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Calculation of Characterization Factors of Mineral Resources Considering Future Primary Resource Use Changes: A Comparison between Iron and Copper

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Abstract: The future availability of mineral resources has attracted much attention; therefore, a quantitative evaluation of the potential impacts of resource use on future availability is important. Although the surplus cost model is often recommended among the existing endpoint characterization models of mineral resources, it has a shortcoming as it does not consider the changes in future primary resource use. This paper introduces a new characterization model considering future primary resource use changes, due to future changes in total demand and secondary resource use. Using material flow analysis, this study estimated time-series primary resource use for iron and copper for five shared socioeconomic pathways (SSPs) and a constant total demand scenario. New characterization factors, i.e., demand change-based surplus costs (DCSC), are calculated for each resource. In all of the SSPs, the calculated DCSCs are larger than the conventional surplus costs (SC) for both iron and copper. The DCSC, relative to the SC of copper, is larger than that of iron for all of the SSPs, which suggests that the potential impacts of copper use, relative to iron, will be underestimated, unless future primary resource use changes are considered. In calculating DCSC for other resources, it is important to choose an appropriate approach for forecasting future total demands.

Keywords: life cycle impact assessment; material flow analysis; characterization factor; surplus cost; future demand; secondary resource; shared socioeconomic pathways

1. Introduction

Mineral resources, including a variety of metals, are indispensable in modern life, and large amounts have been consumed. Particularly in recent years, the global demand for mineral resources has increased markedly. For example, global demand for engineering materials, such as steel and cement, has quadrupled over 50 years, since 1960 [1]. Since mineral resources are non-renewable, their depletion and future availability have been of great research interest [2–4]. It should be noted that the potential impacts of current resource use on future availability are dependent on future demand for the resource.

Metals do not physically disappear due to mining and use, and are rather accumulated (or sometimes dispersed) in society as “in-use stock”, which will partly become available as future secondary resources, due to their recycling. Gerst and Graedel [5] pointed out the phenomenon of a substantial shift in metal stocks, from the lithosphere to the anthroposphere, during the 20th century. If secondary resources are used as substitutes for primary resources, it would diminish primary resource use. On the other hand, primary resource use leads to an increase in the amount of in-use stock and will diminish the future primary resource use only if this in-use stock becomes a secondary resource source.

There is no doubt that total demand will continue to grow in the future. The United Nations Environment Programme (UNEP) [6] highlights three important trends that are bound to increase the future total demand for metals:

- The building up of infrastructure in rapidly developing economies will cause continuously-rising demand for steel and other base metals.
- The electronics revolution, expressed in products like smartphones, flat screen televisions, or USB sticks, is leading to growing demand for many minor and precious metals.
- The shift towards renewable energy technologies, like wind and photovoltaic energy, will contribute to increased global metal demand.

An evaluation of the potential impacts of mineral resource use is the topic of much debate in life cycle assessment [7–9]. For example, the task force on natural resources of the UNEP-the Society for Environmental Toxicology and Chemistry (SETAC) Life Cycle Initiative’s flagship project on life cycle impact assessment (LCIA), recently confirmed as a priority for further research in the area of minerals and metals [10]. Environmental impacts of mineral resource use are addressed in various impact categories (e.g., global warming and acidification). Resource depletion, in which the seriousness of resource depletion or potential impact on future availability is evaluated, is one of the main impact categories in LCIA [11]. Various characterization models have been developed for resource use, including the abiotic depletion potential (ADP) [12], exergy [13], user cost [14], surplus cost [15], and willingness-to-pay [16]. However, characterization of mineral resource use is still under development and many challenges still remain [9,17,18].

Although there is a lack of consensus about which characterization model should be chosen for mineral resource use [18,19], the surplus cost model is often recommended among the existing endpoint characterization models from several viewpoints, such as scientific robustness [20–22].

Surplus cost was adopted in ReCiPe2008 [15]. By focusing on the relationship between the cumulative yield of a commodity and a decrease in ore grade, it provides characterization factors for mineral resources and fossil resources, which represent the additional net present cost society has to pay as a result of a marginal increase in the extraction costs, due to a decrease in ore grade, caused by the extraction of 1 kg of resource. Although it depends on the future primary resource use (which depends on total demand and secondary resource use), it assumes constant primary resource use over time (see Section 2.1). Since Goedkoop et al. [15] published this model, several studies have expanded its concepts. Ponsioen et al. [23] calculated the surplus cost for the three main fossil resources (crude oil, natural gas, and coal), taking into account future changes in primary energy production (as this study targets fossil fuels, secondary resource use is outside the scope of evaluation). Vieira et al. [24] calculated the surplus cost potential for 12 metals, taking account of co-production and mine-specific differences in costs, which are adopted in ReCiPe2016 as endpoint characterization factors [25]. The surplus cost potential of each resource indicates the cumulative operation cost that is expected until its reserve is completely depleted; it is determined regardless of the resource demand. Thus, future changes in resource use, including secondary resources, have not been incorporated into the calculation of the surplus cost of metals in previous studies.

Besides the surplus cost, most of the existing characterization models do not take account of either future total demand or in-use stock (which affects future secondary resource use). The anthropogenic stock extended abiotic depletion potentials (AADP), introduced by Schneider et al. [26,27], is the only characterization model taking account of the fact that raw materials are stored in society. Schneider et al. [26] calculated the AADP of resource x with Equation (1):

$$AADP_{x,resources} = \frac{\text{extraction rate } x}{(\text{resources } x + \text{anthropogenic stock } x)^2} \times \frac{(\text{resources } ref + \text{anthropogenic stock } ref)^2}{\text{extraction rate } ref} \quad (1)$$

where *resources* (kg) are defined as the amount of mineral in such concentrated form that economic extraction is currently or potentially feasible [28], Schneider et al. [26] determined *anthropogenic stock* (kg) as the accumulated extraction rate (kg/year) since 1900, and *ref* represents the reference resource (antimony). The difference between the anthropogenic stock and in-use stock is that the former includes the landfilled amount, whereas the latter does not. Schneider et al. [27] modified Equation (1) in an attempt to improve the reliability of the work. They used the *ultimately extractable reserves* (representing the amount available in the upper earth's crust that is ultimately recoverable) instead of *resources* and considered a dissipation rate of 20% in the determination of the anthropogenic stock. The authors focused on the fact that large amounts of raw material are stored in material cycles within the technosphere, and introduced AADP by modifying the conventional ADP characterization model. However, this characterization model does not consider either future total demand changes or differences in the recycling rates among resources. In this model, it is assumed that all in-use stocks can be used as secondary resources in the future. It means that the potential impacts caused by the primary use of a resource, the total demand of which will increase, and the recycling rate of which is relatively low, are underestimated (lower recycling rate means that smaller part of in-use stocks will be used).

The aim of this paper is to introduce “demand change-based surplus costs (DCSC)”, by improving the conventional surplus cost (SC). DCSC is the surplus costs, taking into account future primary resource use changes due to future changes in total demand and secondary resource use. DCSC are calculated for iron and copper (which are vital to industry and have been used in large quantities, resulting in large amounts of in-use stocks) and compared with SC, given by conventional modeling. The future total demand of these two metals is associated with the first of the three above-mentioned trends, which are bound to increase the future total demand for metals [6]. This paper estimates the total demand for future scenarios, based on population and gross domestic product (GDP). Differences in DCSCs across future scenarios are also analyzed.

2. Model

2.1. Demand Change-Based Surplus Cost

In the surplus cost model, it is assumed that the extraction cost of a commodity increases according to its cumulative yield, as a result of a decrease in ore grade. The SC of resource *x* (\$/kg), adopted in ReCiPe2008 [15], is calculated with Equation (2).

$$SC_x = \sum_{t=1}^{\infty} \left\{ MCI_x \times P_x \times \frac{1}{(1+r)^t} \right\} \quad (2)$$

where MCI_x is the marginal cost increase of resource *x* (\$/kg/kg), defined as the increase in extraction cost (\$/kg) resulting from the extraction of 1 kg of resource *x*, P_x is the annual primary resource use of resource *x* (kg), and r is the discount rate (default value is 3%). For calculation of characterization factors in ReCiPe 2008, P_x is assumed to be constant over time at the current level. Therefore, P_x can be written as P_{x,t_c} (t_c indicates the current year). Similarly, MCI_x can be expressed as MCI_{x,t_c} , which means the increase in extraction cost resulting from the extraction of 1 kg of resource *x* in year t_c . Consequently, SC_x can be expressed as SC_{x,t_c} .

This study replaces P_x in Equation (2) with time-series primary resource use, P_{x,t_c+t} (kg) (t_c is set at the year 2012 in this study due to data availability), and calculates the DCSC of resource *x* (\$/kg) as follows:

$$DCSC_{x,t_c} = \sum_{t=1}^{\infty} \left\{ MCI_{x,t_c} \times P_{x,t_c+t} \times \frac{1}{(1+r)^t} \right\} \quad (3)$$

In Equation (3), $MCI_{x,t_c} \times P_{x,t_c+t}$ represents the additional cost the society has to pay in year $t_c + t$ as a result of the extraction of 1 kg of resource *x* in year t_c , which is converted to the present value by

multiplying $1/(1+r)^t$. Both SC_{x,t_c} and $DCSC_{x,t_c}$ indicate the additional net present cost the future society has to pay (impacts on future availability) as a result of the extraction of 1 kg of resource x in year t_c . By using P_{x,t_c+t} , Equation (3) can calculate surplus cost, taking into account future primary resource use changes due to future changes in secondary resource use and total demand. Whereas MCI_{x,t_c} may change when the base year of characterization shifts from t_c to t_c' , the portion of the increase in extraction cost in year $t_c + t$, which is attributed to the extraction of 1 kg of resource x in year t_c , is regarded as independent of t , in accordance with the conventional model [15]. In this study, we focus exclusively on the effect of consideration of future primary resource use changes on the surplus cost.

Although Equation (3) is similar to the equation developed by Ponsioen et al. [23] (which calculates the surplus costs of each fossil resource considering the time-series production), the two equations differ, in that the model in this study considers future secondary resource use changes and does not define the depletion year. This model is not based on the fixed stock paradigm (which implies that resources are limited and will eventually deplete [29]), but on the idea that costs are the limiting factor for the use of resources [24]. Thus, depletion year is not defined and the additional cost for each year is summed up indefinitely in Equation (3). This study is concerned with how the results of calculating the surplus cost change when considering future primary resource use changes, and it focuses on the ratio of DCSC to SC.

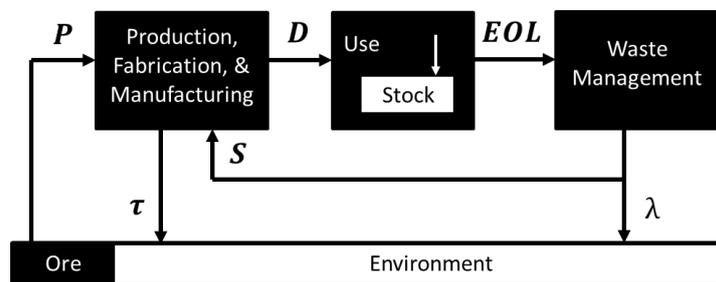
2.2. Time-Series Primary Resource Use

This study uses dynamic material flow analysis (MFA) [30] to estimate time-series primary resource use. This is based on Figure 1, which represents the life cycle of metals [31]. From the mass balance in the production, fabrication and manufacturing stage, and waste management stage in Figure 1, primary resource use and flow to end-of-life of resource x , in year t , are described by Equations (4) and (5), respectively.

$$P_{x,t} = D_{x,t} + \tau_{x,t} - S_{x,t} \quad (4)$$

$$EOL_{x,t} = S_{x,t} + \lambda_{x,t} \quad (5)$$

where $P_{x,t}$ is the primary resource use of resource x in year t (time-series primary resource use) (kg); $D_{x,t}$ is the total demand of resource x in year t (kg); $\tau_{x,t}$ is the net loss to tailings and slag of resource x in year t (kg); $S_{x,t}$ is the secondary use of resource x in year t (kg); $EOL_{x,t}$ is the flow to end-of-life of resource x in year t (kg); and $\lambda_{x,t}$ is the landfilled amount of resource x in year t (kg).



- P: Primary resource use
- D: Demand
- EOL: Flow to end-of-life
- λ: Landfilled
- S: Secondary resource use
- τ: Net loss to tailings and slag

Figure 1. Flows related to the life cycle of metals (Based on Graedel et al. [31]).

Furthermore, the net loss to tailings and slag can be described with yield rates using Equation (6), the secondary resource use with recycling rate using Equation (7), and the flow to end-of-life with lifetime distribution using Equation (8).

$$\tau_{x,t} = P_{x,t}(1 - y_{1,x}) + S_{x,t}(1 - y_{2,x}) \quad (6)$$

$$S_{x,t} = EOL_{x,t} \times \frac{S_{x,t}}{S_{x,t} + \lambda_{x,t}} = EOL_{x,t} \times RR_x \quad (7)$$

$$EOL_{x,t} = \sum_{t'=t_0}^t D_{x,t'} \times L_{x,t-t'} \quad (8)$$

where $y_{1,x}$ and $y_{2,x}$ are the yield rates of primary and secondary resource production of resource x (%), respectively; RR_x is the recycling rate of end-of-life products of resource x (%); t_0 is the initial year (=1900); and $L_{x,t}$ is the lifetime distribution (the probability that a product will exit the use stage t years after it enters this stage) of resource x (%). The initial year is 1900, because it can be assumed that the total demands before 1900 were negligibly small, in comparison to those after 1900 [2]. From Equation (1) and Equations (6)–(8), the time-series primary resource use is described by Equation (9).

$$P_{x,t} = \frac{1}{y_{1,x}} \left(D_{x,t} - y_{2,x} \sum_{t'=t_0}^t RR_x \cdot D_{x,t'} \cdot L_{x,t-t'} \right) \quad (9)$$

Because recycling rates and lifetime distributions are different among final use sectors, this study estimates (or determines) the total demands, recycling rates, and lifetime distributions, by final use sector. Therefore, Equation (9) is converted into Equation (10).

$$P_{x,t} = \sum_k \frac{1}{y_{1,x}} \left(D_{x,t,k} - y_{2,x} \sum_{t'=t_0}^t RR_{x,k} \cdot D_{x,t',k} \cdot L_{x,t-t',k} \right) \quad (10)$$

where subscripts k , represent final use sectors. Based on previous studies, we used four final use sectors for each metal; for iron, they were construction, transportation, machinery, and products [32–34], and for copper, they were building and construction, electrical and electronic, infrastructure, and transportation [35–37].

For $D_{x,t,k}$, we collected data for the historical total demand ($t < 2013$) (see Section 3.2) and forecast the future total demand ($2013 \leq t \leq 2100$) using future scenarios. Since future scenarios are not considered after 2100, primary resource use after 2100 is assumed to be the same as that in 2100. This assumption affects the additional cost the society has to actually pay as a result of the extraction of 1 kg of resource x in year t_c ($MCI_{x,t_c} \times P_{x,t_c+t}$) after 2100 in Equation (3). However, it will not significantly affect DCSC because it is transposed to the present value with the discount in Equation (3).

2.3. Future Total Demand

In forecasting the total demand of resources, several studies have been based on the intensity of use hypothesis (IU hypothesis), which assumes that the intensity of use (defined as resource use per GDP) rises first and then falls as per capita income grows. The resulting curve of intensity of use against per capita income shows an inverted U-shape. This hypothesis can be explained by certain trends, such as the economic transition from agriculture (low IU) to manufacturing and construction (high IU) and then to services (low IU) [38].

However, Müller et al. [39] pointed out that approaches based on the IU hypothesis lack robustness, because IU is an abstract ratio of two flow variables that tend to fluctuate. Instead, they propose an approach based on patterns of in-use stock evolution. Observing the in-use stocks has certain advantages, e.g., the in-use stocks have physical meaning as products in use (which form in-use stocks), provide services to people and define their lifestyles, and the in-use stocks have more

robust behavior, due to their inertia. This approach is based on the idea that in-use stocks do not increase infinitely, i.e., they will reach saturation. Actually, Müller et al. [40] used dynamic MFA to determine that in-use iron stocks per capita in the United States have remained at a constant level (12 t/capita) since the early 1980s. Bader et al. [41] pointed out that an approach focusing on in-use stocks is appropriate for durables with a long lifespan, and several studies have forecast the future total demand for iron or copper using this approach [34,42,43].

Based on these previous studies, this study forecasts future total demands by correlating the in-use stocks per capita with GDP per capita by region. Conducting the analysis not on a global, but on a regional scale, is necessary because both in-use stocks per capita, and GDP per capita, may differ substantially among countries.

The historical in-use stocks are estimated by region, as follows:

$$U_{x,t,k,r} = \sum_{t'=t_0}^t D_{x,t',k,r} \times (1 - L_{x,t-t',k}) \quad (11)$$

where $U_{x,t,k,r}$ is the total in-use stock of final use sector k of resource x in region r in year t (kg). The historical total demands also need to be estimated by region in order to estimate the historical total in-use stocks by region. Following Pauliuk et al. [34], this study considers 10 world regions, each comprising countries at a similar stage of economic development: North America, Latin America, Western Europe, Commonwealth of Independent States, Africa, Middle East, India, China, Developed Asia and Oceania, and Developing Asia.

Historical data on population and GDP on the basis of purchasing power parity (PPP) by region, is collected; thereby, the in-use stock per capita, and GDP (PPP) per capita, by region, are derived. The logistic curve is used to model the in-use stocks per capita and determine the two parameters, $\alpha_{x,k}$ and $\beta_{x,k}$, with nonlinear regression, against the historical data (Equation (12)).

$$u_{x,t,k,r} = \frac{u_{max,x,k}}{1 + \exp(\alpha_{x,k} - \beta_{x,k} \times g_{t,r})} \quad (12)$$

where $u_{x,t,k,r}$ is the in-use stock per capita of final use sector k of resource x in region r in year t (kg/capita), $u_{max,x,k}$ is the saturation value of in-use stock of final use sector k of resource x (kg/capita), and $g_{t,r}$ is GDP (PPP) per capita in region r in year t (US\$2005/capita).

We derive the future in-use stock per capita by applying future scenarios of population and GDP, by region, to Equation (12). We calculate the in-use stock for future scenarios by multiplying the future in-use stock per capita by future population. Then, the total demand for future scenarios by region is estimated by Equation (13).

$$D_{x,t,k,r} = \Delta U_{x,t,k,r} + EOL_{x,t,k,r} = U_{x,t,k,r} - U_{x,t-1,k,r} + \sum_{t'=t_0}^t D_{x,t',k,r} \times L_{x,t-t',k} \quad (13)$$

where $\Delta U_{x,t,k,r}$ is the net addition to in-use stock of final use sector k of resource x in region r in year t (kg). $D_{x,t,k}$ in Equation (10) is calculated by summing up $D_{x,t,k,r}$ for all regions:

$$D_{x,t,k} = \sum_r D_{x,t,k,r} \quad (14)$$

3. Parameter Estimation

3.1. Yield Rate

According to the estimate of the global iron cycle for the year 2000, losses to tailings were 13.2% and losses to slag were 3.9% [44]. In addition, according to Pauliuk et al. [33], losses to slag for the year 2009 were 6.0%. In this study, it is assumed that a metal is lost to both tailing and slag during primary

resource production and to slag only in secondary resource production. Following previous studies, this study assumes that y_1 of iron is 80.8% and y_2 of iron is 94.0%.

This study determines the yield rates of copper, following a previous study (Gordon [45]), which has been referred in other previous studies [36,37,46]. Gordon [45] estimated the loss rate of copper during each processing and smelting stage for the years 1900–1999. Using the newest estimates (for the years 1990–1999) by Gordon [45], this study calculates y_1 of copper as the product of processing efficiency and smelting efficiency (84.9%) and y_2 of copper as the smelting efficiency (98.4%).

3.2. Historical Total Demand

To estimate the historical total demand, the apparent steel consumption of each country for the years 1988–2012 [47] (the iron content of steel is assumed to be 98% [44]) and refinery copper production of each country for the years 1988–2012 [48] are obtained. However, the trade of metals is not considered in these data. Thus, the trade of copper, and steel and copper embedded in final products (this is termed indirect trade) need to be estimated.

Trade data for copper and various final products can be obtained from the Commodity Trade Statistics Database [49]. Based on Nakamura et al. [50], this study estimates the steel and copper content in each final product traded in Japan using the Japanese input-output (IO) table for the year 2011 [51], as follows. Assuming that the steel and copper content in each final product is not greatly different among countries, compared with the traded amount of each final product, the estimated content is then applied to other countries.

The Japanese IO table for the year 2011 comprises 518 rows and 397 columns in a rectangular matrix form (518×397 matrix) for the basic sector classification. In this study, some sectors are aggregated to a 395×395 matrix and the input coefficient matrix A is derived. Let $\Phi = [\phi_{ij}]$ be a 395×395 matrix, the i th row/ j th column element of which is unity if both input i and output j are physical (with mass) (otherwise it is zero). Henceforth, Φ is termed the mass filter matrix. Multiplication of A by Φ removes non-physical flows, such as electricity and services from A . Let $V = [V_{ij}]$ be a 395×395 matrix, the i th row/ j th column element of which is v_j/v_i (v_i is the unit price of sector i). Let $C = [c_{ij}]$ be a 395×395 matrix, the i th row/ j th column element of which is the content of i per unit of output j . C is calculated by Equation (15).

$$C = V \odot (I - \Phi \odot A)^{-1} \quad (15)$$

where I is the unit matrix and \odot refers to the Hadamard product (the element-wise product of two matrices). The unit price of each sector is estimated using the table on value and quantity, which is a supplementary table of the Japanese IO table for the year 2011, and the value and quantity of the export of final products from Japan in 2011, as obtained from the Commodity Trade Statistics Database [49].

The content of resource x per unit of output j is calculated by Equation (16).

$$Co_{x,j} = \sum_{i_x} c_{ij} \quad (16)$$

where $Co_{x,j}$ is the content of resource x per unit of output j (kg/\$) and i_x is (are) the sector(s) representing the resource x (for steel, i_x are “Crude steel (converters)” and “Crude steel (electric furnaces)”, and for copper, i_x is “Copper”).

In estimating indirect trade, it is necessary to determine which final products are addressed. Therefore, we identify sectors relevant to the indirect trade of each metal from the content of each metal, and the import and export value of each sector in Japan. Then, we use commodity trade data from the harmonized system (HS) code, which corresponds to identified sectors for the years 1988–2012. The numbers of HS codes, used for estimating the indirect trade of steel and copper, are 412 and 438, respectively. Finally, the historical trade of steel and copper for each country is obtained

by multiplying the historical traded value of final products and copper itself by the content of each metal, in each sector.

The historical total demand for steel and copper, by region, for the years 1988–2012, is obtained from the apparent steel consumption, refinery copper production, and historical trade of steel and copper, for each country. The historical total demand for steel and copper, by region, for the years 1900–2012, is extrapolated using world pig iron production [52], world mine production of copper [48,53], and GDP (PPP) by region [54–56]. The historical total demand for iron is obtained using the iron content of steel (98%) [44].

Next, it is necessary to estimate the historical final use sector split of iron and copper, by region. The final use sector split of iron in Japan, for the years 1971–2012, is obtained from the Committee of Iron and Steel Statistics [57], and that of China, for the years 1949–2009, is obtained from Pauliuk et al. [58]. The final use sector split of copper is estimated from the Japanese IO table, for every 5 year period, from 1970 to 2005, and the year 2011, as follows. Some sectors of the Japanese IO table for each year are aggregated into a square matrix, and the input coefficient matrix for year t (A_t) and the mass filter matrix for year t (Φ_t) are derived. Let n_t be the number of the row or column (sector) of A_t and let $F_t = [F_{tij}]$ be an $n_t \times n_t$ matrix, the i th row/ j th column element of which is the total final demand of j for year t . Let $\tilde{C}_t = [\tilde{c}_{ij}]$ be an $n_t \times n_t$ matrix, the i th row/ j th column element of which is the content of i in annual output of j for year t . \tilde{C}_t is calculated by Equation (17).

$$\tilde{C}_t = F_t \odot (I - \Phi_t \odot A_t)^{-1} \quad (17)$$

The copper content in the annual output of each sector can be derived from \tilde{C}_t . Then, each sector is assigned to final use sectors, and the final use sector split of copper in Japan for each year is estimated. From these data, the historical final use sector split for each metal, by region, is estimated by linear regression analysis using GDP (PPP) per capita as an explanatory variable. From the above, the historical total demand, by final use sector and region, is estimated.

3.3. Recycling Rate

The recycling rates of iron by final use sector are reported in Pauliuk et al. [33], using data from Graedel et al. [59] and the World Steel Association [60]. In addition, Pauliuk et al. [33] assumed that 10% of steel used for the construction sector and leaving the use phase is accumulated as obsolete stock and thus, is not recovered for recycling. Therefore, this study uses values from Graedel et al. [59] and the World Steel Association [60] for three final use sectors (transportation, machinery, and products), and the value multiplied by 0.9 ($= 1 - 0.1$) for construction, as the recycling rates of iron (Table 1). This study determines the recycling rates of copper by final use sector, based on Glöser et al. [61] (Table 1).

Table 1. List of parameters by metal and final use sector.

	Final Use Sector k	Recycling Rate $RR_{x,k}$ (%) [33,59–61]	Lifetime Distribution $L_{x,t,k}$	
			Average Lifetime $\bar{t}_{x,k}$ (year) [39,61]	Shape Parameter $m_{x,k}$ [36,42]
Iron	Construction	76.5	75	3.5
	Transportation	85	20	3.5
	Machinery	90	30	3.5
	Products	59.5	15	3.5
Copper	Building and Construction	59	40	4
	Electrical and Electronic	36	11	1.75
	Infrastructure	52	30	2.5
	Transportation	48	17	1.5

3.4. Lifetime Distribution

The Weibull distribution is used for the distribution function of the lifetime distribution of iron and copper. The accumulated Weibull distribution function is expressed by Equation (18) [62].

$$W_{x,t,k} = 1 - \exp \left[- \left\{ \frac{t}{\bar{t}_{x,k}} \right\}^{m_{x,k}} \times \left\{ \Gamma \left(1 + \frac{1}{m_{x,k}} \right) \right\}^{m_{x,k}} \right] \quad (18)$$

where $\bar{t}_{x,k}$ is the average lifetime of final use sector k of resource x (year), $m_{x,k}$ is the shape parameter of final use sector k of resource x (-), and Γ is the gamma function. Then, $L_{x,t,k}$ is described by Equation (19).

$$L_{x,t,k} = W_{x,t,k} - W_{x,t-1,k} \quad (19)$$

For iron, this study determines the average lifetime by final use sector, based on Müller et al. [39], and it assumes shape parameters of 3.5 for all the final use sectors, based on Hatayama et al. [42]. For copper, this study determines average lifetime by final use sector, based on Glöser et al. [61] and shape parameters by final use sector, based on Nassar et al. [36] (Table 1).

3.5. Future Scenarios

In Equation (12), $u_{max,x,k}$ is assumed from the estimates of $u_{x,t,k,r}$. Results of the estimation of $u_{max,x,k}$, $\alpha_{x,k}$, and $\beta_{x,k}$ for iron and copper are shown in Table 2.

Table 2. Results of parameter estimation by metal and final use sector.

	Final Use Sector k	Saturation Value of In-Use Stock Per Capita $u_{max,x,k}$	$\alpha_{x,k}$	$\beta_{x,k}$
Iron	Construction	11 (t/capita)	3.04	0.15
	Transportation	1.6 (t/capita)	3.11	0.16
	Machinery	1.5 (t/capita)	2.15	0.23
	Products	1.3 (t/capita)	3.45	0.17
Copper	Building and Construction	55 (kg/capita)	2.27	0.14
	Electrical and Electronic	40 (kg/capita)	2.90	0.13
	Infrastructure	70 (kg/capita)	2.27	0.13
	Transportation	25 (kg/capita)	3.41	0.13

This study considers six future scenarios: the “constant total demand scenario” and five shared socioeconomic pathways (SSPs) [54,63].

The constant total demand scenario assumes that the future total demand will not change from the current value. In other words, future changes in secondary resource use are only considered when estimating the time-series primary resource use in this scenario. On the other hand, in SSPs, future changes, in both total demand and secondary resource use, are considered. From the result of the constant total demand scenario and SSPs, we can understand which aspect will affect the surplus costs more.

SSPs were recently developed as five future scenarios of future population and GDP, by country. These were developed from the viewpoint of socioeconomic challenges related to mitigation and adaptation (Figure 2). According to O’Neill et al. [64], socioeconomic challenges for mitigation are “defined as consisting of: (1) factors that tend to lead to high reference emissions in the absence of climate policy because, all else equal, higher reference emissions makes that mitigation task larger, and (2) factors that would tend to reduce the inherent mitigative capacity of a society”. Also, socioeconomic challenges for adaptation are “defined as societal or environmental conditions that, by making adaptation more difficult, increase the risks associated with any given projection of climate change”. For example, Figure 2 shows that SSP5 is the future scenario in which mitigation challenges dominate, and SSP1 is the future scenario with low challenges.

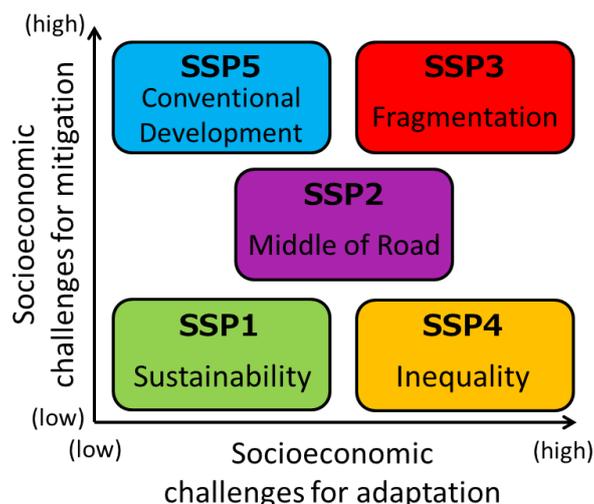


Figure 2. Five socioeconomic pathways (SSPs) (Based on O'Neill et al. [63]).

SSP1 (sustainability) envisions a world making relatively good progress toward sustainability. This world is characterized by an open and globalized economy, with relatively rapid technological change, directed toward environmentally friendly processes and low population growth. SSP2 (middle of road) envisions a world in which trends typical of recent decades continue, and population and GDP per capita grow at a medium pace. SSP3 (fragmentation) envisions a world failing to achieve global development goals. In this world, little international cooperation and low investment in technological development and education slow down economic growth in various regions. Population growth in this scenario is high, as a result of education and economic trends. SSP4 (inequality) envisions a highly unequal world, both within and across countries. In industrialized as well as in developing countries, a relatively small but rich global elite is responsible for much of the emissions, while a larger, poorer group contributes little to emissions but is vulnerable to the impacts of climate change. SSP5 (conventional development) envisions a world oriented toward economic growth as the solution to social and economic problems. In this world, the preference for rapid conventional development leads to an energy system dominated by fossil fuels, resulting in high greenhouse gas emissions and challenges for their mitigation [63,64].

4. Results

4.1. Time-Series Primary Resource Use

Figure 3 shows time-series primary and secondary resource use of iron and copper, estimated based on the case where future primary and secondary resource use are assumed not to change from the current value (constant P_t case) and the constant total demand scenario. The conventional surplus cost can be considered to be based on the constant P_t case. In Figure 3, each value is expressed relative to primary resource use in 2012. Since the constant total demand scenario considers future changes in secondary resource use and assumes constant total demand, the primary resource use of iron and copper will decrease as a result of an increase in secondary resource use, in the future.

Figure 4 shows the time-series primary and secondary resource use of iron and copper, estimated based on SSPs, which consider future changes in total demand. In Figure 4, each value is expressed relative to primary resource use in 2012.

In all of the SSPs, primary resource use of iron and copper is projected to increase in the future. In SSP1, SSP2, and SSP5, which show relatively large economic growth and negative population growth, primary resource use will peak and then fall. This is because in-use stocks reach saturation faster and populations decrease. Although a peak is not clear in SSP4, primary resource use will

decrease gradually. In SSP3, which shows high population growth, primary resource use will not peak but will continue to increase. These tendencies are common for iron and copper. Furthermore, secondary resource use will continue to increase in the future, in all of the SSPs. This suggests that the secondary resource will become more significant in the future.

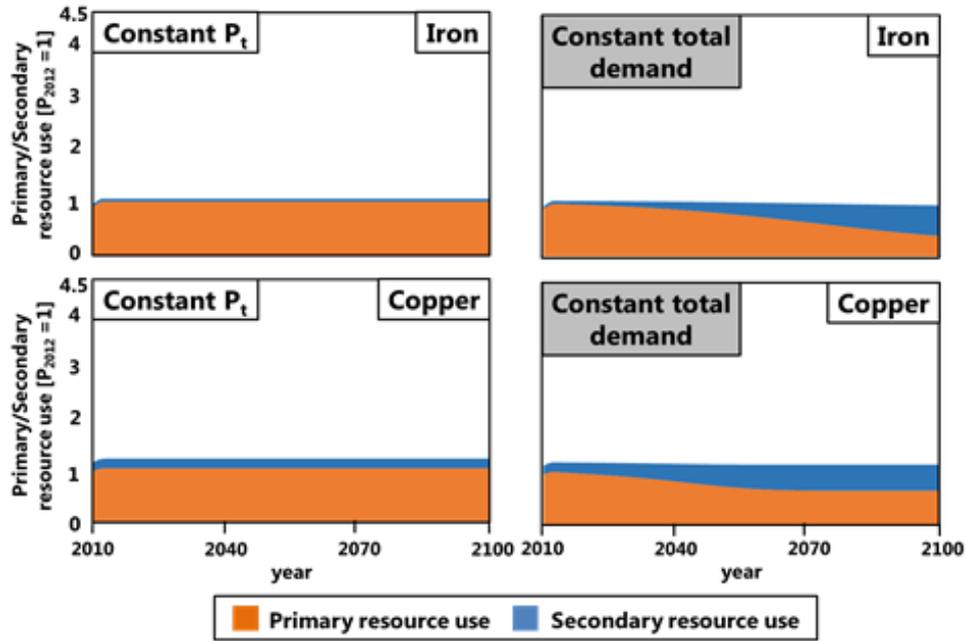


Figure 3. Time-series primary/secondary resource use of iron and copper, based on the constant P_t case and the constant total demand scenario. Each value is expressed relative to the primary resource use in 2012 (iron: 1626.2 million ton, copper: 20.6 million ton).

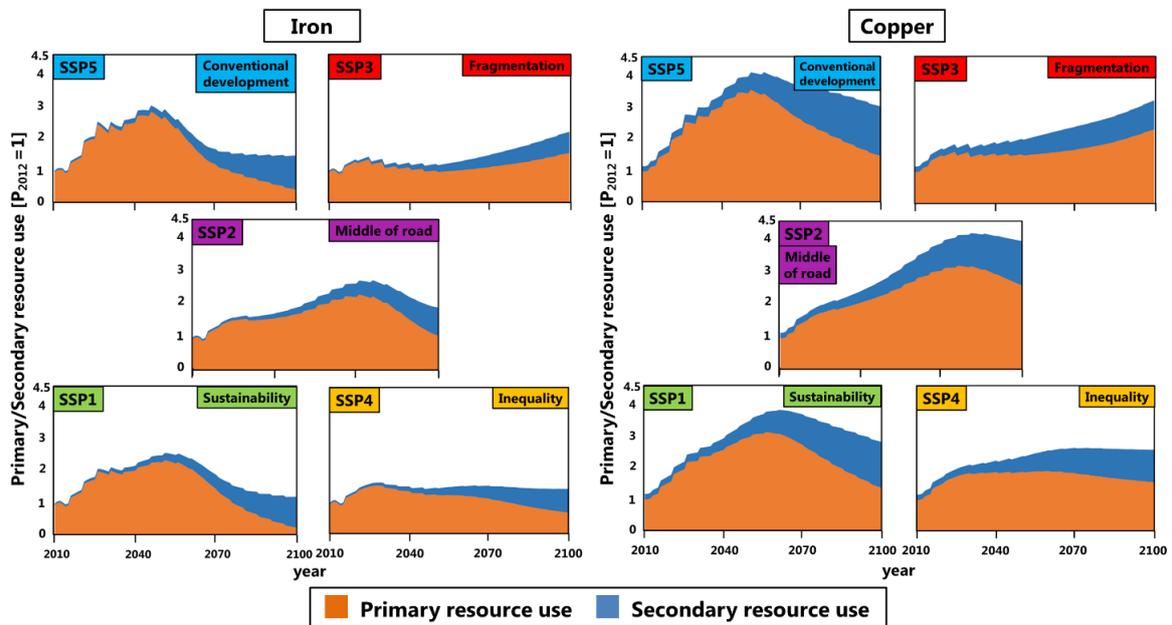


Figure 4. Time-series primary/secondary resource use of iron and copper in each SSP. Each value is expressed relative to primary resource use in 2012.

In SSP1, SSP2, and SSP5, primary resource use of iron reaches its peak more rapidly than copper—the peak year for iron in each scenario is 2051 (SSP1), 2071 (SSP2), and 2046 (SSP5), whereas

the peak year for copper in each scenario is 2056 (SSP1), 2081 (SSP2), and 2051 (SSP5). This is because the in-use stock of iron per capita reaches saturation more rapidly (at lower GDP per capita) than does copper. In all of the SSPs, the primary resource use of copper, relative to that in 2012, will increase more than that for iron in the future. We can interpret from these points that iron use will increase less than copper in the future because iron has been used more, to date.

4.2. Demand Change-Based Surplus Cost

Figure 5 shows the DCSC values of iron and copper by future scenario, as calculated from Equation (3). In Figure 5, each value is expressed relative to SC (hereinafter referred to as the DCSC/SC ratio) of each metal based on the constant P_t case.

In all of the scenarios, except the constant total demand scenario, the calculated DCSCs are larger than the SC. This is due to the increasing future demand, and it indicates that the effect of the increasing future demand is larger than that of the increase in the substitution of the secondary resource for the primary resource. For both iron and copper, the DCSC/SC ratio is largest for SSP5, followed by SSP1, SSP2, SSP4, and SSP3 (in that order). This order corresponds with the order of GDP per capita. A higher GDP per capita leads to larger future demand and then a larger DCSC. As a result of the differences among the SSPs, the largest DCSC/SC ratio for copper is 1.5 times larger than the smallest value.

For the constant total demand scenario, there is no difference between the DCSC/SC ratio of iron to that of copper. On the other hand, the DCSC/SC ratio of copper is larger than that of iron for all SSPs (a maximum of 1.4 times larger for SSP4). From the results for the constant total demand scenario, we can say that future total demand will affect the DCSC more than will the in-use stock or recycling rate. The results for the SSPs imply that the conventional model, which assumes constant primary resource use over time, will underestimate the surplus cost of copper relative to that of iron.

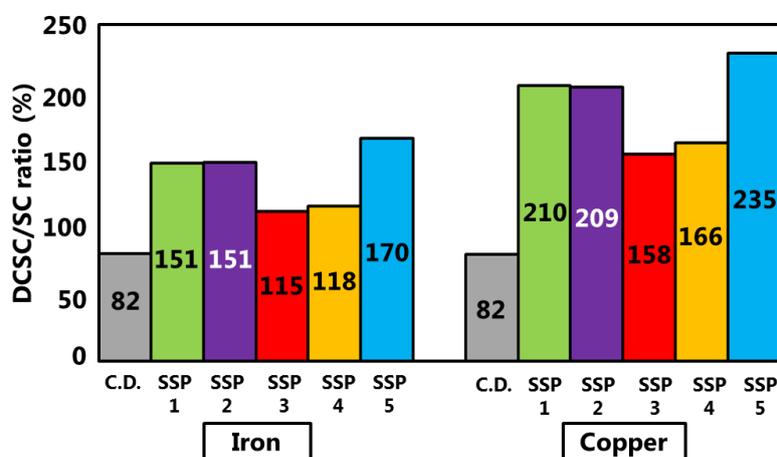


Figure 5. Demand change-based surplus costs (DCSC) of iron and copper by future scenario, expressed relative to surplus costs (SC) (C.D. = constant total demand scenario).

4.3. Sensitivity Analysis

In calculating DCSC, we take into account several parameters which are not considered in SC (e.g., recycling rate). Since these parameters may become a source of uncertainty, it is necessary to understand the effect on DCSC caused by changes in these parameters. Furthermore, it is also worthwhile to understand the effect on the results from changes in the discount rate. The higher and lower discount rates mean that the effects of changes in future primary resource use are smaller and larger, respectively. In this study, a sensitivity analysis was conducted for the following four parameters: recycling rate ($RR_{x,k}$), average lifetime ($\bar{t}_{x,k}$), saturation value of in-use stock per capita ($u_{max,x,k}$), and

discount rate (r). A change of approximately 10% was assumed for recycling rate, average lifetime, and saturation value of in-use stock per capita, and that of 1% was assumed for discount rate.

Table 3 shows the results of the sensitivity analysis. The higher and lower recycling rates lead to the smaller and larger DCSC, respectively. Meanwhile, whether changes in the average lifetime and the saturation value of in-use stock per capita affect DCSC positively or negatively depends on resource types and future scenarios. Average lifetime is related to historical in-use stock (longer and shorter lifetimes lead to larger and smaller historical in-use stocks, respectively). Although historical in-use stocks are related to future in-use stocks, the net addition to in-use stocks and the flow to end-of-life in each year—which determine the future total demands (see Equation (13))—depend on resource types and future scenarios. Since the DCSC depends on future primary resource use, which is related to the future total demands and the flow to end-of-life, the results are different among resources and scenarios. The larger saturation value of in-use stock per capita tends to lead to larger future total demand and DCSC. However, larger saturation values of in-use stock per capita lead to larger $\alpha_{x,k}$ for some sectors. A larger $\alpha_{x,k}$ leads to smaller future in-use stock (see Equation (12)) and total demand, which lead to smaller DCSC. Therefore, the results for the saturation value of in-use stock per capita are also different among resources and scenarios. The results for the discount rate are also different among resources and scenarios. For SSP1 and SSP5 of iron, changes in the DCSC/SC ratio with changes in the discount rate ($d : 3 - 1\%$) are larger than 10%. The lower discount rate means that the effect of change in future primary resource use is larger, and for these scenarios, future primary resource use of iron will, in particular, decline. Other than these scenarios, changes in the DCSC/SC ratio with changes in parameters are smaller than 10% for all scenarios and parameters (7.7% is the largest change for " $u_{max,x,k} : -10\%$ ", SSP5, and iron).

Table 3. Results of the sensitivity analysis.

		DCSC/SC Ratio (%)				
		SSP1	SSP2	SSP3	SSP4	SSP5
Iron	Default	151	151	115	118	170
	$RR_{x,k} : +10\%$	148	149	112	115	167
	$RR_{x,k} : -10\%$	154	154	117	121	173
	$\bar{t}_{x,k} : +10\%$	147	148	114	116	164
	$\bar{t}_{x,k} : -10\%$	156	155	114	120	176
	$u_{max,x,k} : +10\%$	160	158	113	121	182
	$u_{max,x,k} : -10\%$	141	143	115	114	157
	$d : 3 + 1\%$	157	149	113	122	177
	$d : 3 - 1\%$	135	151	119	110	152
	Copper	Default	210	209	158	166
$RR_{x,k} : +10\%$		204	203	153	161	228
$RR_{x,k} : -10\%$		216	215	163	172	241
$\bar{t}_{x,k} : +10\%$		202	202	158	171	247
$\bar{t}_{x,k} : -10\%$		219	216	156	170	249
$u_{max,x,k} : +10\%$		220	216	156	170	249
$u_{max,x,k} : -10\%$		199	201	161	163	220
$d : 3 + 1\%$		207	196	152	165	232
$d : 3 - 1\%$		207	225	169	167	230

5. Discussion

The results of this study are compared with those of Schneider et al. [26,27], who developed the characterization model, taking into account the anthropogenic stock (AADP). These studies were chosen for comparison with this study because they focus on anthropogenic stock (which affects future secondary resource use), which is partly similar to the focus of this study. However, it should be noted that the DCSC (or SC) and the AADP (or ADP) are based on different principles. The former focuses

on the additional effort necessary for extracting a resource in the future, while the latter focuses on the physical finiteness of resources [18,27].

Schneider et al. [26] calculated the AADP, focusing on the extraction rate, *resources*, and anthropogenic stock (see Equation (1)). The extraction rate corresponds to the annual primary resource use, P_x , per year (kg/year) in this study. The authors took into account anthropogenic stocks in addition to lithospheric stocks (*resources*). On the other hand, our study takes into account in-use stocks in calculating the time-series primary resource use ($P_{x,t}$) in Equation (3).

Table 4 shows the ratios of characterization factors, calculated by the updated (i.e., AADP and DCSC) and conventional (i.e., ADP and SC) models for iron and copper. The AADP values, relative to the conventional ADP values (AADP/ADP ratios), were about 35 and 1.2 times larger for iron than for copper, in Schneider et al. [26] and Schneider et al. [27], respectively. These results oppose the results of this study, where the DCSC/SC ratio of copper is larger. In addition, the results differ between Schneider et al. [26] and Schneider et al. [27], due to the choice of stock indicators, i.e., *resources* and *ultimately extractable reserves*. For example, *resources* of iron is 8.00×10^{11} (t) and *ultimately extractable reserves* of that is 6.46×10^{12} (t) [26,27]. As mentioned by Schneider et al. [27], in calculating the ADP and the AADP, stocks of material are of comparably higher importance than extraction rates, due to the squaring of the denominator. On the other hand, the iron/copper ratios of the DCSC factors or DCSC/SC ratios are nearly constant across different SSP scenarios (Table 4), which indicates that DCSC factors are robust against the choice of future demand scenarios, at least when comparing iron and copper.

Table 4. Ratios of characterization factors, calculated by the updated and conventional models for iron and copper.

		Iron	Copper	Iron/Copper (—)
ADP (kg Sb-e./kg) [65]		8.43×10^{-8}	1.94×10^{-3}	4.35×10^{-5}
AADP (kg Sb-e./kg)	[26]	2.38×10^{-6}	1.57×10^{-3}	1.52×10^{-3}
	[27]	2.75×10^{-8}	5.41×10^{-4}	5.08×10^{-5}
AADP/ADP ratio (—)	[26]	28.2	0.809	34.9
	[27]	0.326	0.279	1.17
SC (\$/kg) [15]		7.15×10^{-2}	3.05	2.34×10^{-2}
DCSC (\$/kg)	C.D.	5.89×10^{-2}	2.49	2.37×10^{-2}
	SSP1	0.108	6.41	1.69×10^{-2}
	SSP2	0.108	6.37	1.70×10^{-2}
	SSP3	8.19×10^{-2}	4.82	1.70×10^{-2}
	SSP4	8.45×10^{-2}	5.08	1.66×10^{-2}
	SSP5	0.122	7.16	1.70×10^{-2}
DCSC/SC ratio (—)	C.D.	0.824	0.817	1.01
	SSP1	1.51	2.10	0.721
	SSP2	1.51	2.09	0.725
	SSP3	1.15	1.58	0.725
	SSP4	1.18	1.66	0.710
	SSP5	1.70	2.35	0.725

6. Conclusions

This study introduced a new characterization model to calculate DCSC, in which the characterization factors take into account future primary resource use changes due to future changes in total demand and secondary resource use, by modifying the conventional surplus cost model. The DCSC were calculated for iron and copper in future scenarios and compared with the conventional model. As a result, the consideration of changes in future primary resource use increased the characterization factors of copper relative to those of iron for all of the SSPs (a maximum of 1.4 times larger for SSP4). These results mean that the potential impacts of copper use, relative to iron use, will be underestimated, unless future primary resource use changes are considered.

Further research is required to improve the reliability of parameters, such as recycling rates. Although this study assumes constant recycling rates over time, these will change, due to various factors, such as the price of primary resources [66]. By considering such parameter changes, a more reliable estimation of time-series primary resource use, and consequently, an improved calculation of characterization factors, can be achieved.

Calculation of the DCSC for other resources is also required. The potential impacts caused by the use of resources may be underestimated by applying conventional models if their demands have been increasing recently (such as minor metals). The model proposed in this paper is useful for evaluating the potential impacts of the use of such metals. However, forecasting the future total demand may be a challenge when applying the model to other resources. The approach used to forecast the future total demands of iron and copper focuses on the in-use stock. This approach is not necessarily appropriate for resources whose use dates only few decades ago, with insufficient historical in-use stock data and, hence, with a risk of high uncertainty. In calculating DCSC for such resources, it is necessary to develop new, or adapt current, approaches to suit cases where there is a lack of historical data for forecasting future total demands. Since the results of this study suggest that the future total demand has a relatively large effect on the DCSC, forecasting future total demand may be an important issue when applying this model to other resources.

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