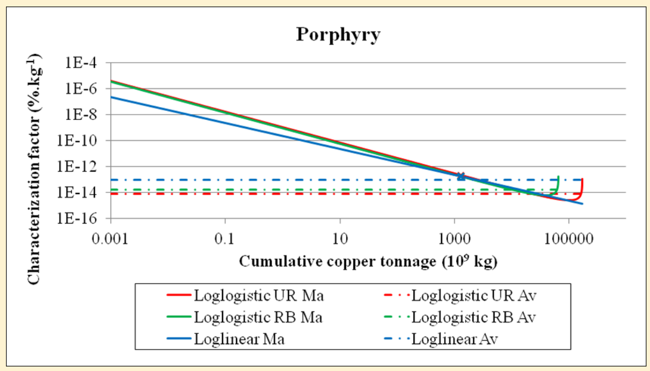
Marisa D. M. Vieira,*,† Mark J. Goedkoop,† Per Storm,‡ and Mark A. J. Huijbregts§

†PRé Consultants bv, Printerweg 18, NL-3821 AD Amersfoort, The Netherlands

‡Kopparberg Mineral AB, Verkstadsvägen 52, S-714 36 Kopparberg, Sweden

§Department of Environmental Science, Faculty of Science, Radboud University Nijmegen, P.O. Box 9010, NL-6500 GL Nijmegen, The Netherlands

ABSTRACT: In the life cycle assessment (LCA) of products, the increasing scarcity of metal resources is currently addressed in a preliminary way. Here, we propose a new method on the basis of global ore grade information to assess the importance of the extraction of metal resources in the life cycle of products. It is shown how characterization factors, reflecting the decrease in ore grade due to an increase in metal extraction, can be derived from cumulative ore grade-tonnage relationships. CFs were derived for three different types of copper deposits (porphyry, sediment-hosted, and volcanogenic massive sulfide). We tested the influence of the CF model (marginal vs average), mathematical distribution (loglogistic vs loglinear), and reserve estimate (ultimate reserve vs reserve base). For the marginal CFs, the statistical distribution choice and the estimate of the copper reserves introduce a difference of a factor of 1.0−5.0 and a factor of 1.2−1.7, respectively. For the average CFs, the differences are larger for these two choices, i.e. respectively a factor of 5.7−43 and a factor of 2.1−3.8. Comparing the marginal CFs with the average CFs, the differences are higher (a factor 1.7−94). This paper demonstrates that cumulative grade-tonnage relationships for metal extraction can be used in LCA to assess the relative importance of metal extractions.



■ INTRODUCTION

Life cycle assessment (LCA) is a methodology that can help to assess and improve the resource efficiency of products and services. LCA considers the entire life cycle of a product or service, from extraction and processing of raw materials, manufacturing, distribution, use, to end-of-life. In Life Cycle Impact Assessment (LCIA), an impact category indicator can be defined anywhere along the environmental mechanism which links inventory data to environmental impacts, such as global warming, acidification, and human toxicity. Indicators for pollution-related impacts are relatively well established.[1] There is, however, lack of consensus on the issue of concern when resource scarcity, particularly metals, is assessed.[2,3]

Several LCIA methods were developed expressing the impact of metal resource use, and yet it was found that the methods available often describe different problems.[3−6] A number of resource indicators focuses on inherent properties of metals, such as calorific value and exergy.[7,8] Emergy is also used as a life cycle impact indicator for resource use which accounts for the environmental work associated to a material.[9,10] However, the scarcity of a resource is not addressed with these indicators. Other methods apply simple use-to-stock ratios to assess the scarcity of a metal.[11−13] To assess the importance of the use of metal resources on the basis of use-to-stock ratios, data on metal reserves are necessary. A distinction can be made between ultimate reserves, reserve base, and economic reserves of metals.[14] Ultimate reserves correspond to all resources available in the Earth crust. These are used to determine the "abiotic depletion potential" (ADP) and the "anthropogenic stock extended abiotic depletion potential" (AADP).[12,13] EDIP97 derived the importance of metal resource use on the basis of economic reserves compared to consumption rates.[11] The main drawback of the use-to-stock ratio methods is that they fail to identify the change in quality of the resources available to mine over time, i.e. the ore grade.

Here, we propose a method to assess metal scarcity in LCA that circumvents the drawbacks of current methods by taking the geological scarcity of a metal as a starting point. We define scarcity as the decrease in ore grade of metal due to increased extraction of that metal. This means that metal already circulating in the technosphere, e.g. recovered through recycling, is not included. In LCA, this is already taken into account in the inventory step.[15] The amount of metal used by

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the system as reported in the LCI includes only virgin material, since extraction of virgin metal is already accounted in its first application.

Müller-Wenk,[16] one of the pioneers in addressing resource scarcity in LCA, readily described the potential of using increasing scarcity as the basis of defining the relative importance of metal resources. He, however, did not provide an operational framework and corresponding characterization factors at the level of metal scarcity.

The goal of this paper was to develop a life cycle impact assessment method that addresses the relative importance of metal resource use in product systems. As an example, characterization factors for three copper deposits (porphyry, sediment-hosted, and volcanogenic massive sulfide) were derived to demonstrate how the method can be operated in practice.

MATERIALS AND METHODS

Environmental Mechanism. Metal resources are used in a dissipative way, since they are extracted from a relatively high concentrated deposit and dissipated into different products and later waste.[17−21] In order to express the scarcity of a metal resource, it is important not only to determine the amount of resource still available but also its quality.[22] One of the quality elements of a metal resource is its concentration within an ore, often referred to as its ore grade. The higher the grade of a metal in a deposit, the bigger the volume of metal extracted per ore mined. Following this principle, given no new discoveries, when a metal resource is extracted, its average ore grade worldwide decreases.[16,23−25] Consequently, in order to extract the same amount of metal resource, more ore needs to be mined.

Cumulative Grade-Tonnage Relationships. Geostatistical models generally assume a logarithmic relationship between the grade of a metal ore and the cumulative tonnage of metal extracted.[26−31] Following the principle that mining sites with higher grades are explored first, production sites of a metal can be sorted by decreasing order for average grade of metal.

There are various distributions to describe the relationship between ore grade and tonnage,[26−31] with no sound theoretical foundation to prefer one specific distribution upfront.[27] Here the possibility of using two geostatistical distributions is explored, i.e. the loglogistic distribution and the loglinear distribution. The latter is also known as the Musgrove distribution.[30,31]

A loglogistic relationship between cumulative metal tonnage extracted and ore grade can be defined as

$$CMT_{g_i} = \frac{A}{1 + \exp\left(\frac{\ln(g_i) - \alpha}{\beta}\right)} \tag{1}$$

where CMT is the cumulative metal tonnage extracted up to a certain ore grade g (megaton), A is the reserve estimate of metal available for mining (megaton), g is the ore grade (%), i is an index representing each mining site, α is the location parameter, and β is the scale parameter of the loglogistic distribution. A loglogistic distribution closely resembles the log-normal distribution, proposed by Gerst,[29] with the advantage of an explicit cumulative density distribution. The ore grade as a function of the cumulative metal tonnage extracted can be obtained by rewriting eq 1 into

$$g_{CMT_i} = \exp(\alpha)\cdot\exp\left(\beta\cdot\ln\left(\frac{A}{CMT_i} - 1\right)\right) \tag{2}$$

Alternatively, the loglinear model describes the grade-tonnage relationship for metal resources by[30,31]

$$g_i = a + b\cdot\ln(CMT_i) \tag{3}$$

where a and b are respectively the intercept and slope of the loglinear regression.

Characterization Factor. As LCA applications tend to be change-oriented ("what is the additional environmental impact if one extra product is produced?"), the approach of 'marginal change' is advocated in life cycle impact assessment.[32] It assumes that an additional amount of a certain stressor introduces very small changes on top of a *ceteris paribus* background situation. The change in impact per unit amount of extra extraction of a specific resource represents the relative importance in terms of resource scarcity. This conversion factor is referred to as the characterization factor (CF) for the resource considered.

The marginal CF is determined as the slope of the cumulative grade-tonnage relationship at the current cumulative extraction level ($CMT_{current}$). CFs for metal resource extraction were defined as the marginal decrease in ore grade of a specific metal (in %) with a marginal increase of amount of metal extracted (in kg)

$$CF = \frac{\partial g}{\partial CMT} \tag{4}$$

where ∂g_x is the marginal change in average ore grade of metal x (%), and ∂CMT_x is the marginal additional tonnage extraction of extracted metal x (kg). The characterization factor becomes the symmetric of the derivative of the distribution ($-g_x'$).

For the loglogistic distribution, the CF is defined on the basis of the derivative of eq 2

$$\begin{aligned} CF &= -g' \\ &= \exp(\alpha)\cdot\exp\left(\beta\cdot\ln\left(\frac{A}{CMT_{current}} - 1\right)\right)\cdot \\ &\quad \left(\beta\cdot\frac{A}{CMT_{current}\cdot(A - CMT_{current})}\right)\cdot 10^{-9} \end{aligned} \tag{5}$$

where $CMT_{current}$ is the cumulative metal tonnage extracted up to now (in megaton), i.e. the working point on the curve.

For the loglinear distribution, the CF can be derived on basis of the derivative of eq 3 as

$$CF = -g' = -\frac{b}{CMT_{current}}\cdot 10^{-9} \tag{6}$$

The cumulative grade-tonnage relationships were determined on the basis of the cumulative metal produced in megatons (10^9 kg) hence the multiplication of eqs 5 and 6 by 10^{-9} to express the CF in $\%\cdot kg^{-1}$.

As an alternative for the marginal approach to derive a CF, average modeling in LCIA is also possible.[33,34] The average CF for resource extraction can be derived by calculating the average distance between the current state and the critical state of the environment per unit of extraction increase. However, the critical state may vary per metal so this is evaluated on an individual basis. In the present paper, the average modeling approach takes the slope of the line that links the current ore grade ($g_{current}$) to a critical ore grade ($g_{critical}$) calculated by

$$CF = \frac{g_{current} - g_{critical}}{CMT_{current} - CMT_{critical}} \quad (7)$$

where $CMT_{critical}$ is the cumulative metal extracted at the determined critical ore grade.

Finally, the metal-specific characterization factors can be used to calculate the overall metal scarcity score by

$$IS_{ms} = \sum_{x} CF_x \times M_x \quad (8)$$

where IS_{ms} is the impact score for metal scarcity per functional unit (%); CF_x is the characterization factor for metal x extracted (%·kg^{-1} extracted); and M_x is the amount of metal x extracted per functional unit (kg).

Copper. Copper is a metallic element that is an excellent conductor of heat and electricity as well as being corrosion resistant and antimicrobial.[35] Due to its properties, copper is important in modern technology with wide use in electronic equipment and in the telecommunication and transport sectors. Currently, the yearly copper extraction from mines reaches around 15 megatons (10^9 kilograms) with an average ore grade of around 1.6%.[29] Falling ore grades are considered one of the major constraints in copper supply.[23,35]

Relatively high copper concentrations occur in various deposits, in particular porphyry, sediment-hosted, and volcanogenic massive sulfide (VMS) deposits.[29] The data to derive cumulative grade-tonnage relationships for the three copper deposits were retrieved from global databases compiled by the U.S. Geological Survey.[36−38] Porphyry, sediment-hosted, and volcanogenic massive sulfide deposit data respectively included 38, 85, and 852 individual mine entries with both ore tonnage and grade data.[36−38] We applied a nonlinear least-squares fit with the software R project for statistical computing to derive the location parameter α and the scale parameter β for the loglogistic distribution and the intercept a and slope b for the loglinear distribution.[39] The residual standard error (RSE) was reported of each fit. Additionally, the 95% confidence interval (95% CI) was calculated for these four model parameters.

The cumulative copper tonnage extracted from porphyry, sediment-hosted, and volcanogenic massive sulfide deposits were also taken from the USGS databases.[36−38] Estimated copper reserves in the earth crust are required in the loglogistic distribution. Two types of reserve estimates were tested in the derivation of characterization factors. Ultimate reserves include all estimated copper resources available in the Earth crust regardless of its depth, whereas the reserve base is the copper that is considered to have a reasonable potential for becoming economically available within planning horizons beyond those that assume proven technology and current economics.[14]

The copper reserves for copper from porphyry deposits were estimated by Kesler and Wilkinson, based on a model considering tectonism and exhumation.[40] Their model assumes that ore deposit emplacement occurs at a constant rate and depth and that, after emplacement, the deposits are vertically dispersed by tectonic uplift and/or subsidence.[41] Kesler and Wilkinson[29] estimated 1300 Gton copper as ultimate reserve and 89 Gton copper as reserve base, the latter assuming that mining in the foreseeable future will reach depths of around 3.3 km.[40] The copper estimates per deposit type were calculated based on the cumulative copper tonnage extracted ratio.[36−38] The critical ore grade for copper of 0.1% needed for the determination of the average characterization factor was taken from Skinner.[42]

The characterization factors for global copper can be estimated as the weighted average of the deposit-specific characterization factors based on the production ratio in 2000 from porphyry (80%), sediment-hosted (10%), and volcanogenic massive sulfide (10%) deposits.[29]

RESULTS AND DISCUSSION

Cumulative Grade-Tonnage Relationships. Figure 1 shows the loglogistic and loglinear relationship between cumulative extraction and decrease in copper ore grade for porphyry, sediment-hosted, and volcanogenic massive sulfide deposits. This is based on historic data to determine the cumulative grade-tonnage relationships for these three copper deposits so only copper produced up to now is included.

Figures 1A and 1B indicate low copper grades for some mines. However, this does not mean that porphyry and sediment-hosted copper ores are almost depleted. The low copper grades observed for these two deposit types result from coproduction. These mines have other metals being mined as the main metal such as gold, molybdenum, and/or silver hence also the low tonnage observed for these mines.

Table 1 provides the fitted parameters and their confidence intervals. As it can be seen from the intercept a of the loglinear regression and the location parameter α of the loglogistic distribution, the copper ore grades are the highest for sediment-hosted deposits, followed by volcanogenic massive sulfide deposits and porphyry deposits. The scale parameter β and slope b are smallest for porphyry, implying that the decrease of ore grade per kilogram of extracted copper from porphyry deposits is smaller than that of the other two deposits.

From Table 1 it appears that the loglogistic curve better resembles the observed data, as the residual standard error (RSE) obtained for the loglogistic distribution is smaller than the RSE for the loglinear distribution. The lower RSE is mainly caused by the right part of the curve when the ore grade rapidly decreases. In the case an ore type becomes exhausted, the loglinear distribution tends to overestimate ore grades, particularly for porphyry and sediment-hosted deposits (Figures 1A and 1B). This implies that the loglogistic distribution is favorable to derive characterization factors from a statistical point of view, particular in the situation that ore grades are very low. On the other hand, the loglinear distribution requires less information to derive characterization factors compared to the loglogistic distribution, as it does not depend on the reserves of a metal (see eq 6). This is an important advantage, as information on ore reserves is not always available for all metal resources. In addition, a choice would have to be made on the type of reserves to use as there are different types.

As shown in Table 1, for both the loglogistic and the loglinear cumulative grade-tonnage relationship, the statistical uncertainty is the lowest for porphyry (RSE = 0.04−0.09), followed by volcanogenic massive sulfide (RSE = 0.19−0.25), and sediment hosted deposit (RSE = 0.48−0.61). This finding also indicates that the characterization factor for porphyry has the lowest statistical uncertainty.

Characterization Factors. Figure 2 shows how the marginal CFs of the three copper deposits vary with the cumulative copper tonnage extracted. The marginal CFs derived with the loglogistic distribution decrease with the

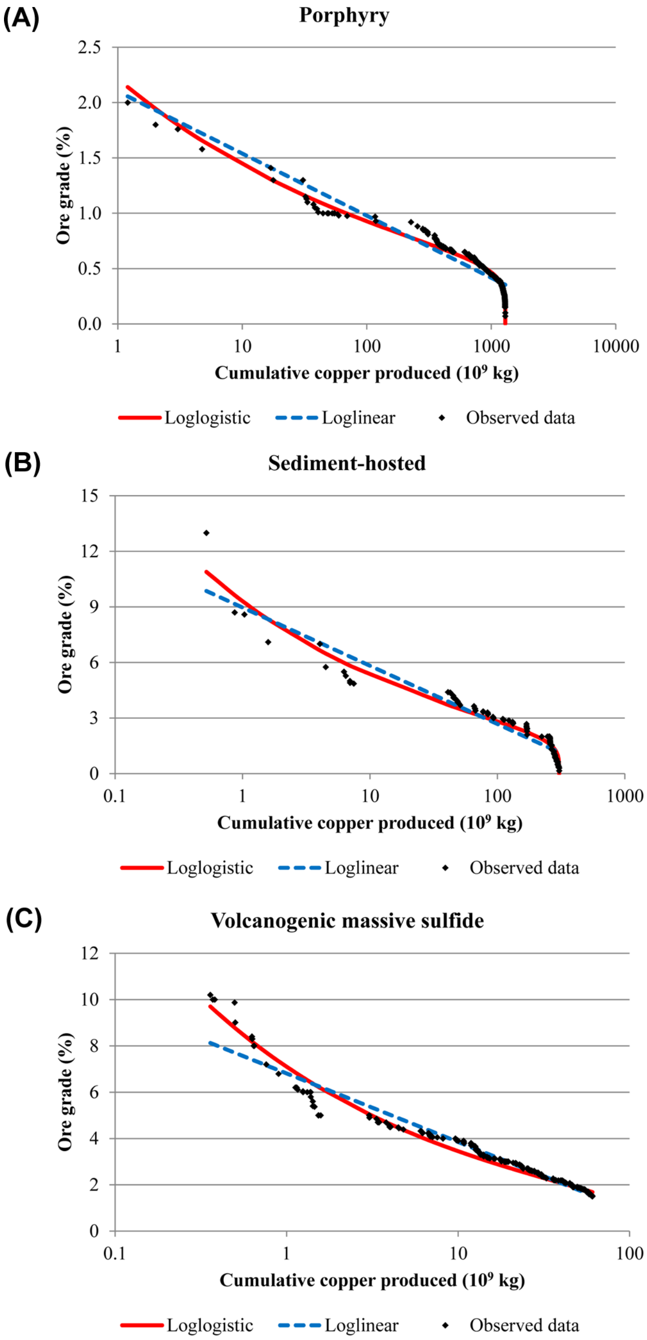

Figure 1. Cumulative grade-tonnage relationships derived with the loglogistic distribution and loglinear distribution for copper from porphyry deposits (A), sediment-hosted deposits (B), and volcanogenic massive sulfide deposits (C). The data were taken from the U.S. Geological Survey.[35−37]

increase of cumulative copper tonnage extracted until the cumulative extraction approximates the ultimate reserve or reserve base and here rapidly increases again. This is a direct consequence of using the loglogistic distribution to derive the cumulative grade-tonnage relationship. In contrast, CFs derived with the loglinear distribution continuously decrease with increased cumulative production.

In the average modeling approach, the CF remains the same regardless of the cumulative copper tonnage extracted. The current copper grade ($g_{current}$) was derived from the current cumulative copper tonnage extracted ($CMT_{current}$) using eqs 2 and 3 for the loglogistic and loglinear distributions respectively. Similarly, the critical cumulative copper tonnage extracted ($CMT_{critical}$) was derived on the basis of the critical copper grade 0.1% for all three copper deposits. The current and critical points per deposit type and distribution and reserve estimate are shown in Table 2.

Figure 3 shows the CFs derived using the current cumulative copper tonnage extraction per deposit as working point following the marginal and average approach. The marginal CF for copper extraction derived with the loglogistic distribution and the ultimate reserve equals $3{\cdot}10^{-12}$ %·kg^{-1} calculated by averaging the CFs for porphyry, sediment-hosted, and volcanogenic massive sulfide deposits on the basis of their current production ratio. This means that for each additional kiloton (10^6 kilogram) of copper mined, there will be a decrease in the average grade in copper extracted of $3{\cdot}10^{-6}$ %. The current annual copper production of 15 megatons results in a decrease in copper grade of approximately 0.01%. Using the ultimate reserve as reserve estimate, the marginal CF does not largely differ between the loglogistic and loglinear distribution. For porphyry deposits the difference is a factor of 1.2, for sediment-hosted deposits the difference is a factor of 3.7, and for volcanogenic massive sulfide deposits the difference is a factor of 5.0. Marginal CFs derived with the loglogistic distribution using the reserve base instead of the ultimate reserve estimate are larger, but the difference is less than a factor of 2 difference. By using the reserve base data, the marginal CFs of the loglogistic curve are even closer to the loglinear marginal CFs. For the average CFs, the statistical distribution choice and the estimate of the copper reserves introduce higher differences, a factor of 5.7−43 and a factor of 2.1−3.8, respectively.

The choice in modeling approach appears to be more relevant for the derivation of CFs for copper, as the CFs derived with the marginal approach are up to 2 orders of magnitude larger (a factor 1.7−94) than the CFs derived with the average approach for the loglogistic distribution. For the loglinear distribution though the difference in the modeling approach is smaller than a factor 2.5 for all three copper deposits.

The virtues of the marginal approach are that it aims at realistically describing the influence of a change in cumulative metal extraction for that specific situation and that it promotes extraction changes with the highest efficiency, i.e., where the slope of the cumulative grade-tonnage curve is most gradual. In the marginal approach, however, the CF decreases with increasing cumulative extraction, i.e., the slope of cumulative grade-tonnage curve approaches zero. This implies that in situations with relatively high absolute resource scarcity any additional resource extraction is judged to be less irrelevant. The advantage of the average approach is that it adopts a long-term perspective, focusing on what society ultimately wants to avoid from a resource extraction point of view.[34]

Given the high share of current copper production by porphyry deposits (~15% from oxide porphyry and ~50% from sulfide porphyry) and their differences in ore grade and extraction technology,[29] a distinction between these two types of porphyry deposits would be beneficial. This distinction is, however, not possible to include in our analysis, as the data set used[36] did not distinguish between sulfide and oxide porphyry deposits. This prevents us from deriving separate cumulative ore grade-tonnage relationships for these two deposit types and requires further research.

Table 1. Parameters Derived for the Loglogistic and Loglinear Cumulative Grade-Tonnage Distributions of Copper Porphyry, Sediment-Hosted, and Volcanogenic Massive Sulfide Deposits[a]

	loglogistic distribution			reserve estimate		loglinear distribution			working point
deposit type	location α (95% CI)	scale β (95% CI)	RSE	ultimate reserves A[40] (megaton)	reserve base A[40] (megaton)	intercept a (95% CI)	slope b (95% CI)	RSE	$CMT_{current}$[36−38] (megaton)
porphyry	-0.53 (-0.53 − -0.52)	0.18 (0.181−0.183)	0.04	170,000	66,700	2.10 (2.07−2.13)	-0.24 (-0.25 − -0.24)	0.09	1,295
sediment-hosted	0.87 (0.85−0.89)	0.24 (0.24−0.25)	0.48	89,700	15,700	9.07 (8.86−9.28)	-1.38 (-1.43 − -1.34)	0.61	305
volcanogenic massive sulfide	0.49 (0.49−0.50)	0.30 (0.301−0.304)	0.19	40,300	6,600	6.81 (6.78−6.84)	-1.29 (-1.29 − -1.28)	0.25	128

[a]CI = confidence interval; CMT = cumulative metal tonnage; RSE = residual standard error.

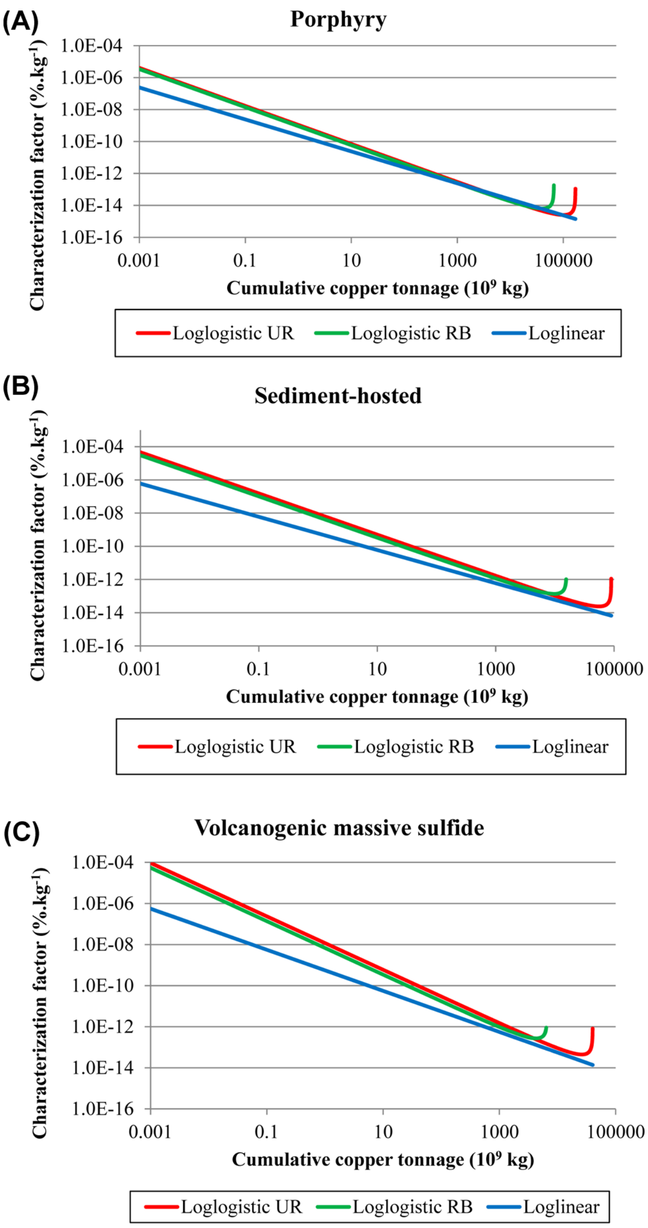

Figure 2. Dependency of the characterization factor derived with the marginal approach on cumulative copper tonnage extracted from porphyry deposits (A), sediment-hosted deposits (B), and volcanogenic massive sulfide deposits (C) (in $\%\cdot kg^{-1}$): RB = reserve base; UR = ultimate reserves.

Note that an important principle of all cumulative grade-tonnage relationships is that metals are mined in decreasing order of ore grade, but this does not always happen. There are other aspects that lead to the exploration of mines with lower ore grades, such as the hardness of the rock, the easiness of access, and the extraction technology considered.[43] A mining site with high ore grade but also hard rock can be left unexplored because it requires larger extraction efforts leading to the exploration of a mine with lower ore grade and thus a larger CF. Similarly, some mines are situated in regions of difficult access, e.g. Siberia, so mines with lower ore grades will be mined instead. Regarding the extraction technology applied, e.g. open pit instead of underground mine, there is evidence that open pit mines are preferred even with a lower ore grade because the operating costs of open pit mines are lower.[44] On the other hand, there are new deposits discovered as a result of exploration projects. There is, however, no indication for copper porphyry deposits that new discoveries considerably influence the shape of the cumulative grade-tonnage curve.[29]

Metal Criticality. In Graedel et al.[45] the relative abundance of the metal (termed "depletion time") and the percentage of the metal mined as a byproduct (termed "companion metal fraction") are taken as indicators for metal scarcity. Depletion time is calculated by considering current economic reserves and determining the time it would take to deplete the metal if demand remains at current rate, assuming present recycling rates. The use of depletion time and companion metal fraction have, however, drawbacks. First, economic reserves fluctuate considerably as response to changes in resource supply and demand. Second, assuming current demand rate and present recycling rates may no longer apply in a near future as response to emerging products and recycling improvements. Our method to address metal scarcity by quantifying ore grade decrease due to metal extraction, when combined with future metal demand, can be seen as an attractive alternative for depletion time and companion metal fraction in the assessment of metal criticality.

Apart from assessing the importance of environmental availability of metal resources in an LCA context, there are other aspects that can constrain the supply of metals. This type of macrosystem analysis is often defined as criticality of raw materials.[46] A key element included in these methodologies is the supply risk of metal resources. One important aspect of supply risk of metals are geopolitical effects such as trade boundaries or strategic stocking of resources. Resources may be physically available in the earth crust and yet not available for trade. Metal supply might be constrained by high concentration of the metal in a few countries and accentuated when these countries face political instability. How to include geopolitical

Table 2. Parameters Derived for the Current State and Critical State Derived for the Loglogistic and Loglinear Cumulative Grade-Tonnage Distributions of Copper Porphyry, Sediment-Hosted, and Volcanogenic Massive Sulfide Deposits

	working point				critical point			
		$g_{current}$ (%)				$CMT_{critical}$ (megaton)		
deposit type	$CMT_{current}$[36−38] (megaton)	loglogistic UR	loglogistic RB	loglinear	$g_{critical}$[42] (%)	loglogistic UR	loglogistic RB	loglinear
porphyry	1,295	1.47	1.23	0.38	0.1	169,984	66,694	4,160
sediment-hosted	305	9.24	6.06	1.13		89,700	15,700	648
volcanogenic massive sulfide	128	9.16	5.30	0.60		40,296	6,599	189

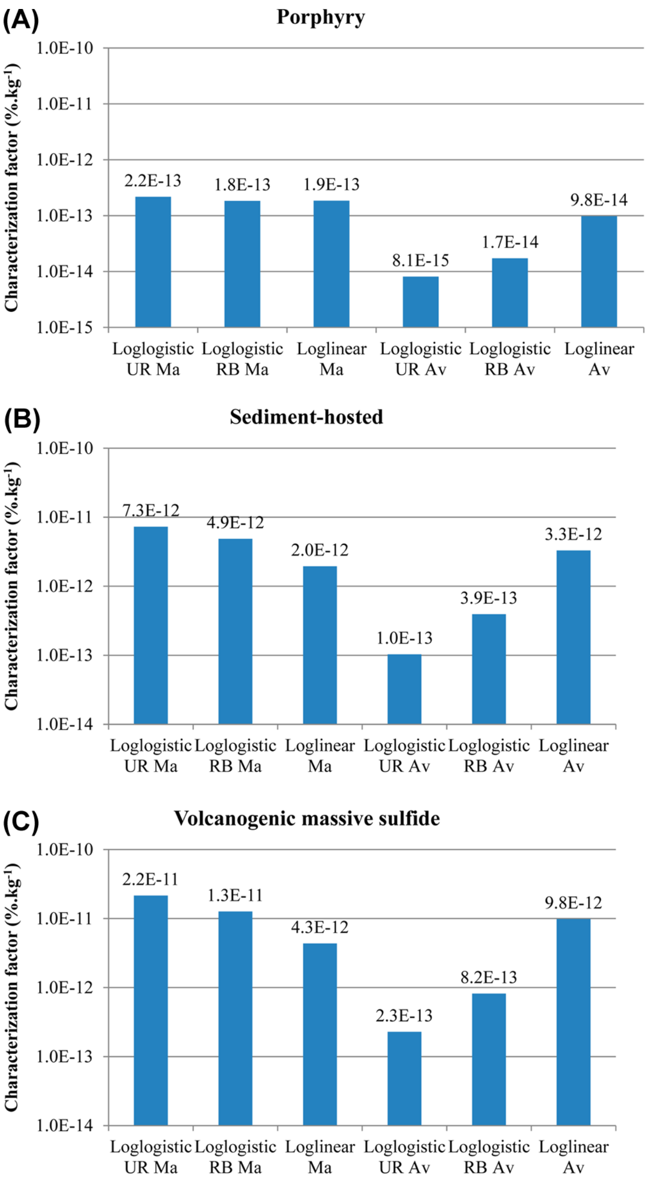

Figure 3. Characterization factors derived at the current cumulative copper tonnage extraction for copper extracted from porphyry deposits (A), sediment-hosted deposits (B), and volcanogenic massive sulfide deposits (C) (in %·kg^{-1}): Av = average modeling; Ma = marginal modeling; RB = reserve base; UR = ultimate reserves.

aspects in the assessment of metal criticality within an LCA context requires further research.

CONCLUDING REMARKS

In this paper, it is demonstrated how characterization factors for resource scarcity, reflecting the decrease in ore grade due to an increase in metal extraction, can be derived from cumulative ore grade-tonnage relationships. Our results emphasize the importance of (1) the selection of an appropriate statistical distribution to describe the cumulative grade-tonnage relationship and (2) the way the environmental problem is defined, i.e. short-term marginal or long-term average. Further research is required to expand the method to include geopolitical aspects in evaluating metal scarcity in an LCA context.

AUTHOR INFORMATION

Corresponding Author

*Phone: +31 33 4555022. Fax: +31 33 4555024. E-mail: vieira@pre-sustainability.com.

Notes

The authors declare no competing financial interest.

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