Stock-driven scenarios on global material demand: the story of a lifetime

Deetman, S.P.

3.

Scenarios for demand growth of metals in electricity generation technologies, cars and appliances

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Abstract

This study provides scenarios toward 2050 for the demand of five metals in electricity production, cars and electronic appliances. The metals considered are copper, tantalum, neodymium, cobalt and lithium. The study shows how highly technology-specific data on products and material flows can be used in integrated assessment models to assess global resource and metal demand.

We use the Shared Socio-economic Pathways as implemented by the IMAGE integrated assessment model as a starting point. This allows us to translate information on the use of electronic appliances, cars and renewable energy technologies into quantitative data on metal flows, through application of metal content estimates in combination with a dynamic stock model.

Results show that total demand for copper, neodymium and tantalum might increase by a factor of roughly 2 to 3.2, mostly as a result of population and GDP growth. The demand for lithium and cobalt is expected to increase much more, by a factor 10 to more than 20, as a result of future (hybrid) electric car purchases. This means that not just demographics, but also climate policies can strongly increase metal demand. This shows the importance of studying the issues of climate change and resource depletion together, in one modeling framework.

3.1 Introduction

Several studies have assessed raw material resource availability based on concerns regarding the security of supply of nonfuel minerals (Speirs et al. 2013; Northey et al. 2014; European Commission 2017; Sykes et al. 2016). These concerns are related to factors such as geological accessibility, geo-political risks, material substitutability (Graedel et al. 2015), recycling rates (Espinoza 2012; Graedel et al. 2011) and current economic importance (Graedel et al. 2012). Another key question in determining the supply risks for different specialty metals, which has received limited attention so far, is whether the available resources are sufficient to meet future demand. Interestingly, future demand for metals remains somewhat of a blind-spot in the criticality discussion. Against this backdrop, this chapter focuses on developing quantitative scenarios for the demand of five specialty metals toward 2050 for a number of crucial applications: appliances, cars and electricity generation technologies.

A number of studies have tried to quantify the global long-term demand for metal resources (Moss et al. 2011; Marscheider-Weidemann et al. 2016). Such studies are based on different approaches and therefore difficult to compare. Some studies assume that the metal demand will continue to grow with a fixed percentage each year over the coming decades (Henckens et al. 2014). This method is severely constrained for long-term trends as it does not account for underlying changes in consumption patterns resulting from development of population and affluence for example, which ultimately drive metal demand. Van Vuuren et al. (1999) as well as van Ruijven et al. (2016) account for these factors by simulating the saturation of metal demand through a set of scenarios assuming changes in intensity of use curve for steel and alloying metals as a function of development. This stock-saturation effect for steel is also observed by Muller et al. (2010) and can be used as an exogenous scenario driver to extrapolate material cycles (Hatayama et al. 2010; Pauliuk et al. 2012b). However, the approach in such studies requires calibration based on long historic time series and cannot capture radical introduction (or phase-out) of new demand categories such as electric cars. More technology-explicit approaches can account for this. An example is the study by Elshkaki and Graedel (2013), who calculate the demand of various technology metals in electricity generation technologies. They find an impressive growth in demand for all considered metals, but only describe a fraction of total demand. Kleijn et al. (2011) also expect a huge growth in metal demand, but again focus only on the electricity generation sector. Their findings are based on life cycle assessment and assumptions on metal demand expressed in grams per kWh. This approach makes it difficult to discern which part of the demand stems from the generation capacity and which stems from upstream production requirements; also, this approach ignores stock dynamics which are relevant to derive actual annual metal demand. De Koning et al. (2017) take a different approach by specifying scenarios for global metal demand based on an environmentally extended Input-Output table, thus covering demand from a wide range of product categories, but without accounting for long-term economic shifts or saturation of product demand at higher levels of income.

Though this chapter does not aim to overcome all constraints of existing studies, we observe that there is presently no comprehensive approach to generating scenarios for global resource use. Moreover, there is a lack of studies and approaches that link macro-scenarios, such as the Representative Concentration Pathways (RCPs, see van Vuuren et al. (2011a)), with scenarios for specific resources such as bulk and specialty metals. So far, only one study has tried to combine macro-scenario information with demand forecasts for copper, using UNEP's GEO-4 scenario family as a starting point (Elshkaki et al. 2016). Such a link would allow studying the linkages between material use, energy use and climate change in a more detailed way than current models allow (Pauliuk et al. 2017).

In this chapter, we address the first steps toward integrating the dynamics of material demand into existing global energy models by developing an approach to generate metal demand scenarios using information from the global integrated assessment model IMAGE. We estimate the metal demand for three application groups that are relevant for energy demand (cars and appliances) and supply (electricity generation). The related research questions are, first, how can we link the outcomes of integrated assessment models to generate metal demand scenarios? Second, what is the expected annual demand for copper, tantalum, neodymium, cobalt and lithium for cars, appliances and electricity generation by 2050? Answering these questions helps to improve the understanding of the combined energy-resource system, which is relevant for both climate policies as well as resource oriented policies.

In the following section on the methodology we discuss how we used the detailed implementation of the Shared Socio-economic Pathways (SSPs) by the IMAGE integrated assessment model (van Vuuren et al. 2017) to produce metal demand projections. Readers interested only in the results and discussion could skip to section 3.3.

3.2 Methodology

3.2.1 Model framework

The starting point for our methodology is the data available from the IMAGE scenarios. IMAGE is an integrated assessment model describing global environmental change based on a detailed description of both energy and land use (Stehfest et al. 2014). The IMAGE model is often used to create scenarios for 26 world regions for energy and land use, and the underlying drivers. Both the activity data of the energy system and the underlying socioeconomic drivers can be used to create metal demand scenarios. On the basis of the available model detail, we used a dynamic stock model to compile the available product and capital stock data from IMAGE into data on the annual demand for cars, appliances and energy generation technologies. Subsequently, we added information on the metal composition of these products (Hawkins et al. 2013; Habib 2015; Widmer et al. 2015; Cullbrand and Magnusson 2012; Moss et al. 2013; Elwert et al. 2015; U.S. Department of Energy 2011; Schneider Electric 2011; Oguchi et al. 2011; Zhang et al. 2012; Truttmann and Rechberger 2006; Namias 2013; Tickner et al. 2016; Patrício et al. 2015; Arai et al. 2011; Seo and Morimoto 2014; Crock 2016; Schulze and Buchert 2016; Sprecher et al. 2014; Deetman et al. 2018; Chancerel et al. 2015; Moss et al. 2011; Öhrlund 2012; Singh et al. 2015; Meier 2002; S&T2 consultants 2006; Pihl et al. 2012; BBF Associates; Kundig 2011; Flury and Frischknecht 2012; Dones et al. 2007; Weitzel et al. 2012; Bhaduri et al. 2004; National Research Council 1986; Alonso et al. 2012; Long et al. 2012; Elshkaki and Graedel 2013) in order to derive the annual demand for five metals; which were selected based on data availability. The information flow is summarized in Figure 3.1. Key data used from IMAGE are the global total person kilometers driven by passenger car annually, the global total number of in use appliances per household and the newly installed power generation capacity, globally. Below we describe the key elements of our method, that is, the IMAGE model and the scenarios created by IMAGE, followed by a detailed description of the use of this data to create metal demand scenarios.

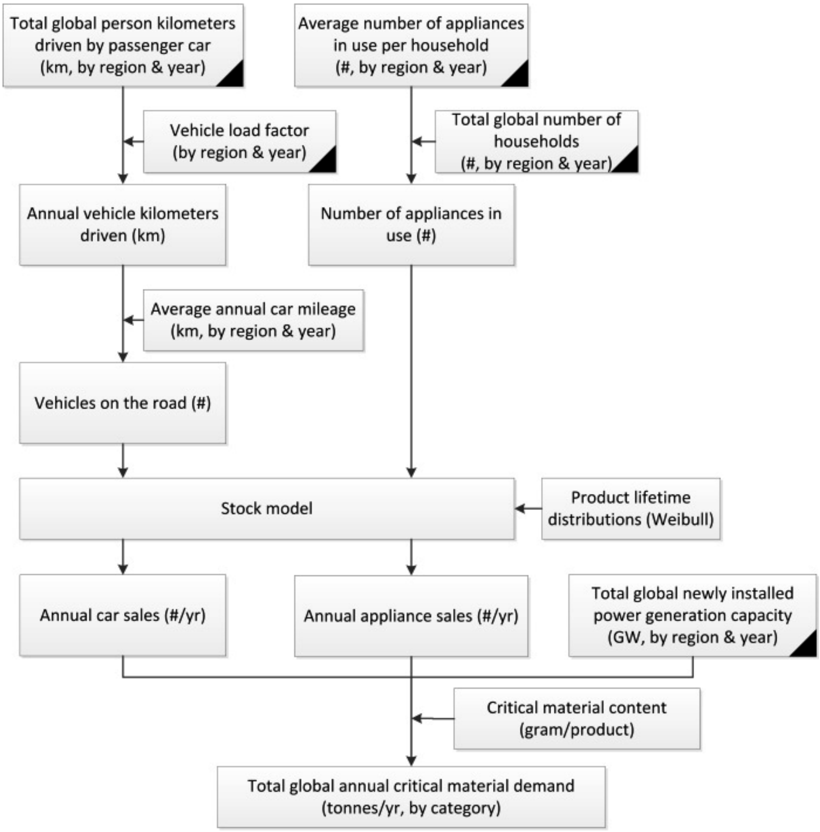

Figure 3.1. *Overview of the calculation steps to translate IMAGE model output (indicated with black triangles) into total metal demand for appliances, cars and electricity generation technologies. Vehicle "load factor" refers to the average car occupancy. Though the input data is specified per region, this study only presents numbers on global metal demand.*

3.2.2 The IMAGE model

The IMAGE model provides a consistent framework to assess how drivers such as population and welfare influence environmental issues. To provide insight into future greenhouse gas emissions the IMAGE model contains a highly detailed energy demand model, which among other things describes the development of households and private transport related energy consumption as well as the stock of power generating capacity in high technological detail. Because the contribution of domestic appliances to overall household electricity consumption is increasing, the IMAGE energy demand model contains indicators on the amount of appliances in use for the given 26 world regions, over the scenario period toward 2050 based on income relation as developed by Daioglou et al. (2012). Similarly, the submodel on transport emissions accounts for the number and the type of cars that are in use, because these determine the efficiency and thus their greenhouse gas emissions (Girod et al. 2012). Regarding power generation the IMAGE model identifies the annually required newly-built capacity for 27 different power generation technologies using a simplified stock model based on technology specific lifetimes, but not lifetime distributions, as described by van Vuuren (2006). The IMAGE model is developed and maintained by The Netherlands Environmental Assessment Agency and a detailed description of the data and the modeling approaches used can be found in the model documentation (Stehfest et al. 2014).

To use the IMAGE scenario output as input for metal demand scenarios we need to take two conversion steps:

1) First, we need to find a match between the level of product detail in the IMAGE model and available information on metal composition of products. Details on this step can be found in Appendix 3.
2) Second, we need to convert the current in use stock of cars and appliances to a demand for new products using a stock model. This also requires assumptions on the lifetimes and distribution of failure rates for all appliances and car types.

The required calculation steps are depicted in Figure 3.1 and are implemented in a dedicated python model, including a dynamic stock model based on work by Pauliuk (2014), for which the source code is available with the original publication. Though the IMAGE model provides the scenario results in regional detail, we focus on aggregate and global indicators.

3.2.3. The SSP scenarios

We use the available detail in model output by taking the IMAGE implementation of the shared socioeconomic pathways (SSP) as a starting point (van Vuuren et al. 2017). The SSPs present a new set of quantified long-term scenarios for climate change research with varying assumptions on the costs of climate change mitigation and adaptation, each leading to different levels of radiative forcing, thus posing different challenges in terms of climate policy (O'Neill et al. 2014; van Vuuren et al. 2014; Riahi et al. 2017). The SSP2 is a middle-of-the-road scenario in terms of the main developments, it represents moderate population growth and a path in which "social, economic, and technological trends do not shift markedly from historical patterns" (Riahi et al. 2017). We used the SSP2 baseline which assumes no additional climate policy. In the literature, the SSPs are combined with forcing targets consistent with the Representative Concentration Pathways (RCPs) to look into the impact of climate policy. In addition to the SSP2 baseline we also use the SSP2-2.6 climate policy scenario which leads to a radiative forcing of 2.6 W/m^2 by the end of the century, corresponding to the two-degree policy target (UNFCCC. Conference of the Parties (COP) 2015), by introducing climate policy. This entails deep greenhouse gas emission reductions (van Vuuren et al. 2011b). To show the impact of different baseline assumptions we also present results for two other baseline scenarios in the sensitivity analysis, that is, the SSP1 and the SSP3. The SSP1 baseline presents a future in line with a more sustainable development pathway, that is, a low population growth, high affluence, rapid technology development, and lifestyle change toward more environmentally friendly behavior. The SSP3 baseline assumes a fragmented world and has the opposite assumption for the key drivers as described for SSP1 (O'Neill et al. 2014). For an elaboration of the narratives behind these scenarios please see Appendix 1. Each of the scenarios present a different notion of the number as well as the types of cars and electricity generation technologies deployed towards 2050. To assess how these key scenario parameters (shown in Table 3.1) eventually influence annual metal demand we developed the methodology described in the following sections.

	SSP2				**SSP1**	**SSP3**
	2010	**2020**	**2030**	**2050**	**2050**	**2050**
Population (billion people)	6.87	7.61	8.26	9.17	8.53	9.96
GDP (trillion US$ per year, in 2005 PPP)	67.5	101.2	143.1	231.3	291.3	173.7
Energy (total primary energy, EJ/yr)	501	580	667	842	747	887

Table 3.1. *key characteristics of the shared socioeconomic pathways (SSP)* (Riahi et al. 2017)*. PPP stands for purchasing power parity.*

3.2.4 Metal composition and demand scenarios

We reviewed a total of 36 sources to obtain a database on metal content for cars (Hawkins et al. 2013; Cullbrand and Magnusson 2012; Elwert et al. 2015; U.S. Department of Energy 2011; Habib 2015; Widmer et al. 2015; Moss et al. 2013), appliances (Zhang et al. 2012; Namias 2013; Tickner et al. 2016; Patrício et al. 2015; Arai et al. 2011; Schulze and Buchert 2016; Deetman et al. 2018; Chancerel et al. 2015; Schneider Electric 2011; Oguchi et al. 2011; Truttmann and Rechberger 2006; Seo and Morimoto 2014; Crock 2016;

Sprecher et al. 2014) and electricity generation technologies (Moss et al. 2011; S&T2 consultants 2006; Pihl et al. 2012; Dones et al. 2007; Bhaduri et al. 2004; National Research Council 1986; Long et al. 2012; Elshkaki and Graedel 2013; Öhrlund 2012; Singh et al. 2015; Meier 2002; BBF Associates; Kundig 2011; Flury and Frischknecht 2012; Weitzel et al. 2012; Alonso et al. 2012). The results are listed as ranges in an overview table, Table A3.1. The values in this table are applied together with the average of the minimum and the maximum values to represent three distinct scenarios on metal composition based on currently available data. We assume that the metal content of each product is constant over time. This means that we do not account for changes in specific metal requirements that may be a consequence of engineering efficiency or miniaturization trends over time. It would be beyond the scope of the study to assess all possible developments in engineering and design for all the products concerned. This exercise should hence be seen as a thought experiment, with a limited predictive value. We focus our conclusions on the change in demand and on the possible ranges in outcomes across the scenarios.

On the basis of the availability as well as the credibility of the data we had to make some assumptions as well as exceptions to derive a metal content for each product category found in the IMAGE model. For fuel cell vehicles (FCV), for example, we only had one available study with vehicle-specific metal content estimates (Moss et al. 2013), so the used metal composition is either from that study or based on the estimates for conventional vehicles using an internal combustion engine (ICE). When no information was available, for example, on metals in air-coolers and fans, we used our own estimates (e.g, 50% or 15% of the metal content of an air-conditioner respectively). An overview of all such assumptions made can be found in Appendix 3.

The three different sets of data on metal content (a low and a high estimate from Table A3.1 as well as the average of the two as a medium estimate), combined with the baseline scenario and the climate policy scenario from the elaboration of the SSP2, give us a selection of six different scenarios for the annual metal demand from three different demand categories. Before presenting the outcomes for these scenarios in the Results section (section 3.3), we first elaborate on the most important assumptions for cars (3.2.4.1), appliances (3.2.4.2), and electricity generation technologies (3.2.4.3), followed by an explanation of the dynamic stock model (section 3.2.5).

3.2.4.1 Cars

We first needed to translate the number of person kilometers to vehicle kilometers driven by dividing by the vehicle load factor (or average occupancy, IMAGE model output).This was subsequently converted to the number of cars in the vehicle fleet to calculate the annual demand for cars by dividing by an average kilometrage (cf. annual car mileage) by region based mostly on Pauliuk et al. (2012a). In 2008, the global average kilometers driven per car per year is 18 000 km. The regionally specific numbers that were applied can be found in Table A3.2.

For the lifetimes of cars we assumed a Weibull distribution with similar distribution parameters for all five car types, as given in Appendix 3. The Weibull distribution parameters (10.3 shape parameter and 1.89 scale parameter) applied are those for “ordinary passenger cars (own use)”, as given by Nomura and Suga (2013), and lead to a relatively short average car lifetime of 9.1 years. The effects of assuming longer car lifetimes are discussed in section 3.3.3, in the sensitivity analysis.

3.2.4.2 Appliances

Since the use of appliances is already expressed in pieces in use per household, the information from IMAGE can be directly applied to back-cast the demand for new appliances using the stock model (as described below). The only issue is with respect to the definition of “other small consumer electronics”. The increasing adoption of high-end digital consumer appliances such as tablets and mobile phones is an important driver for the increase in demand for critical metals that have a high value, but are typically used in small amounts. However, their energy consumption remains low as they are typically battery operated and require little electricity to be charged. The IMAGE energy model therefore specifies a lump category of “other small consumer electrics”. The actual number of these appliances used in our analysis is therefore a rough estimate.

Similar to the approach for cars, assumptions on appliance lifetimes are based on Weibull distributions. The distribution parameters where obtained from Wang et al. (2013) and are listed in Table A3.1.

3.2.4.3 Electricity generation

The IMAGE model already includes stock dynamics on capital investments in electricity generation technologies, so the scenario output includes both an overview of total installed capacity as well as newly installed capacity for electricity generation technologies. The new capacity includes the expansion of the total capacity due to an increase in overall electricity demand, as well as the replacement of end-of-life capacity based on an average 30 year operational lifetime. To derive the annual metal demand from the power generation sector we can thus simply multiply the newly installed MegaWatts (MW) by the metal demand per MW from Table A3.1 of Appendix 3.

3.2.5 Dynamic stock model for passenger vehicles and appliances

To determine annual sales of passenger vehicles and appliances from their total stocks we applied stock-driven modeling originally based on Müller (2006) and Pauliuk (2014) to calculate the required product purchases (annual inflow, in products per year) to fulfill the total demand for cars and appliances (stock, i.e. the total number of products in use). The model tracks the different age-cohorts and uses a survival function based on the Weibull distribution to calculate how many of the cars and appliances bought in year t_0 survive after t years. The survival function (SF) equals 1 minus the cumulative distribution function (CDF) of the product lifetime distribution and is expressed as follows:

$$SF(t) = e^{-\left(\frac{t}{\beta}\right)^{\alpha}} \tag{1}$$

where t is time, β is the Weibull Scale parameter and α is the Weibull shape parameter. The Weibull parameters used for each of the car types and appliances is given in Appendix 3. The survival function gives us the fraction of the products bought in year t_0 that are still in use in year t. For each model year (t), for each model region (r) and for each car or appliance, referred to as a product (p), we can then determine the total number of surviving products (SP) from all previous years (t') given the sales (y) of the previous years:

$$SP_{r,p}(t) = \sum_{t'=0}^{t} y_{r,p}(t') \cdot SF_{r,p}(t - t') \tag{2}$$

The sales (y) in the year of interest (t) are then determined from the stock balance:

$$y_{r,p}(t) = T_{r,p}(t) - SP_{r,p}(t) \tag{3}$$

Where T is the model stock target value, given by the IMAGE stock (products in use). In Appendix 3 an overview of relevant global inputs to the stock model based on direct IMAGE scenario output is presented, as well as intermediate calculations for appliances and cars for the current situation and by the end of the model period.

3.3. Results and discussion

3.3.1 Annual demand for cars, appliances & generation capacity

Because of the continued growth in population and affluence, the number of appliances in use in the original SSP2 scenarios is expected to more than double between 2015 and 2050 (Figure A3.1). This finding also holds for the required electricity generation capacity as well as for passenger car transport demand. Figure 3.2 shows that the increased demand of cars and appliances leads to roughly a doubling of appliance and car sales. Even without considering the particular types of appliances, cars or electricity generation technologies that are deployed, it is clear that the demand for materials embedded in products will increase substantially.

There may be quite a difference between the shares in the stock (Figure A3.1) and the shares in the new product purchases (Figure 3.2). Currently, global capacity of solar and wind based electricity generation is expanding rapidly, hence the shares of these technologies in the purchases is much larger than for nuclear power, whose rate of expansion is decreasing (World Energy Council 2016). Similarly, the transformation toward a (hybrid) electric car fleet, requires a high share of (hybrid) electric vehicles in the new vehicle purchases. Though these are rather obvious conclusions from a stock-dynamic perspective, this exercise shows the importance of stock-dynamics when deriving long-term projections of annual demand for products.

Our results show that climate policy has no effect on the expected demand of appliances, but slightly decreases the demand for cars by 2050 (compared to baseline). This is because alternative modes of transport with a lower carbon footprint, such as public transport, will be favored. The effect of climate policy on the demand for electricity generation technologies is a little more complicated. Because even though the climate policy lowers the demand for total electricity through energy efficiency measures, the annual demand for new electricity generation capacity grows. This can be explained through the intermittency of the renewable energy sources (wind and solar in particular). The newly built capacity represents the peak capacity but, as intermittent energy sources such as photovoltaics and wind turbines operate well below their maximum capacity on average, the peak capacity has to be expanded more than in the baseline scenario, which relies more on baseload technologies such as coal fired power plants. This need for excess capacity offsets the effect of the lower electricity demand under a climate policy regime. The fact that the transition toward a renewable energy system requires more materials, especially while capacity is being expanded, represents an important driver for metal demand.

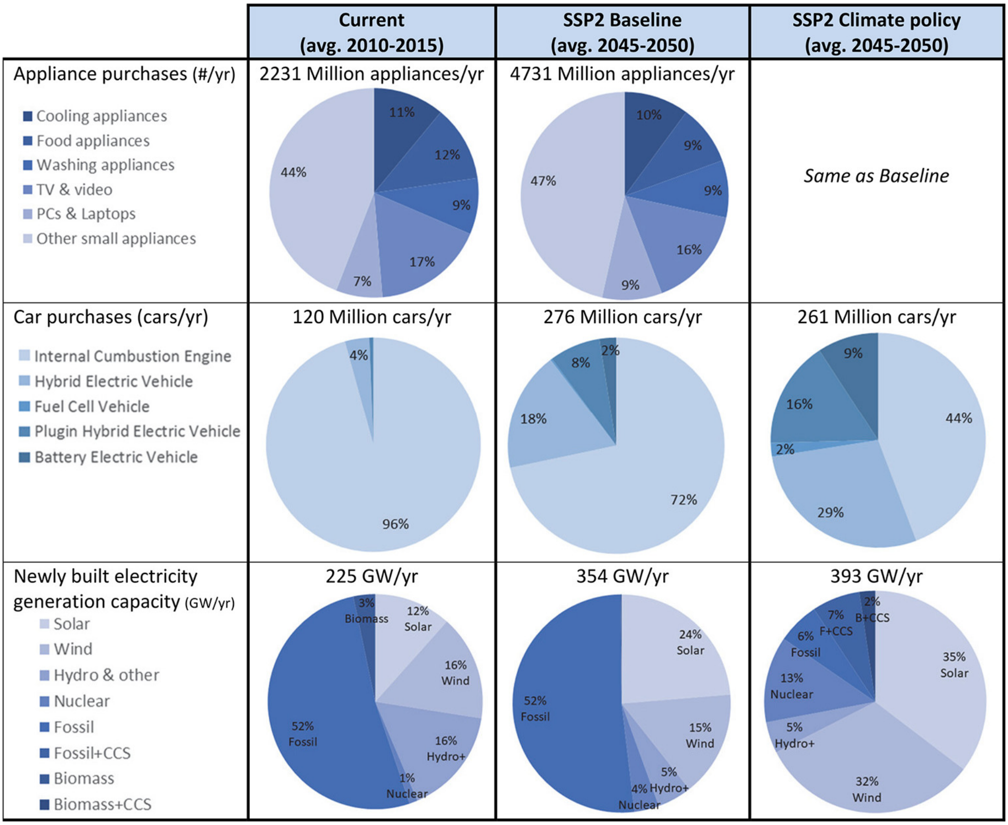

Figure 3.2. *Overview of scenario indicators on annual demand for cars, appliances & electricity generation capacity. i.e. their annual purchases/sales. The numbers above the charts indicate the total annual demand while the shares in the pie-charts indicate the relative market share of specific car types, appliance types or generation technologies.*

3.3.2 Resulting metal demand scenarios

We present a selection of graphs on the annual demand projections for copper and neodymium in a baseline and a climate policy case in Figure 3.3. The graphs for the other metals (for three different assumptions on metal content) can be found in the supplementary information of the original article.

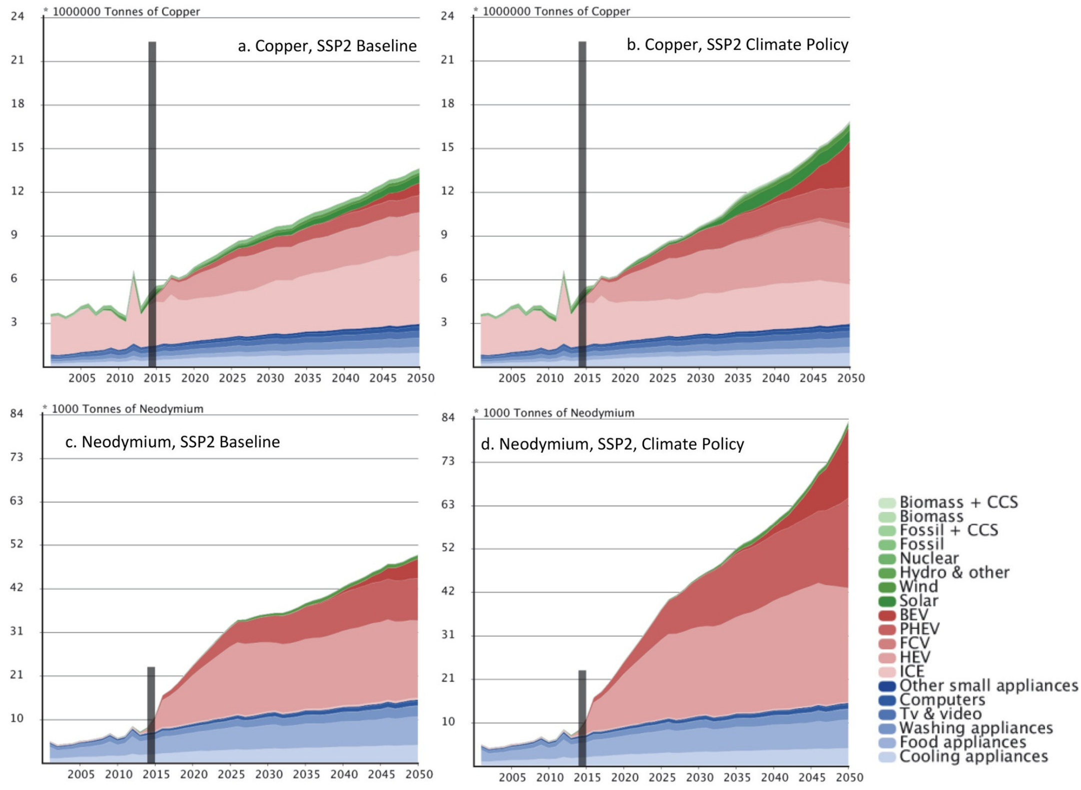

Figure 3.3a-d. *Metal demand projections for copper (a&b, using a medium metal content assumption) and Neodymium (c&d, using a low metal content assumption) in the SSP2 baseline scenario and in its corresponding 2-degree climate policy scenario (in tonnes/yr). Green represents all electricity generation technologies, red all car types and blue is used for appliances. The dark bar in 2015 represents the current total annual consumption estimates for copper* (Brininstool 2014) *and neodymium* (European Commission 2014). *Since this study only addresses 3 categories of demand, the bar gives a feeling for the size of the 'rest' of the demand (e.g. construction, medical applications etc.). For elaboration and results for all other metals, please see the original publication.*

Figure 3.3 shows that both copper and neodymium demand are expected to increase and that climate policy is likely to boost the demand considerably for both metals by 22% (for Cu) and 60% (for Nd) compared to the SSP2 baseline scenario. By the end of the modeling period the metal demand for car production dominates the other two considered product categories. This is an interesting finding, given that much of the current concern about neodymium demand is focused on wind turbines. Two factors are important in understanding this result. First of all, wind turbines have a considerably longer assumed lifetime (30 years) than appliances and cars, thus the demand for windmills to replace the ones that reach end of life will be relatively low, especially because the large-scale deployment of windmills is only a recent development. Another reason for the low annual metal demand from electricity generation technologies is that they are not consumer goods and therefore show much higher ulitization rates. While a single wind turbine may provide power to hundreds of households, many households aspire to own a car, a washing machine and other consumer goods. The impact of appliance and personal transport demand on metal consumption is fairly consistent across all metals considered (Table A3.4). As elaborated in Appendix 3, however, the different metal content estimates may lead to scenarios for which the modeled demand in cars, appliances, and electricity generation technologies surpasses the reported current demand. This is the main reason that we emphasize the need for more knowledge and data on the metal composition of products in the discussion section.

The results as shown in Figure 3.4 indicate that demand for all five metals is going to increase, regardless of the anticipated climate policy ambitions. Apparently, socio-economic developments (GDP, population) and technological change are more dominant factors than climate policies. However, the uncertainty introduced by the range of assumptions on metal content (Table A3.1) is so large that for tantalum and neodymium the low baseline estimates for the period 2045-2050 may actually be lower than the high estimates in the current situation. In most cases the difference between outcomes for high and low metal content estimates is larger than the difference between the baseline and the climate policy scenario.

To explore the differences in metal demand we present the growth factors by product category in Figure 3.4, using a single (medium) set of metal content assumptions. The figure shows that the rise in cobalt and lithium demand toward 2050 are explained by the demand for cars, which is in turn explained by their requirement in battery packs of hybrid and full electric cars. The metal demand from cars is consistently higher in a climate policy scenario, because the metal requirement is higher in all low-emission vehicles. This is however not the case for electricity generation technologies, as the deployment of wind turbines and photovoltaic cells under a climate policy scenario increase the demand for copper and neodymium, while they decrease the demand for tantalum and cobalt. The latter are generally used as alloys in temperature resistant steels, which are only applied in combustion-based power plants. Figure 3.4 shows the metal demand growth index for the period 2015-2050. In appendix 3, an extended table with the absolute numbers for all metal contents is provided (Table A3.4).

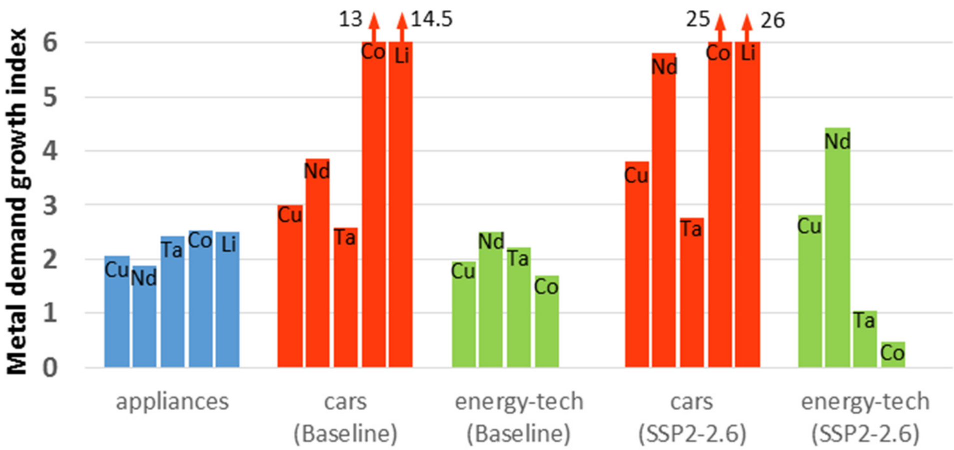

Figure 3.4. *Indexed growth factors of annual demand for five metals, by product category. The growth factor is based on the medium estimates, using the average of 2045-2050 over the average of 2010-2015. For cobalt and lithium in cars, the demand growth factors are much larger as indicated in numbers.*

3.3.3 Sensitivity analysis

To assess the impact of our modeling assumptions on the outcomes we performed a sensitivity analysis consisting of three parts. First, we complemented the results with outcomes for the SSP1 and the SSP3 baselines, to show how the range of outcomes changes under the assumption of different socio-economic baselines. Second, we assessed the importance of the lifetime assumptions for cars and third, the impact of metal content estimates for products that are based on only one reference value.

To provide some context regarding the effects of different socio-economic baselines we used the same approach as described in the Methodology section (Section 3.2) to calculate global metal demand for the SSP1 as well as for the SSP3. These baselines provide a wider range of possible developments in terms of population size, welfare indicators and energy use (see Table 3.1), thus leading to a different demand for appliances, cars and electricity generation technologies. Figure 3.5 shows the results for the total annual demand by product category under three different baselines and medium metal estimates.

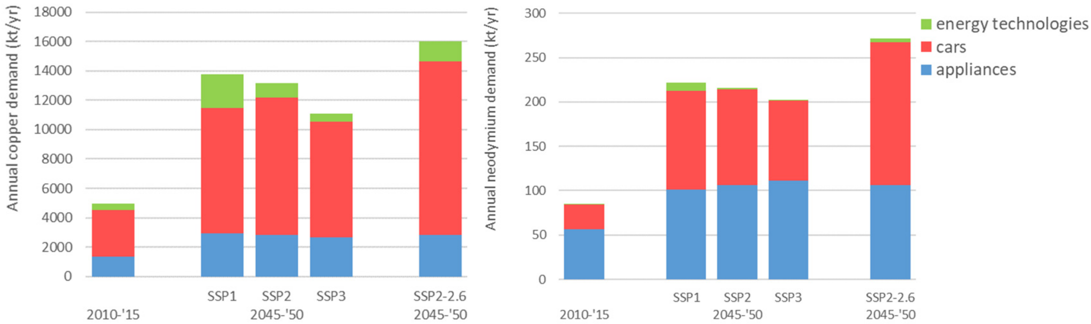

Figure 3.5. *Ranges in annual copper and neodymium demand from three product categories under three different socio-economic baselines. Similar to previous Figure 3.2, we present average annual demand for the period 2010-2015 and 2045-2050. The development of demand for the other metals under the SSP1 and SSP3 scenarios is available with the original publication.*

The changes in total metal demand across the three baselines is considerably smaller than the change between a baseline and a climate policy scenario (Figure 3.5). The total demand decreases consistently from SSP1 to SSP3, demonstrating that the SSP2 is indeed a middle-of-the-road scenario, also in terms of metal demand. In the case for copper the annual demand for the SSP3 baseline is about 20% lower as compared to the SSP1 (average of the annual demand over a five year period). For neodymium the demand is about 9% lower under the SSP3 baseline. A similar conclusion holds for the other three metals (shown in the supplementary information with the original publication), but the difference between baselines is even bigger in the case of cobalt & lithium, for which the annual demand in 2050 decreases by about 35% between the SSP1 and the SSP3 scenario assumptions.

Interestingly, the lower demand for energy in the SSP1 scenario (see Table 3.1) does not translate to a lower metal demand from electricity generation technologies because even in a baseline scenario the SSP1 shows a preference for low-carbon (but more material intense) types of electricity generation. This is in accordance with its storyline, which is oriented at sustainable development. Another consequence of this storyline is that the demand for copper in cars is lower in the SSP1 scenario than in the SSP2, because in this scenario the modal share is more dependent on public transport options, thus reducing the demand for cars, even though per capita income is higher. For neodymium this trend is offset by the higher demand for the (more expensive) battery electric vehicles, which in turn raises the demand for neodymium.

Another interesting result from Figure 3.5 applies to neodymium in appliances, for which demand is higher in the SSP3 scenario, even though the GDP is lower. The explanation is found in the population size, which is larger in the SSP3 scenario, but also the type of appliances purchased differ. Though the total number of appliances bought is larger in the SSP1 scenario, the growth there is mainly attributable to the demand for “luxurious” small appliances and laptops/PCs, while in the SSP3 the growth is mainly due to demand for more “basic” household appliances such as refrigerators and washing machines, which happen to contain higher amounts of neodymium according to the sources used (Arai et al. 2011; Seo and Morimoto 2014; Habib 2015).

The second part of our sensitivity analysis focuses on the lifetime of cars, which is a central model parameter because cars determine a large fraction of the total annual metal demand. The parameters of the Weibull lifetime distribution of cars were assumed to be the same for all considered car types, however, this may be an oversimplification considering the different technological basis of electric vehicles. For regular cars (ICE) and fuel cell vehicles (FCV) we increased the relatively short average lifespan from 9 years to represent the European average of 12.5 years based on Nemry et al. (2008); we did so by only changing the scale parameter of the lifetime distribution. For hybrid electric vehicles we found substantially different estimates for the lifetime distribution from Yano et al. (2016) and implemented their much higher average lifetime (21 years) for all cars with a (partially) electric drivetrain (HEVs, PHEVs and BEVs). This different set of Weibull parameters is applied to the SSP2 with the medium product content assumptions, resulting in much lower metal demand, as the number of scrapped cars is lowered, thus lowering the replacement car purchases. The resulting annual demand by the end of the scenario period (averaged over the years 2045 to 2050) is 24% lower for copper, 18% lower for neodymium, 9% lower for tantalum, 36% lower for cobalt and 45% lower for lithium. Though these numbers highlight the importance of the lifetime assumptions for cars, they should be interpreted carefully. The main reason for higher metal content in cars with an electric drivetrain is the requirement for a large battery pack. Previous studies have found different estimates for the battery lifespan ranging from 5 to maximum 15 years (Richa et al. 2014), which would imply that electric vehicle with a lifetime of over 20 years would have to replace their battery packs at least once during their lifetimes. Though the current model setup does not allow us to assess the effects of different lifetime distributions for product subcomponents, this may be an interesting direction for future research.

Finally, we tested the importance of missing content estimates for tantalum and neodymium (highlighted in gray in Table A3.1). We tested for the effect of introducing a probable range estimate, based on the average range within each metal column. Running the model with these numbers gives either a 4% higher or a 14% lower demand for tantalum over the five last years of the scenario. Using a similar procedure for neodymium, we find a change in average annual demand that is either 1% higher or 9% lower. For additional details, please see Appendix 3.

To provide some perspective, we compared our outcomes for copper to the study by Elshkaki et al. (2016) who found an expected growth in total copper demand of a factor 2.75 to 3.5 in 2045-2050 in comparison to 2010-2015. Our findings, even though they apply only to a fraction of all applications of copper in society, compare surprisingly well, given that over the same period in the SSP2 baseline we find a growth factor of 2.6 and a factor 3.2 when climate policy is considered. Similarly, the study by Henckens et al. (2014) finds an expected demand growth for annual copper demand of 3.3 by 2050. However, for other metals like lithium for example, we find very different results. For the three lithium applications considered in this study we find an expected growth in annual demand of a factor 10 by the end of the scenario, while the estimates for demand growth by Henckens et al. are similar to that of copper. The difference in growth factors underline the importance of distinguishing different metal applications and of using a high technological detail when making long-term scenarios for metal demand.

3.3.4. Outlook

Our analysis demonstrates that it is possible to link technology-rich output from an integrated assessment model to information on metal composition of products to derive scenarios for global metal demand toward 2050 for three product categories. This means that, given the availability of metal composition data, we can develop detailed scenarios for future metal demand that build upon the broad description of societal changes of existing global scenarios.

Baseline assumptions such as future population and demographic growth, can have a large influence on future metal demand, but the impact of climate policy and associated technology interventions could be even larger. The variations between scenarios can be explained by a changing demand for product categories as a whole (e.g., more cars but less energy), but also by the choice for individual products within these categories (less conventional cars, but more off-shore windmills). Our findings underline the importance of adopting a technology specific approach to metal demand scenarios. Our results support the earlier findings that climate policy will increase metal demand. Not renewable electricity technologies, but cars are the application responsible for the major share of the growth in metal demand. This is true for all considered metals, but especially for lithium and cobalt, and is the result of the transformation of the car fleet into an hybrid/electric one.

All five metals (copper, neodymium, tantalum, cobalt and lithium) face a strong growth in annual demand, regardless of the scenario, mostly as a result of population and GDP growth. The demand for lithium and cobalt is expected to increase much more as a result of the assumption of adopting GHG reducing technologies in the car fleet. The results show the importance of assessing the future metal demand under different socioeconomic frameworks and levels of ambition regarding climate change mitigation, while acknowledging the nonlinear dependencies from both the linkage between affluence and product demand modeled by IMAGE data as well as the development and dynamics of the in use stock of those products. This is, however, only a first step in the development of a comprehensive model.

Further research should first of all focus on improving the knowledge and data on the metal composition of products. The range of both the applications (e.g. construction and infrastructure) and the metals (major metals as well as critical ones) should be expanded to cover all relevant parts of societal metabolism, possibly even accounting for radical technological change. More accurate metal content estimates could be achieved by including numbers on the best available technologies, subcomponents and could even include the dynamics of changing product compositions. Having a more comprehensive coverage in metal demand scenarios would eventually allow a comparison of the findings with data about global resource supply. This may help to answer the question: “are global resources sufficient to meet future demand?”.

A next important step would be to translate demand scenarios into technology specific supply scenarios, including energy demand for mining operations, to enable assessing climate change impacts of resource extraction and production. The split between virgin raw material and recycled metals needs to be modeled to enable us to include resource efficiency policies and circular economy policies in the scenarios and to quantify the benefits of a larger share of secondary production for reducing GHG emissions. In this chapter, we generated the demand for the products using an integrated assessment model. Metal demand was calculated exogenously. A third development step could be to further integrate stock dynamic resource models into integrated assessment models used for energy and climate change scenario assessments. Fully internalizing resource demand in integrated assessment models, including their resulting price dynamics, would increase the coherence and relevance of global scenario exercises considerably.

Appendix

Appendix 1 contains an elaboration of the scenario narratives; Appendix 3 contains additional details to the methodology and product compositions applied in this chapter. The python model code as well as graphs for the resulting metal demand scenarios for all metals using the full range of metal composition data can be found in the supplementary information with the original publication.