From the outside in…

Geopolitical Supply Risk and Life Cycle Assessment of Products

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This thesis contains material, primarily in Chapter 3, based on a co-authored article published in the Journal of Cleaner Production (http://dx.doi.org/10.1016/j.jclepro.2017.06.063). I am the lead author of the article, joined by co-authors Steven B. Young, Christoph Helbig, Eskinder D. Gemechu, Andrea Thorenz, Axel Tuma, and Guido Sonnemann. Chapter 3 contains the methods, results, discussion, and conclusion sections of the article, while parts of the introduction – though expanded upon for the purpose of this thesis – are contained within Chapters 1 and 2. Bibliographic information for the article is provided below. Further, Chapter 4 contains material from a manuscript submitted to the International Journal of Life Cycle Assessment (http://www.springer.com/environment/journal/11367). I am the lead author on the manuscript, joined by co-authors Karim S. Karim and Steven B. Young.

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Abstract

Growth in global population and living standards, along with the transition to a low-carbon economy, require increasing supply of an unprecedented variety of material commodities. Consequently, securing availability of "natural resources" is a key priority for sustainable development as it applies to policy and product design.

Life Cycle Assessment (LCA) – which has been applied in policy and product design for decades – has traditionally been a tool for measuring potential environmental impacts of products from "cradle" to "grave." More recently, the term Life Cycle Sustainability Assessment (LCSA) has emerged to incorporate socio-economic considerations alongside environmental issues. While environmental LCA methodology is relatively well developed, socio-economic aspects of "natural resources" have long been controversial in the LCA community. Conventional approaches concern "inside-out" impacts of resource depletion and scarcity *in the long-run*. In contrast, newer approaches for resource "criticality" assessment – which have emerged outside the LCA community – concern "outside-in" mechanisms that can disrupt raw material availability *in the short-run*. Methods for criticality assessment, however, have had limited applicability on a product-level because they do not provide a clear connection to a *functional unit* of a given product – a central concept in LCA.

Therefore, this thesis aims to extend the previously developed Geopolitical Supply Risk (GPSR) method from a relative assessment of raw material criticality to a Life Cycle Impact Assessment characterization model for assessing supply risk in relation to a functional unit under the LCSA framework. The characterization model is based on a socio-economic cause-effect mechanism drawing upon supply chain resilience concepts. Supply risk for a given commodity is defined as the multiple of *probability* of supply disruption and *vulnerability* to supply disruption. The method is demonstrated through LCA case studies of electric vehicles and dental x-ray equipment.

While “minor” commodities are often neglected in environmental LCA, the case studies herein illustrate how small components can “pack a punch” from both a supply risk and environmental perspective. Therefore, the most promising embodiment of the GPSR characterization model “cancels out” the amounts of commodity inputs. As a consequence, comprehensive data are required for product material composition. The x-ray case study, for example, involves tracing unit processes through LCA databases so that commodity inputs can be matched with identification codes for collecting commodity trade data. On the other hand, it is convenient that the *amounts* of commodity inputs need not be known.

Although the GPSR characterization model shows promise as a product-level decision support tool, the method and applications presented in this thesis are limited to single-stage supply chain modelling. Moreover, while the method is presently at the country-level, product supply chains are actually at the firm-level. Recycling, co-production, and commodity stockpiling are other areas for further methodological development. Finally, greater computational power is needed to facilitate practical application of the GPSR method. Nonetheless, this thesis shows the importance of integrating raw material criticality and environmental considerations into LCSA to better inform design and management decisions on a product-level.

Keywords: life cycle assessment, life cycle sustainability assessment, criticality assessment, supply risk, vulnerability, substitutability, electric vehicle, dental x-ray

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List of Abbreviations

AADP: Anthropogenic Stock Extended Abiotic Depletion Potential

ADP: Abiotic Depletion Potential

AoP: Area of Protection

AP: Acidification Potential

CF: Characterization Factor

CML: Institute of Environmental Sciences of Leiden

CMOS: Complementary Metal Oxide Semiconductor

CRM: Critical Raw Material

DALY: Disability-Adjusted Life Year

EnSP: Environmental Scarcity Potential

EP: Eutrophication Potential

ESP: Economic Scarcity Potential

EV: Electric Vehicle

FOP: Fiber Optic Plate

FU: Functional Unit

GeoPol: Probability of supply disruption due to geopolitical factors

GHG: Greenhouse Gas

GOS: Gadolinium Oxysulfide

GPSR: Geopolitical Supply Risk

GWP: Global Warming Potential

HHI: Herfindahl-Hirschman Index

LCA: Life Cycle Assessment

LCC: Life Cycle Cost

LCI: Life Cycle Inventory

LCIA: Life Cycle Impact Assessment

LCM: Life Cycle Management

LCSA: Life Cycle Sustainability Assessment

LCSM: Life Cycle Sustainability Management

ODP: Ozone Depletion Potential

PCB: Printed Circuit Board

REE: Rare Earth Element

SSP: Social Scarcity Potential

WGI: Worldwide Governance Indicator

Chapter 1: Introduction and Background

1.1: Problem Context

Over the last decades, growth in global population and living standards has resulted in more complex products utilizing greater amounts of an unprecedented variety of material commodities. For example, present consumption of industrial minerals is 27 times greater than in the early 1900s (Krausmann et al., 2009), and under a business-as-usual scenario, global extraction of resources by 2030 could be double the level from 2005 (Sustainable Europe Research Institute, 2012). Concurrently, the variety of metals employed in modern products has expanded from just a handful in the early 20th century to nearly the entire periodic table at present (Greenfield and Graedel, 2013; National Research Council, 2008). Further, transitioning to a low-carbon economy will require increased adoption of emerging technologies like electric vehicles (EVs) and renewable energy systems – which will in turn require increased supply of “critical” materials like rare earth elements (REEs) and platinum group metals (PGMs).

Consequently, resource-related issues, such as environmental and human health impacts, geological scarcity, technological constraints, armed conflicts and geopolitical-related supply risks, are particularly important for sustainable development. *Sustainable development* is defined by the WCED (1987) as development that “meets the needs of the present without compromising the ability of future generations to meet their own needs.” Sustainable development is considered to have three dimensions: environmental, social, and economic. Taken together, these three dimensions have been conceptualized as the “triple bottom line” (Elkington, 1997).

According to Porter and Kramer (2006), the inter-relations between sustainable development and business activities can be examined in two ways. The “outside-in” relation describes how firms are impacted by external environmental and socio-economic conditions (Porter and Kramer, 2006). For example, business risks and opportunities are affected by consumer preferences, policy and regulatory regimes, supply constraints, and environmental phenomena such as droughts and other extreme weather events. On the other hand, the “inside-out” relation describes the impacts of internal business operations on society and the environment (Porter and Kramer, 2006).

With regard to the inside-out relation, Life Cycle Management (LCM) is concerned with environmental performance of products from the “cradle” where resources are extracted to the “grave” where the product arrives at the end of its useful life (Balkau and Sonnemann, 2010; UNEP, 2007). This “cradle to grave” concept is operationalized by applying Life Cycle Assessment (LCA) as a tool for measuring potential environmental impacts of a product system across multiple stages of its “life cycle” – such as resource extraction, material production, manufacturing, use, and end-of-life management (ISO, 2006a, 2006b).

1.2: The Life Cycle Assessment Framework

Though the term *life cycle assessment* was not formalized until the 1990s, studies conducted with a "life cycle" approach date to the late 1960s and early 1970s; early examples focused on packaging and waste management (Baumann and Tillman, 2004). At the time, the term "Resource and Environmental Profile Analysis" (REPA) was used (Baumann and Tillman, 2004). Diverging results of early studies prompted calls for methodological standardization to avoid the use of LCA as a "hired gun" biased in favour of a particular product (Baumann and Tillman, 2004). After organizing a series of conferences and working groups, the Society of Environmental Toxicology and Chemistry (SETAC) published the LCA "Code of Practice" in 1993 (SETAC, 1993). According to the Code of Practice, LCA studies need to include four methodological phases: *goal and scope definition*, *inventory analysis*, *impact assessment,* and *improvement assessment* (SETAC, 1993). A study that stops at the inventory phase and does not include impact assessment or improvement assessment is referred to as a Life Cycle Inventory (LCI) (SETAC, 1993).

Following the publication of the SETAC Code of Practice, the International Organisation for Standardisation (ISO) published a series of standards for LCA (the 14040 series). Presently, the two main standards are ISO 14040 (ISO, 2006a) and ISO 14044 (ISO, 2006b). The former describes general principles and lays out a methodological framework. Like the SETAC Code of Practice, the ISO framework includes *goal and scope definition*, *inventory analysis*, and Life Cycle Impact Assessment (LCIA). Rather than "improvement assessment," the ISO framework defines *interpretation* as the final phase required for LCA studies. ISO 14044 provides more detailed guidelines and requirements for each of these methodological phases, as outlined in the following subsections.

1.2.1: Goal and Scope Definition

The first step in an LCA study is to clearly define the *goal and scope* (ISO, 2006a, 2006b). The goal definition includes the reason(s) for carrying out the study and the intended audience(s) to whom the results will be presented (ISO, 2006a, 2006b). Typically, LCA studies are conducted to identify "hotspots" of environmental burdens ("significant issues" per ISO 14044), to evaluate trade-offs and improvement opportunities, and to compare environmental "profiles" of alternative products *with similar functionality*. Regarding the intended audience, LCA studies can be useful for internal purposes such as product design and process improvements. Given specific guidelines – known as Product Category Rules (PCRs) – the results of LCA studies can be disseminated to external audiences in the form of Environmental Product Declarations (EPDs). EPDs can be useful in a business-to-business (B2B) context (for example, informing purchasing decisions and supporting internal LCA studies) and can support "eco-labeling" for marketing purposes. *Life cycle thinking* can also guide public policy and regulatory directions, such as the Integrated Product Policy (IPP) in the European Union (EC, 2001). Importantly, LCA studies intended to support comparative assertions to be disclosed to the public have more rigorous methodological requirements (ISO, 2006b) to avoid the "hired gun" problem.

To fulfil the goal of the LCA study, the *scope* needs to be defined in terms of the functional unit, system boundary, data and data quality requirements, and the environmental impact categories (for example, climate change, acidification, and eutrophication) to be addressed (ISO, 2006a, 2006b). The *functional unit* quantifies the core use or purpose of the product and serves as the central unit of reference in the LCA framework (ISO, 2006b), as illustrated in Figure 1 (the major components of the figure are discussed in the remainder of this section).

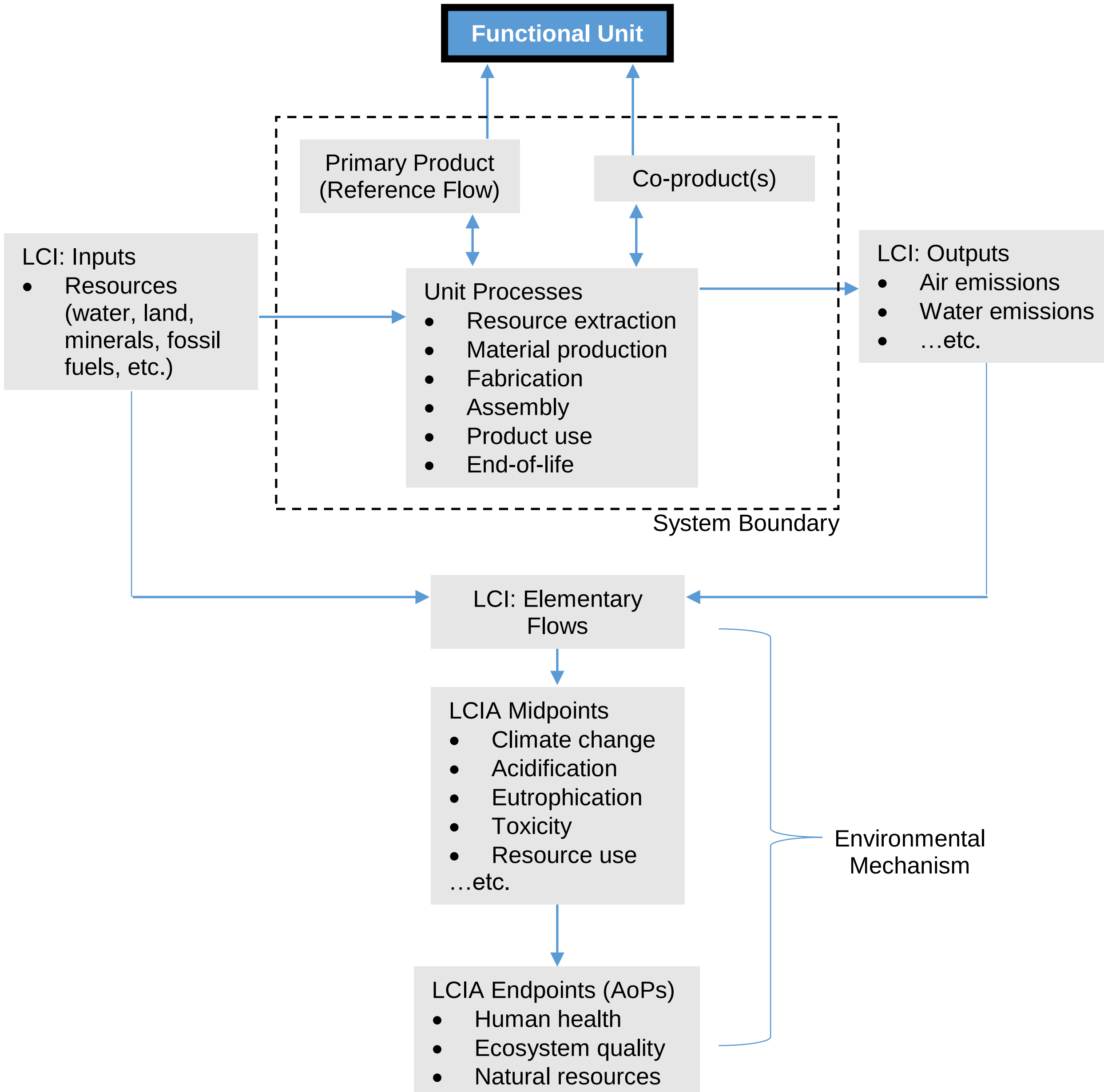


Figure 1: Conceptual framework for Life Cycle Assessment

For example, the functional unit of a light bulb could be defined in terms of a given light output (in lumens) for a given service life (in hours). The functional unit is particularly important when making comparisons between alternative products (ISO, 2006b) – as it enables an "apples to apples" comparison. The *reference flow* represents the physical product needed to actually provide the functional unit (ISO, 2006b). For example, the reference flow for providing a given light output for a given service life would be defined in terms of the number of light bulbs required (depending on the useful life of the bulb). Through the reference flow, the functional unit provides the basis for quantifying the environmental inputs and outputs (for example, mineral ores and emissions) of the *unit processes* (for example, extraction, production, and assembly processes) within the defined system boundary (ISO, 2006b). These inputs and outputs, referred to as *elementary flows*, comprise the Life Cycle Inventory (LCI) phase of the LCA framework (ISO, 2006a, 2006b).

1.2.2: Life Cycle Inventory

The LCI phase is closely tied to the goal and scope, with requirements of ISO (2006b) pertaining to data quality, allocation[i] methods, and system boundaries. When properly scoped, the only things crossing the boundary between the product system (or "technosphere") and the environment (or "ecosphere") are the elementary flows (Figure 1). As illustrated in Figure 1, the functional unit can be thought of as crossing the boundary between the product system and the economy (in which the product serves a specific purpose as defined by the functional unit). Once the LCI is compiled, Life Cycle Impact Assessment (LCIA) methodology is needed to aggregate the LCI data and "translate" elementary flows into potential environmental impacts.

[i] "Allocation" refers to a common methodological problem in LCA that occurs when one process produces multiple product outputs (called "co-products"). Allocation is a very controversial topic in the LCA community because the choice of allocation method can have a significant influence on the results of an LCA study. Therefore, ISO (2006b) requires following a stepwise procedure in which allocation is either avoided entirely (i.e., by adjusting system boundaries), conducted based on physical relationships (such as masses of co-products), or conducted based on other relationships (such as economic values), in order of preference.

1.2.3: Life Cycle Impact Assessment

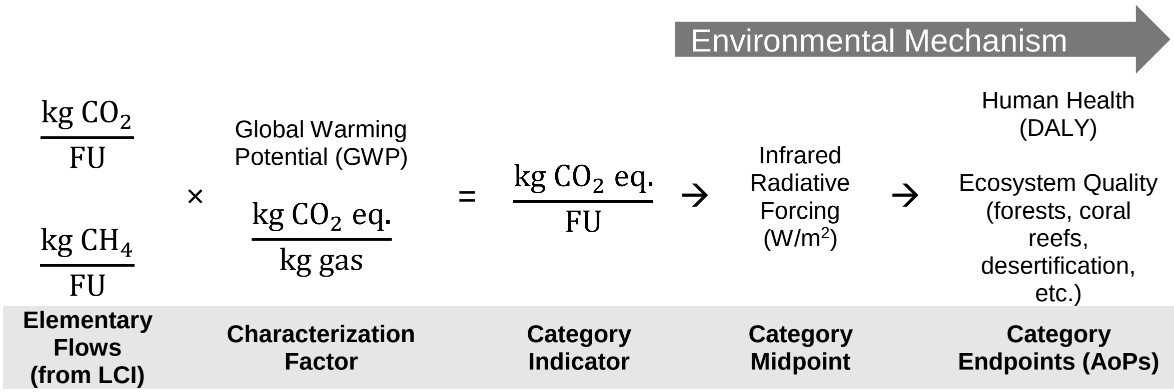
Whereas the elementary flows in the LCI represent environmental *aspects* of the product system, the purpose of LCIA is to provide meaningful information about potential environmental *impacts* (ISO, 2006a, 2006b). According to ISO 14044, LCIA consists of three mandatory elements and three optional elements (ISO, 2006b). The first mandatory element is *selection* of environmental impact categories; for example, climate change, acidification, eutrophication, ozone depletion, toxicity, and photo-oxidant (smog) formation (ISO, 2006b). The next element is *classification* of elementary flows into appropriate impact categories (ISO, 2006b). For example, greenhouse gases (GHGs) such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) can all be classified as contributing towards climate change. The final mandatory element, *characterization*, measures the relative "potency" of each elementary flow to each impact category (ISO, 2006b). For example, using Global Warming Potentials (GWPs), emissions of GHGs can be expressed as a mass of carbon dioxide equivalent (CO_2 eq).

ISO 14044 requires selection of impact categories to "reflect a comprehensive set of *environmental* issues related to the product system being studied, taking the goal and scope into consideration" [emphasis added] (ISO, 2006b, sec. 4.4.2.2.1). Therefore, coverage of environmental issues in an LCA study needs to be sufficiently comprehensive to satisfy the goal of the study. Though not explicitly required by ISO (2006b), there is broad consensus in the LCA community regarding three "areas of protection" (AoPs) for sustainable development: "human health," "ecosystem quality," and "natural resources." AoPs are also known as "safeguard subjects" (Muller-Wenk, 1997). In the ISO standards, the term "category endpoint" is used (ISO, 2006b).

A comprehensive selection of environmental impact categories is important for revealing potential "trade-offs;" for example, lower GWP vs. higher eutrophication and/or acidification potential. However, it is also important to avoid "double counting" across impact categories, which can bias LCIA results by artificially magnifying certain environmental issues (Baumann and Tillman, 2004; ISO, 2006b; Reap et al., 2008). Therefore, environmental impact categories should be collectively exhaustive and mutually exclusive.

For each impact category, a *characterization model* is needed to quantify potential impacts (per functional unit) on the category endpoint (ISO, 2006b). As illustrated in Figure 1, the characterization model should be based on a theoretical "environmental mechanism" – a cause-effect pathway between the elementary flows and the category endpoint (ISO, 2006b). *Characterization factors* (CFs) express elementary flows in common units that are aggregated into a *category indicator* (ISO, 2006b). To enable this aggregation, a CF serves as an "equivalency" factor, often in relation to a reference substance. For example, GHG emissions can be characterized in mass of CO_2 eq., ozone depleting substances in mass of CFC-11 eq., and resource extractions in mass of antimony (elemental symbol Sb) eq.

The category indicator can be chosen from any point along the environmental mechanism (ISO, 2006b). LCIA methods intended to model the entire impact pathway are often referred to as "endpoint" or "damage-oriented" approaches (Finnveden et al., 2009). Methods that partially model the environmental mechanism are often referred to as "midpoint" or "problem-oriented" approaches (Finnveden et al., 2009). Figure 2 illustrates the concepts of characterization models, CFs, and category endpoints using the example of climate change.



FU = functional unit

Figure 2: Characterization model for climate change based on ISO (2006b)

Both the "midpoint" and "endpoint" approaches have strengths and limitations. The midpoint approach simplifies impact assessment methodology, but may provide less useful information in areas of environmental importance (Finnveden et al., 2009). The endpoint approach, on the other hand, requires additional modelling of impact pathways that increases the uncertainty of the results (Finnveden et al., 2009).

Optional elements of LCIA include normalization, grouping, and weighting (ISO, 2006b). In the context of the LCA framework (ISO, 2006b), *normalization* relates category indicator results, such as mass of CO_2 eq, to some reference value, such as the total impact for a country or region. *Grouping* essentially categorizes the impact categories – for example, by sorting them into global / regional / local, terrestrial / aquatic, or high / medium / low priority (ISO, 2006b). *Weighting* is effectively a further aggregation of category indicator results, which themselves represent an aggregation of elementary flows from the LCI. Indeed, in a mathematical sense there is little difference between a "characterization" factor and a "weighting" factor – so it is worth clarifying the distinction. The difference is in how the aggregation factors are determined (Finnveden, 1997). *Characterization* factors have an objective, scientific basis (ISO, 2006b). For example, GWPs express the relative “potency” of different GHGs – such as CO_2, CH_4, and N_2O – according to knowledge from the natural sciences. *Weighting* factors, on the other hand, are based on subjective value choices and cannot be scientifically determined (Finnveden, 1997; ISO, 2006b).

The subjective, value-laden nature of weighting factors makes them a particularly controversial part of LCIA methodology (Finnveden, 1997, 1996). For this reason, ISO (2006b) prohibits inclusion of weighting factors in LCA studies intended to support comparative assertions to be disclosed to the public. In any case, to preserve transparency, LCI data and category indicator results should still be reported when normalization, grouping, and/or weighting steps are conducted (ISO, 2006b).

Despite the controversy, however, weighting is ultimately necessary – whether explicit or not – for decision-making (Reap et al., 2008). Often, there are trade-offs between impact categories; for example, higher GWP from fossil fuels versus higher eutrophication potential and water use for production of biofuels (Weiss et al., 2012). Therefore, the effect of a formal weighting step is to take what would otherwise be an implicit judgement and make it explicit. Provided the underlying LCI data and category indicator results remain accessible, and the basis of weighting choices is clearly explained, an explicit weighting step could actually improve transparency and rigour of decision-making.

1.2.4: Life Cycle Interpretation

The final phase of the LCA framework, life cycle interpretation, involves:

- identifying "significant issues" based on the LCI and LCIA results;
- evaluating the reliability and robustness of the LCA study, and;
- forming conclusions and recommendations (ISO, 2006b).

In practice, "identification of significant issues" (ISO, 2006b) takes the form of *contribution analysis* to identify environmental "hotspots" of the product system. It is common for particular processes or life cycle stages (such as material production, manufacturing and assembly, product use, and product end-of-life management) to dominate environmental loads. Experience in the LCA community has shown that products tend to have characteristic environmental "profiles" (Ashby, 2013; Young, 1996). For durable (long-lived) products that consume energy and/or water during use, the "use" stage of the life cycle tends to dominate environmental loads; examples include civil aircraft, automobiles, and appliances. Products like shopping bags and furniture tend to generate the largest environmental loads in resource extraction and material production processes. Others may be manufacturing-intensive (for example, paper and electronics) and/or have particular implications for end-of-life management (for example, electronics waste and biohazardous matter). Often it is not the absolute value of environmental loads that is important, but rather the *relative ranking* of the contributions of life cycle stages. When contributions are large enough, "precise judgments can be drawn from imprecise data" (Ashby, 2013, p. 68).

According to ISO (2006b), evaluation of an LCA study requires a completeness check, sensitivity check, and consistency check. The *completeness check* aims to ensure that data and information are sufficient to satisfy the goal of the study (ISO, 2006b). The *sensitivity check* examines the influence of uncertainties on the final results (ISO, 2006b). Uncertainty arises from data limitations and methodological choices – including the functional unit, system boundaries, allocation methods, and impact assessment methods. Uncertainty arising from data limitations can be assessed using data quality indicators (for example, the "pedigree matrix" proposed by Weidema and Wesnæs (1996)) and/or statistical methods such as Monte Carlo analysis. Uncertainties arising from methodological choices can be assessed using *sensitivity analysis* (for example, by changing the functional unit, system boundary, and allocation method) and *scenario analysis* (for example, by changing the assumed electricity supply mix). The *consistency check* evaluates the degree to which data, assumptions, and methodological choices are aligned with the goal and scope of the LCA study (ISO, 2006b). It is also especially important for comparative LCA studies to evaluate the consistency of data quality, methods, and assumptions across the compared products (ISO, 2006b).

After contribution analysis and methodological evaluation (i.e., completeness, sensitivity, and consistency checks) have been performed, conclusions are drawn and recommendations are made to the intended audience (ISO, 2006b).

It is important to recognize that modelling of product systems and their environmental implications in LCA studies represents a simplification of reality. Whereas the *actual* impact of an environmental intervention often depends on where and when it occurs, LCA studies typically aggregate elementary flows without regard to their temporal and spatial context (Baumann and Tillman, 2004; Hauschild and Huijbregts, 2015; Reap et al., 2008). While this is not a concern for global phenomena like climate change, other important environmental issues – such as toxicity, freshwater use, and ambient air quality – have spatial and temporal variability. Accounting for this variability would require spatially and temporally explicit CFs in the LCIA phase, and corresponding contextual information about location and timing of elementary flows in the LCI phase. In practice, such advanced LCIA methods and LCI data (for example, in LCA software and databases) are not readily available. Improvement of LCI data and LCIA methods is an area of ongoing research in the LCA community – for example, through the Life Cycle Initiative of the United Nations Environment Programme (UNEP) and SETAC.

To facilitate practical application of LCA, software programs such as SimaPro feature built-in LCI databases (for example, Ecoinvent, ELCD, and the United States Life Cycle Inventory) for common processes, materials, and product components, along with “ready made” LCIA methods. However, the LCA practitioner still needs to be responsible for defining the goal of the study, functional unit, and system boundary, as well as managing LCI data, choosing appropriate LCIA method(s), and applying uncertainty, sensitivity, and/or scenario analyses.

1.3: Towards Life Cycle Sustainability Assessment

As Dewulf et al. (2015) point out, the three AoPs of interest in the LCA community – "human health," "ecosystem quality," and "natural resources" – actually extend beyond the environmental dimension of sustainable development. Human health is not an "environmental" issue per se, and arguably issues pertaining to "natural resources" are largely socio-economic in nature (Finnveden, 2005; Sonnemann et al., 2015; Stewart and Weidema, 2005). Therefore, the term Life Cycle Sustainability Assessment (LCSA) has emerged to incorporate socio-economic dimensions alongside conventional environmental impact categories (Heijungs et al., 2010; Traverso et al., 2012; Valdivia et al., 2013; Zamagni et al., 2013).[ii]

According to ISO 14040, "LCA typically does not address the economic or social aspects of a product, but the *life cycle approach* […] can be applied to these other aspects" [emphasis added] (ISO, 2006a, p. vi). LCSA therefore embodies the "triple bottom line" concept of sustainable development (Elkington, 1997) by combining environmental LCA, social LCA, and (often economic) life cycle costing (LCC) (Kloepffer, 2008; Parent et al., 2013; Sala et al., 2013; Traverso et al., 2012; Valdivia et al., 2013).

Of these three tools, environmental LCA is the most mature and the only one to be internationally standardized. Social LCA is particularly challenging because of the difficulty in relating social issues – such as employment practices, pay equity, working conditions, and stakeholder relations – to a functional unit of a given product (Kloepffer, 2008). Arguably, social issues tend to arise at an organizational level rather than a product level. Moreover, whereas LCC and (environmental) LCA are *efficiency*-oriented approaches (i.e., minimizing costs and environmental loads per functional unit), social issues are largely matters of *equity* (or fairness) – a concept that is inherently difficult to

[ii] In parallel, Life Cycle Sustainability Management (LCSM) has been proposed as the management equivalent of LCSA (Finkbeiner, 2011).

quantify. Although environmental LCA methodology is relatively well developed with respect to the AoPs “human health” and “ecosystem quality,” the “natural resources” AoP has long been controversial in the LCA community (Dewulf et al., 2015; Drielsma et al., 2016; Finnveden, 2005; Finnveden et al., 2009; Schneider et al., 2015, 2014, 2011).

1.4: The "Natural Resources" Area of Protection

Despite more than two decades of debate in the LCA community (Guinée and Heijungs, 1995; Heijungs et al., 1997; Sonderegger et al., 2017), it remains unclear how to address the "natural resources" AoP in LCA. A variety of LCIA methods have been proposed, with potential to produce significantly different results (Rørbech et al., 2014). However, there is actually rather strong agreement on the *anthropocentric view* (Dewulf et al., 2015; Finnveden, 2005; Sonnemann et al., 2015; Stewart and Weidema, 2005). That is, to satisfy human needs (and wants), resources are processed into *commodities* like usable materials and chemicals, which are then assembled into end products in the economy. Demand for resources is thus "derived" from demand for end products (Graedel et al., 2014).

Newer approaches for assessing "criticality" of resources and commodities have emerged outside the LCA community. Criticality is typically defined in terms of "risk" of supply disruption (or "supply risk") and vulnerability to supply disruption (Achzet and Helbig, 2013; Erdmann and Graedel, 2011; Helbig et al., 2016b; Mancini et al., 2016; Sonnemann et al., 2015). However, as Glöser et al. (2015) point out, what is referred to as "risk" in the context of criticality arguably represents *probability* of supply disruption. Therefore, this thesis uses the term "supply risk" to refer to the multiple of probability *and* vulnerability. Examples of criticality assessment methods include those developed by Graedel et al. (2012) and Oakdene Hollins (2013), along with the Mining Risk Footprint (MRF) by Nansai et al. (2015). The methodology of Oakdene Hollins (2013) underpins the critical raw material (CRM) report of the European Commission (EC, 2014). Mancini et al. (2016) explored the potential for integrating criticality indicators into LCSA, testing 6 different methods on LCI data (from Ecoinvent version 2) for a laptop computer – with greatly diverging results.

The next chapter reviews the area of "natural resources" in more detail – from an LCA perspective and a "criticality" perspective. This discussion aims to highlight synergies between the two fields and suggest directions for further methodological development to better inform design and management decisions on a product-level.

Chapter 2: Life Cycle Assessment and Resource "Criticality"

Chapter 1 highlighted the importance of "natural resources" for sustainable development and introduced the ISO framework for Life Cycle Assessment (LCA) along with its emerging extension towards Life Cycle Sustainability Assessment (LCSA). While environmental LCA is relatively well developed with respect to the "areas of protection" (AoPs) "human health" and "ecosystem quality," conventional approaches for the "natural resources" AoP are controversial. Newer approaches for assessing resource "criticality" have emerged outside the LCA community. This chapter examines both approaches in more detail, and reviews recent attempts to integrate criticality assessment into the LCSA framework. The chapter concludes with a research aim.

2.1: Conventional Approaches Towards the "Natural Resources" AoP in LCA

The "natural resources" AoP is one of the most debated topics in LCA (Dewulf et al., 2015; Drielsma et al., 2016; Finnveden, 2005; Finnveden et al., 2009; Schneider, 2014; Schneider et al., 2015, 2014, 2011; Stewart and Weidema, 2005). For starters, there are different ways of conceptualizing "natural resources" as an AoP. The *biophysical view* considers only the physical endowments of energy and matter (Dewulf et al., 2015). In contrast, the *anthropocentric view* is more concerned with the functional value of resources for humans (Dewulf et al., 2015; Finnveden, 2005; Sonnemann et al., 2015; Stewart and Weidema, 2005).

Within the anthropocentric view, Dewulf et al. (2015) defined five perspectives for the "natural resources" AoP. The "asset" perspective acknowledges the instrumental value of resources for humans, but does not assess the *effects* of resource use on human welfare; thus, it is at the midpoint level (Dewulf et al., 2015). Resources provide "provisioning capacity" for human needs such as nourishment, energy, materials, and space (Dewulf et al., 2015). To satisfy human needs (and wants), resources are processed into *commodities* (or "intermediate products" per ISO (2006b)) like usable materials and chemicals, which are then assembled into *end products* in the economy. These production activities form the "supply chain" perspective. Resources also have other "global functions" such as satisfying human social and cultural needs and maintaining ecosystem functions (Dewulf et al., 2015). Ultimately, the "supply chain" of goods and services, combined with the "non-provisioning" and ecological functions of resources, provide human welfare. It may be problematic, however, that the "global functions" perspective includes the functional importance of resources for ecosystem functions (which contribute indirectly to human welfare). This could lead to "double counting" with the AoP "ecosystem quality." As explained in the previous chapter, double counting can bias LCIA results by artificially magnifying certain issues relative to others.

Another challenge with LCIA methodology for the "natural resources" AoP is the confusion surrounding the terminology of "resources" and "reserves" (Drielsma et al., 2016). As illustrated in Figure 3, the "resource base" is the *geological presence* of substances that may be of interest to humans. "Reserves" constitute a *subset* of the resource base that is defined by parameters of geological certainty, technological constraints, and economical accessibility. While the resource base is fixed and finite, reserves can be increased (within the resource base) through geological prospecting and/or improved technologies for extraction and processing.

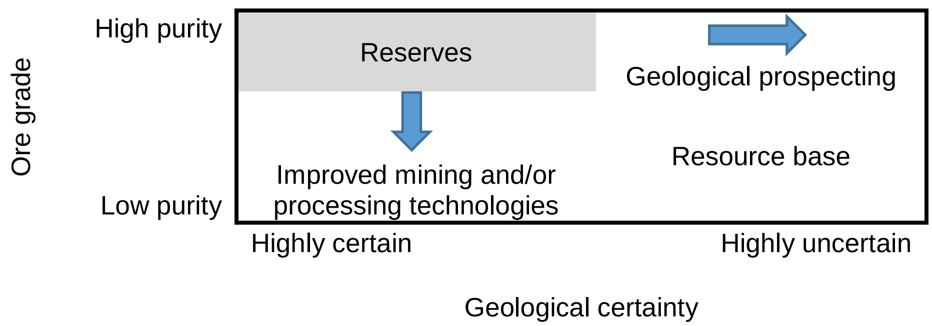


Figure 3: The concepts of "resources" and "reserves"

Based on these concepts, several terms and definitions have been formulated for different indicators of resource availability (Table 1).

Table 1: Definitions of “resources” and “reserves”

van Oers et al. (2002)	**Drielsma et al. (2016)**	**USGS (1980)**	**CRIRSCO (2006)**	**Definition (synthesized)**
Ultimate reserves	Crustal content	N/A	N/A	Physical amount of a substance in the Earth’s crust
Ultimately extractable reserves	Extractable global resource (EGR)	N/A	N/A	Subset of crustal content that can ultimately be extracted for human uses
Reserve base	Mineral resource	Reserve base	Mineral resource	Substances with potential for economical extraction
Economic reserves	Mineral reserves	Reserves	Mineral reserves	Resources that are economical to access given *present* technological and socio-economic conditions

As Drielsma et al. (2016) suggest, the main point of confusion is the persistent use of the term “reserve.” This term implies some degree of economical availability of a resource – which depends on many factors, including geological knowledge and technologies for extraction and processing. Therefore, classifications and estimates of “reserves” can vary significantly. As a theoretical upper limit, the entire geological resource base could, in the (very) long-run, be accessible through advancements in technology and new discoveries – hence the term “ultimate reserve” according to van Oers et al. (2002). But this is an extremely optimistic assumption, so “crustal content” is a more accurate term.

As part of the UNEP-SETAC Life Cycle Initiative, Sonderegger et al. (2017) categorized three types of LCIA methods for the “natural resources” AoP:

1. “accounting” methods;
2. “depletion” methods; and
3. “future effort” methods.

The first falls under a biophysical view, whereas the other two are more anthropocentric.

2.1.1: Accounting Methods

"Accounting" methods include mass-based aggregation as in Material Input per Service-unit (MIPS) (Saurat and Ritthoff, 2013), energy-based aggregation as in Cumulative Energy Demand (CED), or thermodynamic concepts as in Cumulative Exergy[iii] Demand (CExD) (Bösch et al., 2007). Methods based on mass and energy accounting are appealing for their simplicity, while thermodynamic methods are more comprehensive, covering energetic and non-energetic resources (Sonderegger et al., 2017). However, "accounting" methods do not provide an explicit indication of potential *impacts* on resource availability or human welfare, and thermodynamic concepts like exergy are difficult to interpret.

[iii] The first law of thermodynamics states that energy cannot be created or destroyed, but only converted from one form to another. The second law of thermodynamics states that every conversion involves an increase in *entropy* – energy that is not in a useful form. Conversely, the *exergy* (or useful energy) decreases.

2.1.2: Depletion Methods

"Depletion" methods include the Abiotic Depletion Potential (ADP) developed by Guinée and Heijungs (1995) and commonly applied in LCA. The ADP for a given resource is the ratio of the extraction rate to the square of the "assumed stock," normalized to antimony (elemental symbol Sb) as a reference substance[iv] (Equation 1).

$$ADP_i = \frac{ER_i / {X_i}^2}{ER_{Sb} / {X_{Sb}}^2} = \left(\frac{ER_i}{{X_i}^2}\right)\left(\frac{{X_{Sb}}^2}{ER_{Sb}}\right)$$

Where

- i = a particular resource
- Sb = the reference resource (antimony)
- X = "assumed stock"
- ER = extraction rate

Equation 1 (Guinée and Heijungs, 1995; van Oers et al., 2002)

An alternative version of the ADP omits the extraction rates and uses only the stock sizes in the calculation (Equation 2).

$$ADP_i = \frac{1/X_i}{1/X_{Sb}} = \frac{X_{Sb}}{X_i}$$

Where

- i = a particular resource
- Sb = the reference resource (antimony)
- X = "assumed stock"

Equation 2 (van Oers et al., 2002)

Milà i Canals et al. (2009) extended the ADP (per Equation 1) to accommodate renewable resources such as surface water (Equation 3).

[iv] As noted in a recent update by van Oers and Guinée (2016), antimony was chosen as a reference substance for practical reasons, but the choice of reference substance is ultimately arbitrary.

$$ADP_i = \left(\frac{ER_i - RR_i}{{X_i}^2}\right)\left(\frac{{X_{Sb}}^2}{ER_{Sb}}\right)$$

Where
- i = a particular resource
- Sb = the reference resource (antimony)
- X = “assumed stock”
- ER = extraction rate
- RR = renewal rate

Equation 3 (Milà i Canals et al., 2009)

A similar approach could be applied for recyclable resources such as metals.

“The devil is in the denominator.” Due to the nature of the equation, the category indicator results are highly dependent on the “assumed stock” (Drielsma et al., 2016). The terminology of “resources” and “reserves” discussed previously is particularly important here. As suggested by Guinée and Heijungs (1995), van Oers et al. (2002), Tilton (2003), Drielsma et al. (2016), and van Oers and Guinée (2016), the “assumed stock” can be measured in physical terms or economic terms. An advantage of physical terms, like crustal content, is that they are stable and reliable quantities (Drielsma et al., 2016; van Oers and Guinée, 2016). However, measures of crustal content overestimate the amount of the resource base that will ultimately be available for human uses.

The “extractable global resource” (EGR) as defined by Drielsma et al. (2016) is “the amount of crustal content that will ultimately prove extractable by humans” (p. 89). While this is a better measure of resource availability, it depends on future technological developments and is therefore highly uncertain (Drielsma et al., 2016; van Oers and Guinée, 2016). A subset of the EGR is the “reserve base,” defined by the USGS (1980) as “that part of an identified resource that meets specified minimum physical and chemical criteria related to *current* mining and production practices” [emphasis added]. Given that the reserve base fluctuates due to technological and socio-economic factors, and the USGS no longer reports estimates of this indicator, Drielsma et al. (2016) and van Oers and

Guinée (2016) argue that the reserve base should *not* be used for calculating ADP factors. Similarly, reserve estimates are dynamic quantities that produce unreliable and misleading results when applied in the ADP calculation (Drielsma et al., 2016; Sonderegger et al., 2017).

Another limitation of commonly applied measures of the "assumed stock" in the ADP calculation is that they only account for what Schneider et al. (2015, 2011) refer to as the *lithospheric stock* of resources. The law of conservation of matter implies that the *physical* resource base cannot be "depleted" (Kleijn, 2000).[v] Resources extracted from the environment are transformed into "anthropogenic stocks" in the technosphere (Schneider et al., 2015, 2011). Anthropogenic stocks consist of materials that are actively "employed" in provision of goods and services, "hibernating," or "expended" from end-of-life products (Kapur and Graedel, 2006; Schneider et al., 2011). Expended stocks are either "deposited" (for example, material in landfills) or "dissipated" (for example, metals "lost" due to corrosion and wear) (Kapur and Graedel, 2006; Schneider et al., 2011). Together, the lithospheric and anthropogenic stocks comprise the *total stock* of the resource base (Figure 4).

[v] However, the stocks of *economically available* resources (i.e., reserves) *can* be depleted – for example, lithospheric resources may become costlier to extract and materials may be diffused throughout the anthroposphere.

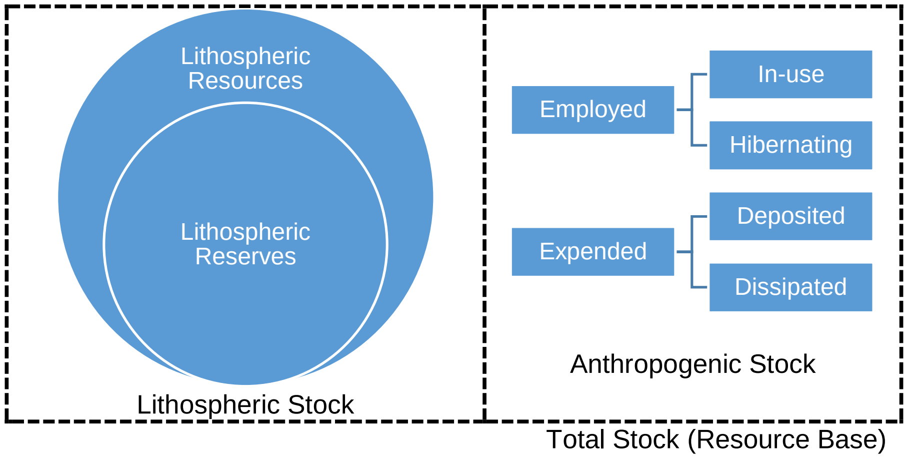


Figure 4: The concepts of lithospheric and anthropogenic stocks based on Kapur and Graedel (2006) and Schneider et al. (2011)

Therefore, as suggested by van Oers and Guinée (2016), the concepts of "resources" and "reserves" can be extended to include *both* lithospheric and anthropogenic stocks – where "reserves" are a subset of physical "resources" that are deemed available for human uses.

To account for the "man-made" part of the resource base, Schneider et al. (2015, 2011) developed the Anthropogenic Stock Extended Abiotic Depletion Potential (AADP), which is calculated in the same way as the ADP (in Equation 1) but adjusts the "assumed stock" (X) to include anthropogenic stocks (Schneider et al., 2015, 2011). Anthropogenic stocks can be estimated based on cumulative extraction of lithospheric stocks and by applying material flow analysis (MFA) techniques (Schneider et al., 2011).

Further, as van Oers and Guinée (2016) argue, this broader conception of "resources" and "reserves" implies that the "extraction" rate is meaningless. Extraction of resources from the environment to feed the supply chain of goods and services in the economy is nothing more than a transfer from lithospheric to anthropogenic stocks. Thus, the *numerator* of the ADP also needs to be rethought. The "real" problem, as van Oers and Guinée (2016) argue, is “dilution” of resources (as illustrated in Figure 4, Schneider et al. (2011) refer to diluted resources as “dissipated stock”). Therefore, van Oers and Guinée (2016) suggest replacing the extraction rate with the “leakage” rate of resources from the economy. Moreover, elementary flows could be reconceptualized as *emissions* of diluted resources rather than extractions of concentrated resources from the environment (van Oers and Guinée, 2016). This new approach to the ADP is reasonable in theory, but largely due to data gaps regarding anthropogenic stocks and “leakage” rates, it has yet to be operationalized (van Oers and Guinée, 2016).

2.1.3: "Future Effort" Methods

"Future effort" methods like the Environmental Priority Strategies (EPS) (Steen, 1999), Eco-Indicator 99 (Goedkoop and Spriensma, 2001), ReCiPe (Goedkoop et al., 2009), IMPACT2002+ (Jolliet et al., 2004), and Surplus Cost Potential (SCP) (Vieira et al., 2016) are attractive because they reflect sustainable development principles – particularly inter-generational equity. That is, resource exploitation by the present generation may incur external costs for future generations due to the loss of readily available, high-quality resources (Vieira et al., 2016). Therefore, potential damage to welfare of future generations can be modelled as increased effort required for future extraction (for example, higher processing costs and energy consumption due to declining ore grades).

An implicit assumption of this approach is that the highest "grade" (and thus lowest cost) resources will be exploited first, followed by progressively lower grades (Drielsma et al., 2016; Vieira et al., 2016). Theoretically, this is a reasonable assumption given rational decision-making based on perfect information and fixed technology. In reality, however, geological uncertainty violates the assumption of perfect information (Drielsma et al., 2016). Moreover, as illustrated in Figure 3, technological advancements can make extraction of lower grade deposits economical and *increase* reserves. Indeed, this pattern can be observed for many mineral resources (West, 2011). Therefore, as Drielsma et al. (2016) argue, declining ore grades are not necessarily indicative of resource scarcity.

However, reserve estimates may not fully capture the "true" cost of resource extraction. There may be external environmental and socio-economic costs imposed by extraction and processing of lower grade resources (Ali et al., 2017). For example, as consumption of fossil fuels continues to rise, controversial and risky new ways of accessing these resources have emerged, such as mountaintop removal for coal, hydraulic fracturing (or "fracking") for natural gas, and oil sands operations for petroleum products. Of course, investments in research and development of new technologies to access lower grade resources also come at a cost. Consequently, reserve estimates may be overly optimistic.

Some have argued that future resource extractions are a matter for the LCI phase rather than LCIA (Finnveden, 2005). However, “future efforts” are more accurately seen as a proxy for reduced availability of resources in the future as a *consequence* of present consumption (Sonderegger et al., 2017). Moreover, it is logical to expect that “dilution” indicators derived by modifying “depletion” methods like the ADP would correlate with “future effort” indicators – as “dilution” by definition means that a resource is more difficult to access.

2.2: Water, Land, and Biotic Resources

With the exception of thermodynamic accounting methods, coverage of "natural resources" in LCA has been mostly limited to non-renewable abiotic resources like minerals and fossil fuels. More recently, methods for assessing water use (Berger and Finkbeiner, 2010; Boulay et al., 2015a, 2015b, 2011a, 2011b; Kounina et al., 2013), biotic resources (Emanuelsson et al., 2014; Langlois et al., 2014), and land use (Alvarenga et al., 2015, 2013; Beck et al., 2010; Brandão and Milà i Canals, 2013; Koellner et al., 2013; Milà i Canals et al., 2007; Taelman et al., 2016) have been put forth in various stages of development. Detailed discussion of these topics is beyond the scope of this thesis, but in principle, the "natural resources" AoP needs to cover *all* resources that may be of interest to humans.

2.3: Resource "Criticality" Assessment

While conventional LCIA methods for the "natural resources" AoP are largely concerned with physical exhaustion or "dilution" of resource availability *in the long-run*, resource availability can also be constrained by geopolitical and socio-economic factors *in the short-run* (Figure 5).

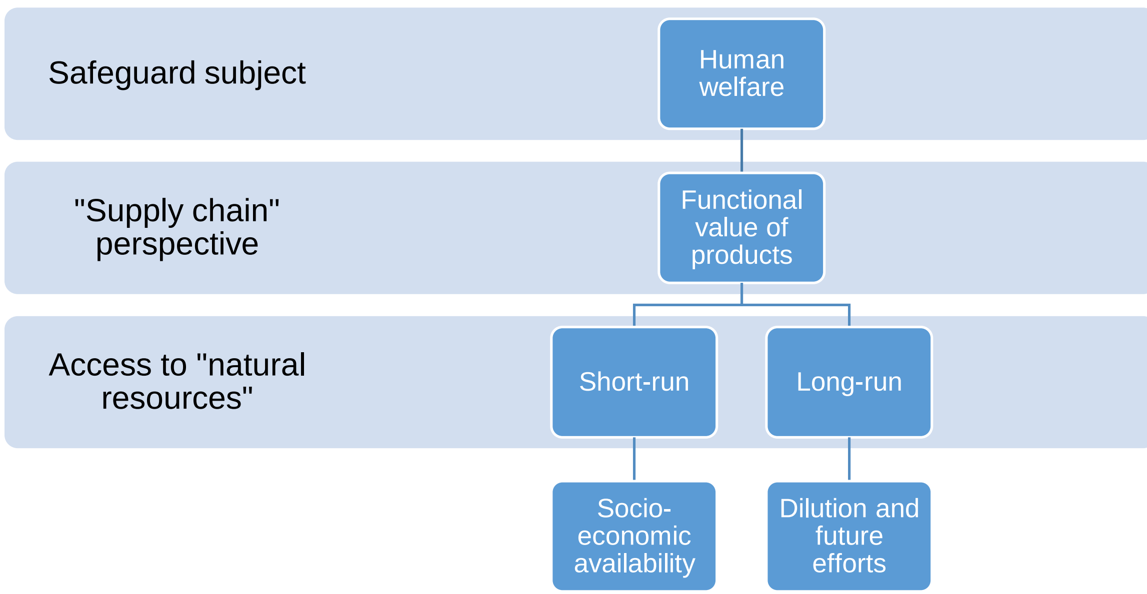


Figure 5: Framework for "natural resources" area of protection

Regarding the latter, newer approaches for assessing "criticality" of resources and commodities have emerged outside the LCA community. Criticality is typically defined in terms of "risk" of supply disruption (or "supply risk") and vulnerability to supply disruption (Achzet and Helbig, 2013; Erdmann and Graedel, 2011; Helbig et al., 2016b; Mancini et al., 2016; Sonnemann et al., 2015). However, as Glöser et al. (2015) point out, "risk" is typically conceptualized as a function of the probability and severity of an event. Accordingly, this thesis uses the term "supply risk" to refer to the multiple of probability *and* vulnerability. Graedel et al. (2012) added a third dimension – environmental implications of resource extraction – to their criticality assessment method. However, as environmental implications are addressed in conventional LCA, this section focuses on supply risk assessment.

2.3.1: Probability of Supply Disruption

According to a review by Achzet and Helbig (2013), commonly applied notions for *probability* of supply disruption include country concentration, country risk, depletion time, by-product dependency, and recyclability.

Country concentration is often measured by the Herfindahl-Hirschman Index (HHI), which is defined as the sum of the squared market shares of all producing countries (Equation 4).

$$HHI_A = \sum_{i=1}^{n} {S_i}^2$$

Where
- A = a given commodity
- S_i = market share of supplier i

Equation 4

The HHI ranges from 0 (indicating a perfectly competitive market) to 1 (indicating a pure monopoly). Examples of commodities with high country concentration include “rare”[vi] earth elements (REEs), molybdenum (elemental symbol Mo), and tungsten (elemental symbol W). Some criticality assessment methods use firm-level supply concentration (i.e., “company concentration”) as an indicator of potential supply disruption (Erdmann et al., 2011; IW Consult, 2009; Rosenau-Tornow et al., 2009). In any case, a high HHI value implies a tendency towards “having all your eggs in one basket.”

Of course, the quality of the “basket” is also an important factor in resource criticality assessment. Measures of “country risk” are applied for this purpose (Achzet and Helbig, 2013). Indicators of country risk include the Worldwide Governance Indicators (WGIs),

[vi] These elements are not “rare” in a geological sense, but are often considered “critical” because of the difficulty in securing a reliable and economical supply (Habib and Wenzel, 2014; Haque et al., 2014).

Global Political Risk Index (GPRI), Policy Potential Index (PPI), and Human Development Index (HDI).

The WGIs include six composite indicators that enable comparisons of governance quality and political stability across countries (Kaufmann et al., 2011):

1. Voice and Accountability;
2. Political Stability and Absence of Violence/Terrorism;
3. Government Effectiveness;
4. Regulatory Quality;
5. Rule of Law; and
6. Control of Corruption.

The less frequently used GPRI aggregates political, social, and economic aspects into a single risk index (IW Consult, 2009). The PPI published by the Fraser Institute measures policy and regulatory risk factors, such as taxes and environmental regulations, that may impose restrictions on resource accessibility. The HDI published by the United Nations Development Programme measures socio-economic wellbeing based on indicators of life expectancy, income, and education. A country with a high HDI score could be seen as a relatively stable, low-risk exporter. On the other hand, an importing country with a high HDI may be less vulnerable to supply disruption (for example, by having greater capacity for material substitution).

Another commonly used indicator for probability of supply disruption is “depletion time” (Achzet and Helbig, 2013). Similar to “depletion” methods for the “natural resources” AoP in LCA, “depletion time” often relates measures of extraction to measures of “assumed stocks” (for example, reserve estimates). While this “static reach” approach is commonly applied in criticality studies, Oakdene Hollins (2008) applies a “dynamic reach” method based on alternative scenarios for future extraction rates. As Achzet and Helbig (2013) argue, the static and dynamic reach are limited in that they are only theoretical values. In reality, resource availability is a complex function of geological, technological, socio-economic, and geopolitical factors.

Raw material supply can also be constrained through “by-product dependency” (Achzet and Helbig, 2013). A “by-product” (or “co-product” per ISO (2006b)) is a commodity produced in conjunction with a “host” commodity. For example, indium and cadmium are common co-products of zinc production. Supply of a co-product cannot be increased without increasing supply of the “host.” In other words, by-product dependency reduces the elasticity of supply (Achzet and Helbig, 2013). Therefore, the fraction of “co-production” is a relevant indicator for probability of supply disruption.

Recycling may reduce probability of supply disruption by providing an alternate source of supply. Recycled (or “secondary”) sources include “new scrap” and “old scrap.” The former, often called “pre-consumer” material, consists of industrial wastes (for example, metal “skeletons” and “swarf”) returned to the same production process. The latter, often called “post-consumer” material, is recovered from products at the end of their service life. Achzet and Helbig (2013) argue that “new scrap” recycling should be seen as a short-term indicator and “old scrap” recycling as a long-term indicator. In the short-run, efficient recycling of “new scrap” increases elasticity of supply (Achzet and Helbig, 2013). “Old scrap” recycling, on the other hand, is constrained by product lifetimes (which delay availability of “post-consumer” material), technological limitations, and economic conditions. Therefore, Achzet and Helbig (2013) suggest that end-of-life recycling is only relevant in the long-run. However, some amount of post-consumer scrap could be available for recycling in the short-run. For example, it is well known that industrial commodities like steel and lead-acid batteries are highly recycled. There is a continuous supply of “old scrap” from discarded, obsolete products – the real question is *how much* of this “deposited stock” (Kapur and Graedel, 2006; Schneider et al., 2011) is available at a given point in time.

Other notions for probability of supply disruption include import dependence, commodity prices, production and exploration costs, capacity utilization, "climate change vulnerability" (Oakdene Hollins, 2008), lag times of supply and demand, and "risk of strategic use" (IW Consult, 2009). A frequently cited example of "strategic use" is the 2010 crisis of REEs, in which China imposed export restrictions that resulted in extreme price spikes for these commodities.

2.3.2: Vulnerability to Supply Disruption

Probability of supply disruption is one factor in resource criticality assessment, but the potential impact of supply disruption depends on *vulnerability* of the sourcing entity. Substitution potential, or “substitutability,” is the most frequently applied notion of vulnerability in criticality assessment, followed by several “importance” calculations like value of products, value of materials, and strategic importance (Helbig et al., 2016b). Substitutability can be seen as an indicator for probability of supply disruption or vulnerability to supply disruption. On the one hand, a supply disruption is less likely to occur if producers can switch to a suitable substitute, thus reducing demand (Duclos et al., 2010; EC, 2014; Pfleger et al., 2015). On the other hand, substitution potential mitigates the impact of supply disruption and thereby reduces vulnerability (Graedel et al., 2015, 2012; National Research Council, 2008). Either way, substitutability serves as a risk mitigation factor.

Substitutability can be measured at multiple levels in product design. For example, Habib and Wenzel (2016) propose a “product design tree” framework comprised of “compositional,” “component,” “sub-assembly,” and “conceptual” levels. Similarly, Smith and Eggert (2016) define five forms of substitution in the context of neodymium-iron-boron (NdFeB) magnets: “element-for-element,” “technology-for-element,” “grade-for-grade,” “magnet-for-magnet,” and “system-for-system.” Therefore, material substitution can be direct (i.e., switching to a different material with similar properties) or indirect (i.e., product design changes that negate the need for particular materials). An example of direct substitution is the use of aluminum in place of copper for electrical wiring. An example of indirect substitution is light emitting diode (LED) lightbulbs, which do not require a tungsten filament, to replace traditional lightbulbs.

Direct substitutability can be measured using economic approaches (for example, based on price elasticity of demand), material science approaches, and expert consultation. Price elasticity of demand (PED) for a commodity is a basic economic concept defined as percentage change in quantity demanded divided by percentage change in price. Therefore, PED measures responsiveness of quantity demanded to changes in the commodity price. As demand curves are usually downward sloping (due to the law of demand), PED is usually negative. However, it is more convenient to work with absolute values. Theoretically, PED (as an absolute value) ranges from 0 to infinity. A value of 0 indicates perfectly inelastic demand; there is no change in quantity demanded regardless of what happens to the price. A PED approaching infinity represents perfectly elastic demand. Holding all other factors constant, the more substitutable a commodity is, the higher its PED (as an absolute value). Theoretically, *perfect* substitutability results in perfectly elastic demand, whereas *perfect* non-substitutability results in perfectly inelastic demand. Therefore, PED is a reasonable proxy for substitutability of a commodity (Nassar, 2015). In practice, however, the main challenge here is data availability – especially with regard to "minor" metals for which markets are not very transparent and trading exchanges are not operating. Presently available estimates of PED for industrial commodities are limited to only a handful of major metals (Evans and Lewis, 2005; Sturmer, 2013) and platinum group metals (PGMs) (Nassar, 2015).

Alternatively, direct substitutability could be measured by counting the number of identified close substitutes for a given material. A "close substitute" could be defined using criteria derived from material properties (for example, strength, stiffness, density, conductivity, etc.) relevant to a given application of the material (Ashby, 2013; Graedel et al., 2015). In principle, specific criteria would need to be defined for each application, though it may be reasonable to identify a few key properties that drive demand for a given material – see the approach of Ashby (2013). For example, tungsten is used for its combination of hardness, toughness, and ability to withstand high temperatures. A close substitute for tungsten would therefore need to share these properties. According to economic theory, greater availability of close substitutes is reflected by more elastic demand. Therefore, both approaches towards measuring material substitutability – material sciences and economics – should yield convergent results. Demonstrating such agreement would strengthen the reliability and validity of the assessment.

Recognizing the relevance of material substitutability in criticality assessment, Graedel et al. (2015) derived relative substitutability scores for all metals and metalloids in the periodic table (62 were assessed). They began by identifying major applications of each element and the primary (i.e., best performing) substitute in each application. Based on literature reviews and expert consultation, performance of the primary substitute was assigned an ordinal ranking of exemplary, good, adequate, or poor. These rankings were assigned scores of 12.5, 37.5, 62.5, and 87.5, respectively (i.e., the respective medians of the ranges 0–25, 25–50, 50–75, and 75–100). Substitutability scores in each application were aggregated to define "overall" substitutability for each element on a scale of 0 to 100, with a score of 0 indicating the highest substitutability (and thus the lowest vulnerability) and a score of 100 indicating the lowest substitutability (and thus the highest vulnerability). However, substitutability is only applicable on a product-level when measured for a particular application. *Application-specific* substitutability scores are published in supporting information to the main text (Graedel et al., 2015). Similarly, if PED is used as a product-level substitutability indicator, it too needs to be application-specific.

Other indicators for vulnerability include product value, future demand, strategic importance, material value, and spread of utilization (Helbig et al., 2016b). Vulnerability may be higher for commodities used in high-value products (i.e., based on the contribution of a given application to company revenue or country GDP). For example, the criticality assessment methodology of Oakdene Hollins (2013), as adopted by the European Commission (EC, 2014), defines "economic importance" (EI) of a commodity as the weighted sum of the gross value added of each end use "megasector" in which the commodity is employed. Future demand is particularly relevant for emerging technologies such as electric vehicles (EVs) and "renewable" energy systems (Helbig et al., 2016b).

Even if a commodity does not have a high value contribution to the overall economy, it may be of “strategic importance” – for example, for national security and/or transitioning to a low-carbon economy (Helbig et al., 2016b). The value of commodities *themselves*, as opposed to the end products in which they are employed, can also be used as a vulnerability indicator. The implication is that a supply shortage may not prevent the end product from being made (and lead to loss of revenue), but rather increase the cost of producing the product (Helbig et al., 2016b). In either case, though, the effect is the same – a decrease in profits or net benefits. Finally, some commonly applied vulnerability indicators aim to measure the spread of utilization of a material; for example, the share of a population using the material in various end use applications (Helbig et al., 2016b).

As reflected in all of the previously described indicators, vulnerability to supply disruption of a commodity depends on its “importance” and “substitutability.” Vulnerability is positively related to the former and negatively related to the latter. Closely related to the probability and vulnerability dimensions of supply risk are aspects of supply chain *resilience* discussed in the next section.

2.4: Supply Chain Resilience

Recognizing the need to better understand how supply chains of critical materials respond to disruptions, Sprecher et al. (2015) constructed a framework for supply chain *resilience*. They suggest that a resilient supply chain is *resistant* to disruption, able to *recover* rapidly from disruption, and *flexible* enough to adopt alternative supply strategies or find substitutes as necessary. Several factors contribute to supply chain resilience, including diversity of supply, substitution potential, "improvement of material properties," and stockpiling (Sprecher et al., 2015).

First, a diversified supply chain increases resilience by ensuring that sourcing entities do not have "all their eggs in one basket" (Sprecher et al., 2015). Diversity of supply depends on supply concentration, sourcing patterns, and recycling. Supply concentration can be measured using the HHI as previously described. Sourcing patterns consist of the relative supply contributions from domestic and imported sources. Notably, while Helbig et al. (2016a) consider domestic production "risk-free," heavy reliance on domestic production would reduce *diversity* of supply and thereby make the supply chain *less* resilient according to Sprecher et al. (2015). Moreover, if global supply is provided entirely through domestic production, the HHI would have its maximum value of 1. However, the methodology of Helbig et al. (2016a) considers not only diversity of supply, but also political stability of suppliers. The latter aspect does not seem to be captured in the resilience framework of Sprecher et al. (2015), but is relevant to supply risk assessment. Therefore, domestic production can mitigate geopolitical-related supply risk despite reduced diversity of supply. Another way of diversifying supply is through *post-consumer* (i.e., "old scrap") recycling; as Sprecher et al. (2015) argue, recycling "new scrap" increases production efficiency rather than providing an alternate source of supply (Sprecher et al., 2015). Nonetheless, increased production efficiency improves resistance to supply disruption.

Substitution potential improves resilience by increasing supply chain flexibility (Sprecher et al., 2015). In contrast, “improvement of material properties” (for example, through improved processing technologies) provides resistance to disruption by reducing the amounts of critical commodity inputs needed to produce materials with required properties (Sprecher et al., 2015). Nonetheless, both substitution and improvement of material properties depend on technological innovation. For example, research and development activities can result in new and/or improved materials, production methods, and product designs that contribute towards supply chain resilience.

Stockpiles (or “safety stocks”) provide resistance to supply disruption by mitigating the impact of price and supply fluctuations (Sprecher et al., 2015). As with some Japanese firms during the 2010 REE crisis, a sudden supply disruption or price spike can induce “emergency” stockpiling, which in turn drives up demand and further raises the price (Sprecher et al., 2015). The price increase then leads to more stockpiling, and so on (Sprecher et al., 2015). However, growing stockpiles reduce the perceived threat of supply disruption, thus limiting the tendency towards further stockpiling (Sprecher et al., 2015).

Although the resilience mechanisms described by Sprecher et al. (2015) reflect dynamic aspects of supply chains (i.e., how supply chains react to disturbances), the concepts closely mirror those of (often static) criticality assessment. A resilient supply chain – one that resists disruption, is able to recover rapidly from disruption, and has the flexibility to adapt to the effects of disruption – presents relatively low supply risk.

2.5: Integrating Resource Criticality into Life Cycle Sustainability Assessment

As highlighted in a review by Sonnemann et al. (2015), several limitations make recently developed criticality assessment methods incompatible with conventional LCA. First, these methods aggregate multiple probability and vulnerability indicators into an "overall" criticality score for a commodity (Achzet and Helbig, 2013; Helbig et al., 2016b). Such aggregation implies *weighting* choices – which are very controversial in the LCA community (Sonnemann et al., 2015). Moreover, potential interrelations between indicators may invalidate the assumption of additive effects in the conventional LCA framework (Sonnemann et al., 2015). The assumption of additive effects is important because it enables environmental loads (or, in the case of criticality assessment, supply risks) to be expressed in common units and aggregated into a category indicator.

Recognizing the need for a product-level assessment tool, Sonnemann et al. (2015) proposed a conceptual framework for integrating criticality aspects into LCSA. Their Geopolitical Supply Risk (GPSR) method, first developed by Gemechu et al. (2015a), aims to quantify the risk of short-run supply disruptions in commodity trading between countries as a function of production concentration, supply chain composition, and political stability of producing countries. The approach has been applied to an LCSA case study of a European-manufactured electric vehicle (EV) based on a widely cited study and LCI data from Hawkins et al. (2012). As noted in the case study (Gemechu et al., 2015b), two of the primary limitations of the approach have been (1) the simplified representation of supply chains (the methodology implicitly assumes a single-stage supply chain, which is unrealistic for complex products) and (2) the lack of an LCIA characterization model to relate supply risk to a functional unit. Helbig et al. (2016a) addressed limitation (1) by extending the methodology for multi-stage global supply chains and demonstrating the extension with a case study of polyacrylonitrile-based carbon fibers. However, limitation (2) remains.

A connection to a functional unit is essential for integrating criticality considerations into LCSA – a framework that can be useful for assessing supply risk in addition to environmental implications of products. By expressing potential environmental and socio-economic impacts of material flows in common units of measure, the LCSA framework puts these “loadings” into an additive form. This allows the *total* load (i.e., category indicator) to be quantified in relation to the *functional unit* of a given product system. The functional unit provides the basis for product-level assessment, which is significant because decisions made at this level (such as product design and material selection) play an important role in supply chain risk management. Moreover, the notion of a functional unit is consistent with the anthropocentric view of the “natural resources” AoP. The “life cycle” approach also facilitates identification of “hotspots” in the product system, whether these are major contributors to environmental loads or “critical” input commodities in terms of supply risk. Finally, the LCI phase identifies the types and amounts of input commodities needed to make the product. Therefore, as Mancini et al. (2016) suggest, product supply risk – which is arguably a socio-economic issue – can be linked to physical processes captured under environmental LCA.

This thesis, therefore, aims at addressing one of the main limitations of previous attempts of integrating criticality into LCSA. It extends the GPSR methodology developed by Gemechu et al. (2015a) and Helbig et al. (2016a) from a relative assessment of raw material criticality to an LCIA characterization model for assessing product supply risk in relation to a *functional unit* under the LCSA framework. In its previously published forms, however, the GPSR methodology arguably measures *probability* of supply disruption. Therefore, it is henceforth referred to as the *GeoPol indicator*. To provide tangible products for discussion, the proposed GPSR characterization model is demonstrated through two case studies:

1. a comparison of an EV and internal combustion engine vehicle (ICEV) building upon the earlier publications by Hawkins et al. (2012) and Gemechu et al. (2015b)
2. a dental x-ray system

The next chapter of this thesis explains the theoretical and methodological basis of the GPSR characterization model and presents the first case study. The fourth chapter presents the second case study, and the final chapter presents conclusions and future research directions.

Chapter 3: Geopolitical Supply Risk – Method and Case Study 1[vii]

The Geopolitical Supply Risk (GPSR) methodology presented in this chapter adopts the "supply chain" perspective proposed by Dewulf et al. (2015), in which the "natural resources" AoP is defined as the *contribution* to human welfare (that is, the functional value) provided by products (including goods and services) for which resources are employed. Further, a characterization model, which is based on an underlying cause-effect mechanism, is proposed to aggregate relevant elementary flows from the LCI phase and assess potential impacts on the "natural resources" AoP in relation to a functional unit. In conventional (environmental) LCA, the elementary flows are physical inputs and outputs that cross the boundary between the product system (or "technosphere") and the environment (or "ecosphere"). In contrast, assessment of product supply risk cannot be done solely on the basis of conventional elementary flows (i.e., raw inputs of unprocessed resources). Rather, the total supply risk associated with a product system depends on *all* upstream stages of the supply chain. Thus, a reasonable approach would be to assign a supply risk characterization factor (CF) to each unit process. As suggested by Mancini et al. (2016), the physical amount of the "intermediate product" (ISO, 2006b) input to each process could serve as the elementary flow for which supply risk is measured.

[vii] The contents of this chapter are published in:
Cimprich, A., Young, S. B., Helbig, C., Gemechu, E. D., Thorenz, A., Tuma, A., Sonnemann, G., 2017. Extension of geopolitical supply risk methodology: Characterization model applied to conventional and electric vehicles. J. Clean. Prod. 162, 754-763. http://dx.doi.org/10.1016/j.jclepro.2017.06.063

3.1: Cause-Effect Mechanism

Whereas conventional LCIA impact categories like climate change and acidification have *environmental* cause-effect mechanisms, product supply risk has a *socio-economic* mechanism. As illustrated in Figure 6, the total supply risk for a product system depends on the probability of supply disruption and vulnerability to supply disruption across all unit processes.

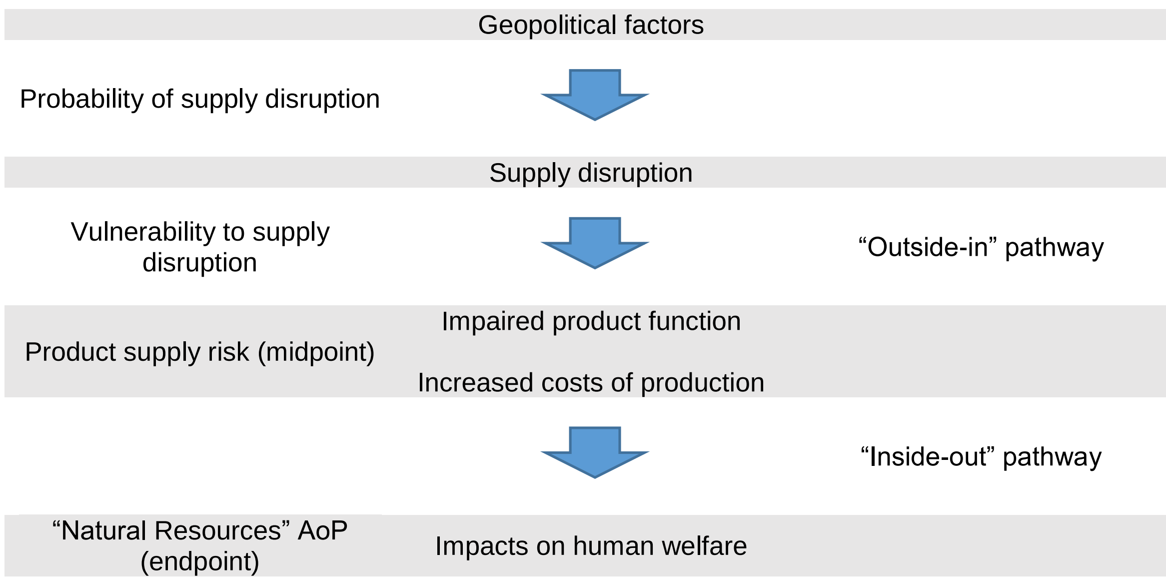


Figure 6: Theoretical cause-effect mechanism for product supply risk

Supply disruption (due to geopolitical factors, for example) could negatively impact the performance of the product (i.e., the ability to actually provide the functional unit) and/or increase the cost of producing the product. This is the “outside-in” impact pathway. Impaired product function and/or cost increases could negatively impact human welfare through the “inside-out” pathway. Impacts on human welfare are at the “endpoint” level, whereas product supply risk is at the “midpoint” level (representing *potential* impacts).

As discussed in the previous chapter, a *resilient* supply chain is resistant to supply disruption, able to recover rapidly from disruption, and flexible enough to adopt alternative supply strategies or find substitutes as necessary (Sprecher et al., 2015). These characteristics reduce the probability and vulnerability factors of supply risk. Sprecher et al. (2015) suggest several factors that determine the resilience of a supply chain, including diversity of supply, substitution potential, improvement of material properties, and stockpiling. These factors serve to mitigate supply risk. The question is how to measure these theoretical constructs and relate them to a functional unit under the LCSA framework. Section 3.4 will revisit these ideas with respect to the proposed GPSR characterization model.

3.2: Characterization Model

The GeoPol indicator according to the methodology proposed by Gemechu et al. (2015a) and Helbig et al. (2016a) represents *probability* of supply disruption due to geopolitical factors, but to assess supply *risk*, a vulnerability indicator is also needed. As illustrated in Figure 7, Geopolitical Supply Risk for a given unit process ($GPSR_{APc}$) depends on the probability of supply disruption of the input commodity ($GeoPol_{Ac}$) – which serves as an "intermediate product" (ISO, 2006b) – as well as the vulnerability to supply disruption ($Vuln_{APc}$).

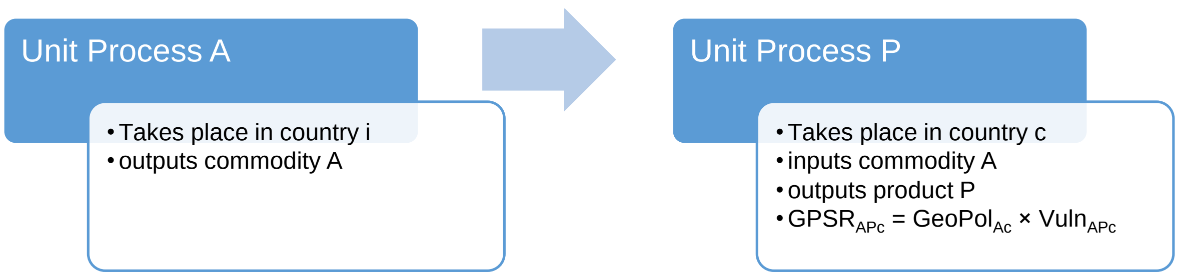


Figure 7: Connection between unit processes and supply risk

The elementary flow for a given unit process is defined as the physical amount of the input commodity (or intermediate product) needed to make the end product (Equation 5).

$$GPSR_{APc} = m_{APc} \times CF_{APc}$$

$$CF_{APc} = GeoPol_{Ac} \times Vuln_{APc}$$

Equation 5

Where

- $GPSR_{APc}$ = Geopolitical Supply Risk for commodity A needed to produce product P in country c
- m_{APc} = amount of commodity A needed to produce product P in country c (from LCI)

- $Vuln_{APc}$ = vulnerability indicator for commodity A needed to produce product P in country c
- $GeoPol_{Ac}$ = GeoPol indicator for commodity A imported to country c. According to Helbig et al. (2016a), it is defined as $GeoPol_{Ac} = HHI_A \sum_i g_i \frac{f_{Aic}}{p_{Ac}+F_{Ac}}$, where HHI_A = Herfindahl-Hirschman Index for commodity A, g_i = political (in)stability of (producing) country i, assessed using the Worldwide Governance Indicator (WGI) – Political Stability and Absence of Violence/Terrorism, f_{Aic} = import tonnage of commodity A from country i to country c, F_{Ac} = total import tonnage of commodity A to country c, p_{Ac} = domestic production of commodity A in country c

While probability of supply disruption is measured using the GeoPol indicator (Gemechu et al., 2015a; Helbig et al., 2016a), vulnerability is another construct that needs to be operationalized. Conceptually, the vulnerability of a product system to supply disruption of a commodity depends on the importance of the commodity input to product performance (i.e., the functional unit) and the potential for substitution. "Substitutability" is the most frequently used indicator for vulnerability in criticality assessment, followed by several "importance" calculations like value of products, value of materials, or strategic importance (Helbig et al., 2016b). Vulnerability is positively related to importance and negatively related to substitution potential (the latter being a risk mitigation factor). *From an economy-wide perspective*, the "economic importance" (EI) of a commodity can be calculated according to the methodology by Oakdene Hollins (2013) as applied in the critical raw material (CRM) report of the EC (2014). This calculation defines EI as the weighted sum of the gross value added (GVA) of each end use "megasector" (s) in which the commodity is employed. The demand shares of the megasectors (D_{As}) are used as the weights (Equation 6).

$$EI_{Ac} = \sum_s (GVA_s \times D_{As})$$

Equation 6 (Oakdene Hollins, 2013)

The EI indicator can be used to measure vulnerability for calculation of supply risk CFs by normalizing the EI of each commodity to a reference commodity. Here, tungsten (elemental symbol W) is used as a reference – as it is a particularly critical commodity – though the choice of reference commodity is ultimately arbitrary. When normalizing the EI indicators, it is important to account for the apparent consumption of the commodity to derive a mass-based “equivalency” ratio (Equation 7).

$$EI_{A/Wc} = \frac{EI_{Ac}}{M_{Ac}} \times \frac{M_{Wc}}{EI_{Wc}}$$

Equation 7

Where

- $EI_{A/Wc}$ = economic importance of commodity A to country c, normalized to tungsten (W)
- EI_{Ac} = economic importance of commodity A to country c (per Equation 6)
- EI_{Wc} = economic importance of tungsten (W) to country c (per Equation 6)
- M_{Ac} = apparent consumption of commodity A in country c
- M_{Wc} = apparent consumption of tungsten (W) in country c

Apparent consumption is defined as the sum of total imports and domestic production minus total exports. As a simplification for the purpose of this chapter, domestic production and total exports for the European Union (EU-27) are assumed to be zero, so the total imports are used as a first approximation (see Appendix A). While this is a limitation, it is overcome by further methodological developments presented in the remainder of this chapter. The rationale for dividing EI by apparent consumption is discussed in section 3.4.

Whereas the methodology by Oakdene Hollins (2013) measures “importance” at an *economy-wide* level, LCA (or LCSA) is a *product-level* assessment tool. On a product-level resolution, the resulting vulnerability factor is the ratio of the amount of the reference commodity to the amount of a given commodity (per functional unit), as seen in Equation 8.

$$EI_{APc} = \frac{GVA_{Pc}}{M_{Ac}\left(\frac{m_{APc}}{M_{Ac}}\right)} = \frac{GVA_{Pc}}{m_{APc}}$$

$$EI_{A/RPc} = \left(\frac{GVA_{Pc}}{m_{APc}}\right)\left(\frac{m_{RPc}}{GVA_{Pc}}\right) = \frac{m_{RPc}}{m_{APc}}$$

Equation 8

Where

- EI_{APc} = economic importance of commodity A for product P produced in country c
- GVA_{Pc} = gross value added by product P in country c
- M_{Ac} = apparent consumption of commodity A in country c
- m_{APc} = amount of commodity A needed to produce product P in country c (from LCI)
- $EI_{A/RPc}$ = economic importance of commodity A for product P produced in country c, normalized to a reference commodity (R)
- m_{RPc} = amount of the reference commodity (R) needed to produce product P in country c (from LCI)

It follows that the category indicator result is the multiple of the GeoPol indicator and the amount of the reference commodity (which is effectively a constant). This further implies that the *total* category indicator for the product is effectively the sum of the GeoPol values of all materials in the product, multiplied by a constant. Therefore, replacing m_{RPc} with a constant of 1 would not change the effect of "cancelling out" the elementary flows, and it is justified to use $1/m_{APc}$ in place of $EI_{A/RPc}$ when calculating the supply risk CF.

By supplementing the GeoPol indicator – which serves as a proxy for probability of supply disruption – with the aforementioned vulnerability indicators, two embodiments of the GPSR characterization model (as defined in Equation 5) are constructed. The first applies the *economy-wide* EI methodology according to Oakdene Hollins (2013), normalized to tungsten as a reference commodity (Equation 9).

$$CF_{APc} = GeoPol_{Ac} \times EI_{A/Wc}$$

Equation 9

As seen in Equation 10, the second embodiment applies the *product-level* importance factor ($1/m_{APc}$).

$$CF_{APc} = GeoPol_{Ac} \times \frac{1}{m_{APc}}$$

Equation 10

In the next section, these two embodiments of the GPSR characterization model are applied to a comparative case study of a European-manufactured electric vehicle (EV) and internal combustion engine vehicle (ICEV) based on a widely cited study and LCI data from Hawkins et al. (2012). As the focus of this chapter is the GPSR methodology, the *environmental* LCIA results previously published by Hawkins et al. (2012) are not duplicated here.

3.3: Results

This section presents the results of the two embodiments of the GPSR characterization model defined in Equations 9 and 10. Table 2 presents CFs for 14 commodities included in the LCI for the EV and ICEV, assuming the vehicles are produced in the EU-27. Values of the GeoPol indicator used to calculate the CFs are provided in Appendix A. For comparison, Abiotic Depletion Potentials (ADPs), as are commonly used in LCA (Guinée and Heijungs, 1995; van Oers et al., 2002; van Oers and Guinée, 2016) are also presented. The ADPs presented in Table 2 were calculated by Mancini et al. (2016) using estimates of the reserve base and ultimate reserves (also known as "crustal content"). Note that for the ADP and Equation 9, the CFs are identical for the EV and ICEV, whereas for Equation 10, the CFs differ between the two vehicle types. The rationale for applying different CFs to different products is explained in section 3.4.

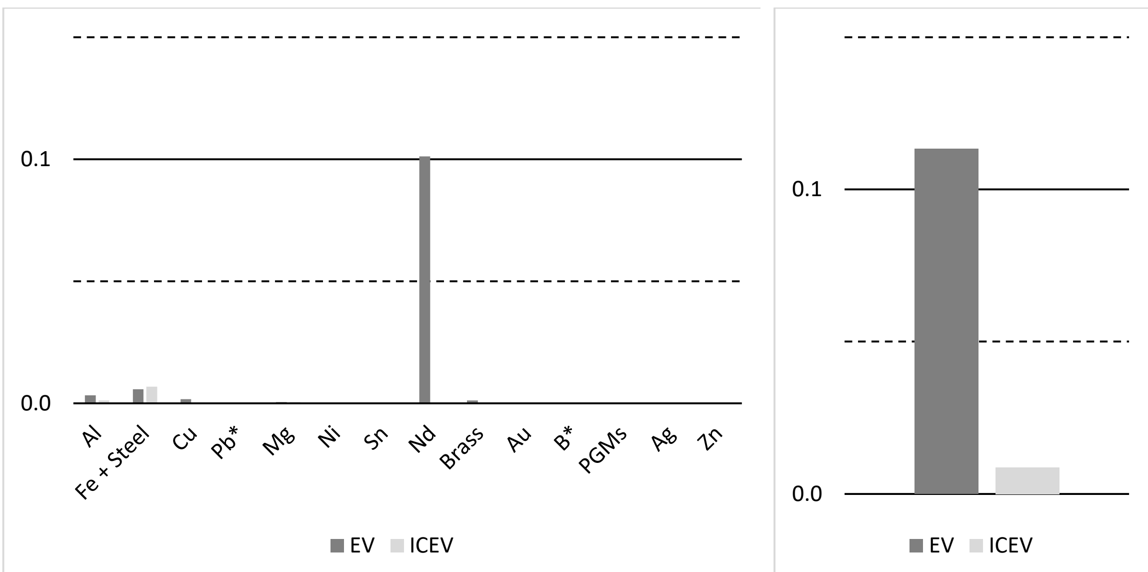
Table 2: Characterization factors for EV and ICEV (EU-27)

	CF Equation 9 (kg W eq / kg A)	CF Equation 10 (kg^{-1} A)		ADP Crustal content (kg Sb eq / kg A) according to Mancini et al. (2016)	ADP Reserve base (kg Sb eq / kg A) according to Mancini et al. (2016)
Commodity (A)	**EV and ICEV**	**EV**	**ICEV**	**EV and ICEV**	**EV and ICEV**
Al	1.57E-05	3.97E-04	1.15E-03	1.09E-09	2.53E-05
Fe + Steel	6.80E-06	1.13E-04	9.50E-05	5.24E-08	1.66E-06
Cu	1.37E-05	5.67E-04	3.20E-03	1.37E-03	2.50E-03
Pb	No data available	3.66E-01	3.78E-01	No data available	No data available
Mg	2.31E-03	2.22E+00	2.22E+00	2.02E-09	2.48E-06
Ni	4.03E-05	4.20E+01	0.00E+00	6.53E-05	4.18E-03
Sn	6.93E-04	1.28E+01	0.00E+00	1.62E-02	1.15E-01
Nd	5.95E-02	3.05E-01	0.00E+00	No data available	No data available
Brass[a]	4.76E-03	4.16E-01	0.00E+00	1.37E-03	2.50E-03
Au	6.00E-07	1.64E+02	0.00E+00	5.20E+01	3.60E+01
B	No data available	3.71E+00	0.00E+00	4.27E-03	4.27E-03
PGMs	1.48E-04	0.00E+00	1.78E+01	2.22E+00	2.22E+00
Ag	2.87E-05	3.34E+02	0.00E+00	1.18E+00	8.42E+00

	CF Equation 9 (kg W eq / kg A)	CF Equation 10 (kg^{-1} A)		ADP Crustal content (kg Sb eq / kg A) according to Mancini et al. (2016)	ADP Reserve base (kg Sb eq / kg A) according to Mancini et al. (2016)
Commodity (A)	**EV and ICEV**	**EV**	**ICEV**	**EV and ICEV**	**EV and ICEV**
Zn	1.73E-04	7.07E-01	7.07E-01	5.38E-04	3.65E-03

[a]Copper used as proxy for ADP

When applying Equation 9, the only substantial "hotspot" from a supply risk perspective is neodymium in the EV (Figure 8A).



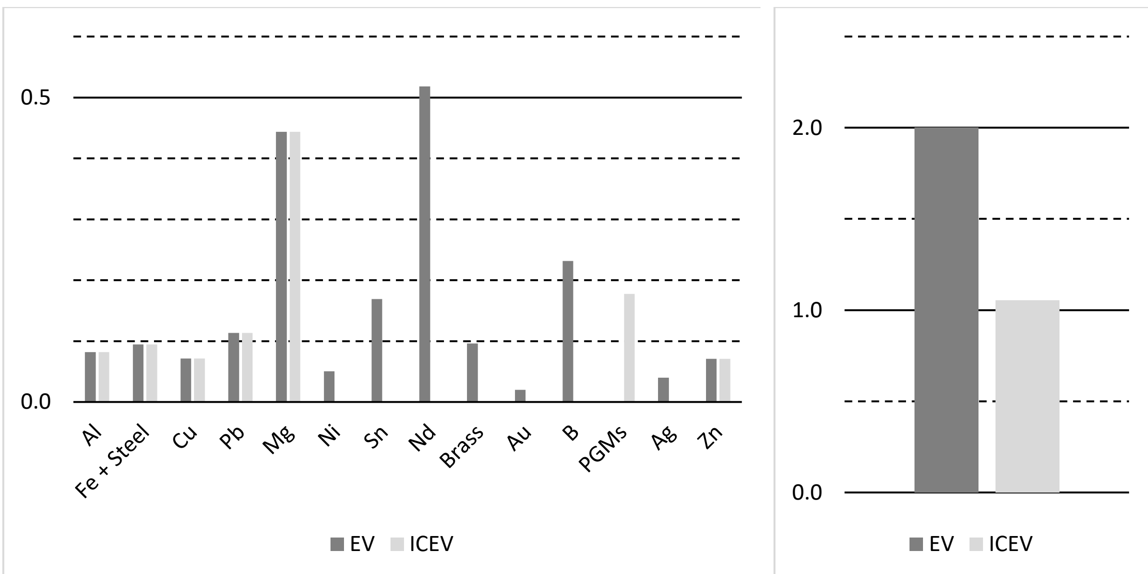
A: supply risk contributions of individual materials
*Data missing for economic importance

B: total supply risk per functional unit (sum for all materials)

Figure 8: GPSR, economic importance (kg W eq.)

This curious finding is a result of methodological aspects of Equation 9, as discussed in section 3.4. It should also be noted that Oakdene Hollins (2013) does not report EI values for lead and boron. Therefore, the supply risk associated with these commodities is not accounted for. Another gap is that, according to the LCI data from Hawkins et al. (2012), neodymium is not present in the ICEV (see Appendix A). Consequently, the supply risk for the ICEV is likely underestimated.

As can be seen in Figure 9A, the biggest hotspots when applying Equation 10 are neodymium, magnesium, boron, tin, and platinum group metals (PGMs).



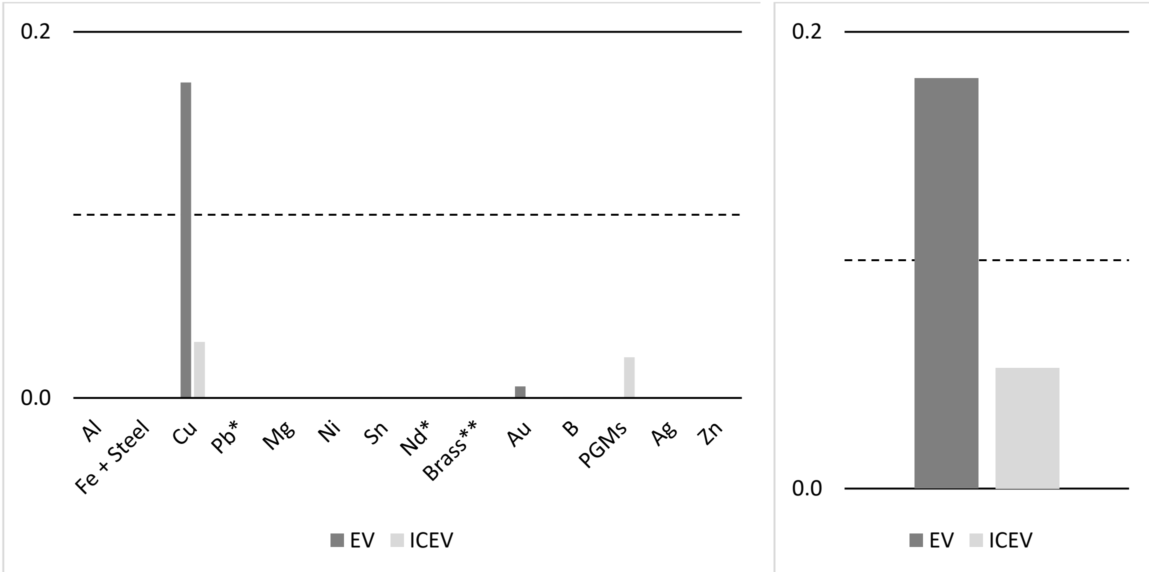
A: supply risk contributions of individual materials

B: total supply risk per functional unit (sum for all materials)

Figure 9: GPSR, product-level importance (dimensionless)

As Equation 10 "cancels out" the elementary flow and replaces it with the GeoPol indicator, the proportional contribution of each commodity to the total supply risk associated with the EV is *identical* to that in the earlier publication by Gemechu et al. (2015b). That publication, however, did not compare the supply risk of the EV and ICEV, as seen in Figures 9A and 9B. As the category indicator results per Equation 10 are determined solely by the GeoPol indicator – which is independent of the product(s) under consideration – the supply risk contribution of a given material is identical provided said material is present in the LCI for each product. For example, aluminum, steel, copper, lead, magnesium, and zinc are present in both the EV and ICEV, so the GPSR results for these materials are the same for both vehicles (Figure 9A). It does not matter *how much* of a material is needed to produce the product, as long as the amount is greater than zero. However, if the same material is sourced from different suppliers, the GeoPol indicator will reflect the relative riskiness of those suppliers. According to the LCI data from Hawkins et al. (2012), nickel, tin, neodymium, brass, gold, boron, and silver are present in the EV, but not in the ICEV (see Appendix A). Therefore, these materials contribute only to the supply risk of the EV (Figure 9A). On the other hand, PGMs are present only in the ICEV exhaust system, and thus contribute only to the supply risk of the ICEV (Figure 9A).

Using estimates of crustal content – as recommended by Drielsma et al. (2016) and van Oers and Guinée (2016) – the ADP method flags copper (especially in the EV) and PGMs in the ICEV as the most critical commodity inputs (Figure 10A). Similar results are obtained using estimates of the reserve base for the ADP calculation.



A: Abiotic Depletion Potentials of individual materials
*No data available
**Copper used as proxy for brass

B: total Abiotic Depletion Potential per functional unit (sum for all materials)

Figure 10: Abiotic Depletion Potential, crustal content (kg Sb eq.)

While the *relative contributions* of the 14 materials to the category indicator results vary widely depending on the method, the *total* category indicator results are remarkably consistent; the EV is found to have significantly higher supply risk and resource depletion potential. However, as discussed in the next section, the difference may be overestimated due to data limitations. Nonetheless, the facility for making such comparisons is a strength of the GPSR characterization model.

3.4: Discussion

The GPSR characterization model presented in this chapter significantly advances the integration of criticality assessment into LCSA and provides a new approach towards the "natural resources" AoP. In that regard, it is important to distinguish between a characterization *factor* and a characterization *model*. Whereas previous attempts at integrating criticality into LCSA (Gemechu et al., 2015a; Mancini et al., 2016; Schneider et al., 2014) have proposed characterization *factors*, a valid characterization *model* is not only a set of operational CFs, but is grounded in a theoretical cause-effect mechanism (ISO, 2006b). In particular, the Economic Scarcity Potential (ESP) method proposed by Schneider et al. (2014), which is further accompanied by the Environmental Scarcity Potential (EnSP) and Social Scarcity Potential (SSP) (Schneider, 2014), aggregates a number of indicators to derive *characterization factors* (CFs) for economic, environmental, and social aspects of criticality. Though it is a step forward, this approach has important drawbacks from an LCA perspective. First, the definition of the relevant AoP is not clear, though Drielsma et al. (2016) argue the implicit safeguard subject is *the product itself* – corresponding to the "outside-in" relation as defined by Porter and Kramer (2006). Second, there is no clear cause-effect mechanism; rather the CF is a constructed index. Aggregation of indicators also implies *weighting* choices – which are very controversial in the LCA community. Finally, the use of global average values for the indicators masks important regional variations and therefore limits utility for decision-making.

Therefore, this thesis chapter takes a step forward by proposing a cause-effect mechanism – albeit of socio-economic rather than environmental basis – for the GPSR characterization model. A novel feature of the cause-effect mechanism is that it includes both "outside-in" and "inside-out" impact pathways as defined by Porter and Kramer (2006). While conventional LCA is concerned with "inside-out" pathways (i.e., the potential environmental impacts of a product system), resource criticality assessments have been more concerned with "outside-in" pathways (i.e., the potential impacts of supply disruptions on provision of goods and services).

The "outside-in" impact pathway has important implications for the GPSR characterization model. In conventional LCA, the CFs are independent of the studied product system. For example, the global warming potential (GWP) of methane is the same for an EV and ICEV. Of course, the category indicator could differ, but only because of differences in the LCI. Even where environmental impacts exhibit spatial variability (for example, localized emissions), the CF may vary by the location of an emission but not by the product system responsible for the emission. Conventional approaches towards the "natural resources" AoP, which do not address "outside-in" mechanisms, also apply CFs that are independent of the product system. For example, the ADP of copper is the same regardless of whether the product is an automobile or a dishwasher. Similarly, Equation 9 applies the same CFs to the EV and ICEV. Neither the GeoPol indicator nor the "tungsten equivalent" EI differs between the two vehicle types. In contrast, the *product-level* importance factor included in Equation 10 is defined by product-specific elementary flows (i.e., the amounts of the various input commodities needed to make the product).

Equations 9 and 10 define two embodiments of the GPSR characterization model, so it is important to consider the strengths and limitations of each. For starters, Equation 9 applies the EI methodology by Oakdene Hollins (2013) – which, though a valuable contribution, introduces several problems. First, as can be seen in Equation 6, the EI indicator for a given commodity is determined solely by the distribution of the commodity across the economy (i.e., demand shares of end use "megasectors") and the GVA of each "megasector." This further implies that the *relative* EI of commodities can change merely due to changes in definitions of the megasectors (i.e., how commodities are assigned to various end uses). This property of the calculation is a major weakness with respect to the validity and reliability of the methodology.

Another potential problem is that the EI values of commodities according to Oakdene Hollins (2013) are relatively close together, and when normalized to the commodity with the highest EI, range from 0 to 1. The elementary flows, however, theoretically take on values from 0 to infinity. For example, according to LCI data from Hawkins et al. (2012), the mass of gold in the EV is less than 1 g, whereas the mass of iron and steel is over 800 kg. Consequently, the mass contribution could become the dominant factor in the supply risk calculation – as observed by Mancini et al. (2016). This means that materials used in small amounts, regardless of their supply risk, are unlikely to be assessed as "critical." Therefore, some suggestions have been to apply crude mathematical transformations, such as exponential magnifications, to give more weight to criticality indicators (Mancini et al., 2016). Instead, Equation 9 addresses this problem by dividing the EI values from Oakdene Hollins (2013) by apparent consumption (approximated by total imports) to derive an EI indicator in monetary units per mass of a given commodity. This calculation dramatically increases the spread of the EI factors so that the mass contribution is not the dominant factor in the characterization results. Moreover, in contrast to the approach of Mancini et al. (2016), Equation 9 is based on an underlying cause-effect mechanism and conceptual definition of supply risk – the multiple of a probability indicator and a vulnerability indicator. By calculating EI per unit of mass of each commodity, it is possible to express the "equivalency" of commodities – in terms of vulnerability – on a mass basis.

But perhaps the biggest gap when applying the EI methodology by Oakdene Hollins (2013) is that the *level of analysis* is incongruent with the LCA (or LCSA) framework. Whereas the methodology by Oakdene Hollins (2013) measures EI of commodities at an *economy-wide* level, LCSA is a *product-level* assessment. This discrepancy is problematic because a given commodity may not be very "important" in terms of GVA to the economy as a whole, but could be critical to the functionality of particular products. For example, gold scores relatively low in terms of EI (see Appendix A), but has unique and desirable properties in products such as electronics and jewelry. Rare earth elements (REEs) and lithium do not have very high EI either, yet these commodities are particularly critical for emerging "clean" energy technologies such as EVs and wind turbines. Emerging technologies by definition do not yet have a high value added for the whole economy, but are of strategic importance. Moreover, as can be seen in Figure 8A, neodymium in the EV appears to be the only critical input commodity according to Equation 9. This curious finding is a result of the fact that the apparent consumption of neodymium is up to 3 orders of magnitude smaller than that of the other commodities (see Appendix A). As Equation 9 divides the EI according to Oakdene Hollins (2013) by apparent consumption, the resulting ratio is higher for commodities with lower apparent consumption. This implies that the CF for a given commodity input to a product system *increases* as economy-wide apparent consumption of the commodity *decreases*. Thus, applying an economy-wide measure of EI to a product-level assessment yields misleading results from an LCSA perspective.

In contrast, Equation 10 measures "importance" in relation to product performance (i.e., the *functional unit*). In that regard, it does not matter whether a tonne or a gram of material is needed to produce the product; every input to the product system is, by definition, equally necessary to produce the end product that provides the functional unit. If supply of any number of inputs becomes disrupted – regardless of the *amounts* of the inputs required – a completed product cannot be produced. Therefore, it is justified that Equation 10 "cancels out" the elementary flows and *eliminates* the mass dominance problem observed by Mancini et al. (2016). It follows that the relative contribution of each input commodity to the total supply risk is determined solely by the GeoPol indicator – which represents the *probability* of supply disruption.

With regard to the supply chain resilience factors defined by Sprecher et al. (2015), the GPSR characterization model accounts for the diversity of supply (based on the HHI and import shares), as well as the political stability of suppliers (based on the WGI). The latter aspect does not seem to be captured in the resilience framework of Sprecher et al. (2015), but is relevant to supply risk assessment. Notably, however, the GPSR characterization model does not presently account for the risk mitigating effects of material “substitutability” and stockpiles (or “safety stocks”). This thesis chapter considers the situation in the EU-27, so it is assumed that there are no safety stocks in this case. It would be useful to measure the risk mitigating effect of safety stocks, but this raises a number of methodological complications that are worthy of further study. The issue of substitutability is further explored in the next chapter of this thesis.

It is tempting to compare the GPSR characterization model with the ADP method commonly used in conventional LCA. While this temptation is understandable, the two approaches are not really comparable, as they measure different things. The objective of the ADP is to measure physical depletion of resource availability *in the long-run*. It should also be noted that the Anthropogenic Stock Extended Abiotic Depletion Potential (AADP) method proposed by Schneider et al. (2015, 2011) extends the ADP by accounting for resources that remain (potentially) available in the anthroposphere. However, this chapter presents the ADP merely for the sake of illustration; the topic of interest is the risk of geopolitically induced supply disruptions *in the short-run* (for example, over a 2- to 3-year timeframe).

In that regard, the GPSR characterization model is useful to LCSA practitioners in a number of ways. First, the model expresses supply risks of different input commodities in common units of measure, thus enabling summation of risks per functional unit. This facilitates comparisons of supply risk for alternative product designs, as demonstrated by comparing the EV and ICEV. Moreover, the summation of risks implies that the *total* risk will inevitably be higher for more complex products (i.e., those having a greater variety of materials employed). The more complex the product, the higher the probability that supply of *at least* one material or component will be disrupted. For example, a passenger vehicle consists of numerous assemblies and subassemblies – and supply disruption of any one component could halt vehicle production. Finally, the methodology facilitates identification of supply risk “hotspots” and highlights opportunities to mitigate risk (for example, by increasing diversity of supply and/or sourcing from more reliable suppliers).

However, the GPSR characterization model as defined in Equation 10 ignores the *amounts* of commodity inputs to the product, and thus provides no incentive for using less material – despite "resource efficiency" being part of the EU Raw Material Initiative (RMI). This raises the question of how resource efficiency relates to resource "criticality." There is a tension between promoting resource efficiency, on the one hand, and avoiding the mass dominance problem observed by Mancini et al. (2016), on the other hand. The former would require placing emphasis on the amounts of commodity inputs to a product system, whereas the latter would require de-emphasizing or even ignoring them. As resource extraction has environmental impacts (as assessed in conventional LCA), resource efficiency is of environmental relevance. Resource extraction also has potential to lead to *physical* depletion of geological resource availability (as is the underlying rationale for the ADP method). Notably, the contribution of brass to the total ADP of the EV and ICEV is negligible compared to that of copper (Figure 10A), even though the same CF is applied to both materials. The difference can only be explained by the mass contribution of the materials. Therefore, resource efficiency is relevant to the environmental and geological aspects of criticality, but not to the geopolitical and socio-economic factors presently covered by the GPSR characterization model. One way of accounting for resource efficiency in product supply risk assessment could be to incorporate the risk mitigating effect of "safety stocks," as a product that requires a larger amount of material may require a larger safety stock. However, the issue of safety stocks needs further work and is not captured in the GPSR characterization model at this time.

LCSA practitioners need to be mindful of a number of methodological complications associated with the GPSR characterization model. First, there is an important conceptual difference in the definition of the "elementary flow." Applying the conventional LCA approach according to the ISO standards would define input elementary flows as raw concentrations of resources (i.e., ores) extracted from the environment. However, the total supply risk associated with a product system depends not only on resource extractions, but on *all* upstream stages of the supply chain. Therefore, the "elementary flow" from a supply risk perspective should be defined as the amount of “intermediate product” (ISO, 2006b) input to each unit process.

Second, application of the GPSR characterization model imposes data and data quality requirements that in some ways exceed those of conventional (environmental) LCA. For example, the LCI data from Hawkins et al. (2012) do not identify any neodymium or other REEs present in the ICEV; the data suggest that neodymium is only present in the EV powertrain. This is questionable for modern automobiles that contain many electric motors (and therefore magnets) for numerous functional aspects of the vehicle (for example, power seat and door/window controls and windshield wiper motors). This is not to fault the work of Hawkins et al. (2012), which provides a commendable balance between transparency and data quality. The objective of Hawkins et al. (2012) was to assess *environmental* implications of EVs in comparison to ICEVs; whereas the main interest in this thesis is supply risk assessment. In that regard, LCSA practitioners need to take extra care when applying “cut-offs” or threshold values – particularly in the LCI phase. Materials present in small amounts may be negligible from an environmental perspective, but *not* from a supply risk perspective. In fact, Equation 10 implies that the amount is irrelevant as long as it is greater than zero. On the one hand, this implies extreme sensitivity to LCI data. On the other hand, the data can be of *lower* quality than for environmental LCA, as the actual *amounts* of elementary flows need not be known. Processes that have been found to contribute little to environmental loadings (for example, assembly and transportation processes) may contribute significantly to the total supply risk of a product system (for example, if assembly takes place in a small number of unstable countries). Moreover, as the probability of supply disruption depends on the suppliers from which commodities are sourced, LCI data need to be spatially explicit – identifying locations where unit processes take place. The importance of geographical information has already been highlighted with respect to assessment of water use in LCA (Bayart et al., 2010; ISO, 2014).

While the GPSR characterization model presented in this chapter appears to be a step in the right direction, a number of important limitations remain. First, despite the work of Helbig et al. (2016a) towards modelling multi-stage supply chains, the GPSR characterization model presented in this thesis chapter still does not assess supply risks over an entire supply chain. Doing so would require further methodological development (for example, to measure "vulnerability" with respect to fabrication and assembly processes). It should be noted that the methodology by Helbig et al. (2016a) adopts a supply chain management perspective and is not a "life cycle" approach in its previously published form. Second, there are a number of challenges pertaining to availability and quality of data, to which the GPSR characterization model is extremely sensitive. Finally, the GPSR characterization model in its present form assesses supply risk at a country-level, whereas supply chains actually consist of sourcing relationships between firms. However, the methodology could be adapted to a firm-level resolution.

3.5: Conclusion

This thesis chapter extends the Geopolitical Supply Risk (GPSR) methodology from a relative assessment of raw material "criticality" to a Life Cycle Impact Assessment (LCIA) characterization model under the Life Cycle Sustainability Assessment (LCSA) framework. The GPSR characterization model is based on a socio-economic cause-effect mechanism drawing upon supply chain resilience concepts. The cause-effect mechanism consists of an "outside-in" pathway (i.e., the potential impact of supply disruption on the product system) and an "inside-out" pathway (i.e., the impact of impaired product performance and/or cost increases on human welfare). The outside-in pathway is represented by a "midpoint" indicator – *product supply risk* – defined as the multiple of *probability* of supply disruption and *vulnerability* to supply disruption. The elementary flow is defined as the physical amount of the "intermediate product" input to a given unit process. The supply risk associated with the intermediate product serves as the characterization factor (CF).

Two embodiments of the characterization model are presented, each supplementing the previously proposed probability indicators with different indicators for vulnerability. The first applies the methodology by Oakdene Hollins (2013) to derive an "economic importance" (EI) indicator for each intermediate product. However, as this methodology measures EI at an *economy-wide* level, it is not suitable for LCSA. Therefore, the second approach adapts the EI concept to a *product-level* resolution, with the implication that every input to the product system is equally important. The two methods are demonstrated with a comparative case study of an electric vehicle (EV) and internal combustion engine vehicle (ICEV).

The second method is evidently the more reasonable embodiment of the GPSR characterization model. However, it introduces a number of methodological complications and is highly sensitive to data availability and quality. Nonetheless, this thesis chapter sheds new light on the integration of criticality assessment into LCSA and illustrates how environmental LCA methodology can be adapted to cover socio-economic issues like product supply risk.

The next chapter further extends the GPSR characterization model by incorporating measures of material substitutability. The case study from this chapter is updated to demonstrate the extension. A new case study of dental x-ray equipment is also presented.

Chapter 4: Geopolitical Supply Risk – Substitutability and Case Study 2[viii]

The first chapter of this thesis highlighted the importance of "natural resources" for sustainable development and introduced the framework of Life Cycle Assessment (LCA) along with its emerging extension towards Life Cycle Sustainability Assessment (LCSA). Chapter 2 reviewed conventional LCA-based approaches for "natural resources" along with newer approaches for resource "criticality" assessment that have emerged outside the LCA community. While the former have long been controversial, the latter have had limited applicability on a product-level because they lack a connection to a *functional unit* of a given product – a central concept in LCA. Some attempts have been made to integrate criticality assessment into LCSA (Gemechu et al., 2015a; Helbig et al., 2016a; Schneider et al., 2014; Sonnemann et al., 2015), but the link of criticality to a functional unit has not been adequately demonstrated.

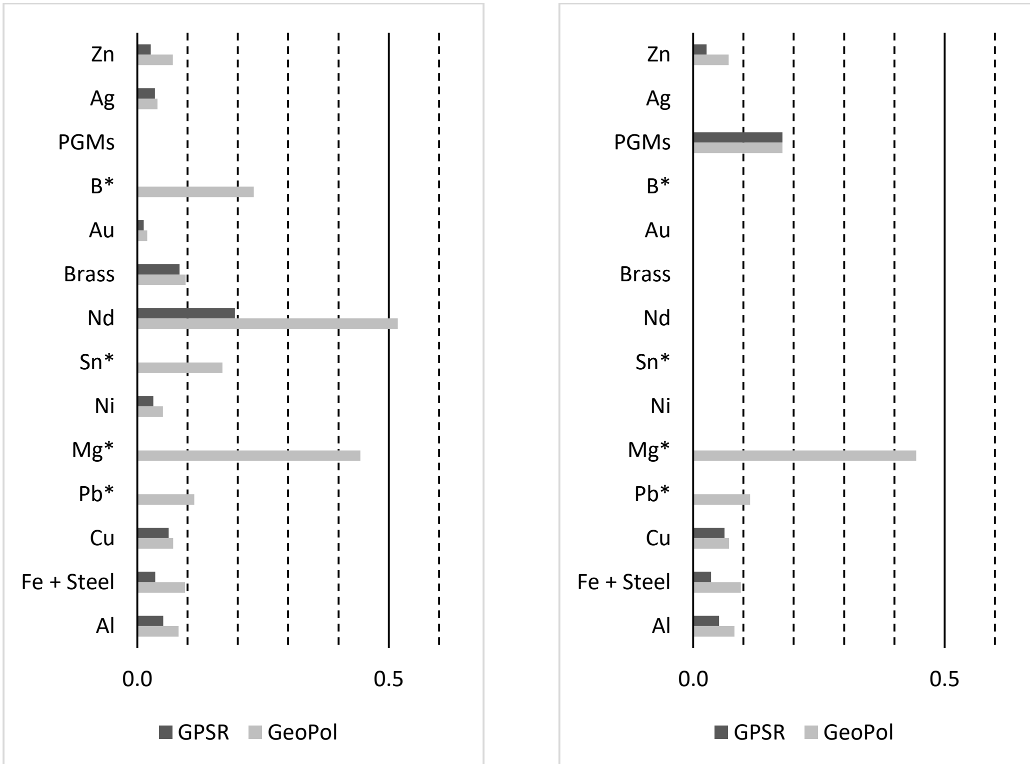
This thesis aims to address that limitation by extending the Geopolitical Supply Risk (GPSR) method developed by Gemechu et al. (2015a) and Helbig et al. (2016a) from a relative assessment of raw material criticality to a Life Cycle Impact Assessment (LCIA) characterization model for assessing product supply risk in relation to a functional unit under the LCSA framework. Chapter 3 demonstrated the characterization model with a comparative case study of an electric vehicle (EV) and internal combustion engine vehicle (ICEV). This chapter further extends the method by incorporating material "substitutability" as a potential risk mitigation factor. To provide tangible products for discussion, the extension is demonstrated with an update of the case study from the previous chapter along with a novel case study of dental x-ray equipment.

[viii] The contents of this chapter have been submitted for publication in the International Journal of Life Cycle Assessment: http://www.springer.com/environment/journal/11367

4.1: Update of Case Study 1 – Conventional and Electric Vehicles

One of the remaining limitations of the GPSR characterization model presented in the previous chapter is that it does not account for material "substitutability." As discussed in chapter 2, substitutability serves to mitigate supply risk. While price elasticity of demand (PED) of a commodity is theoretically a reasonable proxy for substitutability (Nassar, 2015), presently available estimates of PED for industrial commodities are limited. Probably the most rigorous, transparent, and comprehensive study of material substitutability to date is by Graedel et al. (2015), which provides relative substitutability scores for all metals and metalloids in the periodic table (62 were assessed). While the main text provides a high-level overview of substitution potential, the supporting information provides substitutability scores for each major application of each metal. As this thesis aims to develop a *product-level* supply risk assessment tool within the LCSA framework, the *application-specific* substitutability scores are applied. As applied in this work, the scores range from 0 (indicating the highest substitutability and thus minimizing supply risk) to 1 (indicating the lowest substitutability and thus maximizing supply risk). Details are provided in Appendix C.

The effect of accounting for material substitutability is demonstrated by updating the comparison of an EV and ICEV from the previous chapter. As each material fulfils a different role towards the overall performance (i.e., *functional unit*) of the vehicle, quantitative material substitutability indicator values are applied for the applications that most closely represent these roles. For example, neodymium (elemental symbol Nd) is used for "Nd magnets," gold (elemental symbol Au) is used for "electrical and electronics," and zinc (elemental symbol Zn) is used for "galvanizing" (see Appendix C). As can be seen in Figure 11, aluminum, steel, copper, nickel, brass, gold, silver, and zinc are assessed with relatively low probability of supply disruption (as measured by the GeoPol indicator described in chapter 3), and accounting for substitutability further lowers their estimated supply risk.



Electric Vehicle (EV) Internal Combustion Engine Vehicle (ICEV)

*No data available for substitutability

Figure 11: GeoPol and GPSR (with substitutability), contribution analysis, EV and ICEV (dimensionless)

Neodymium has a very high GeoPol factor for the EV, but when accounting for substitutability, its supply risk estimate is much lower (though still relatively high). Due to data gaps, magnesium, boron, tin, and lead have not been assessed for substitutability, but these materials have relatively high GeoPol factors. Therefore, they may be prioritized for further investigation of substitutability and other supply risk mitigation strategies. In light of these gaps in substitutability data, the total supply risk of the vehicles is not shown. Nonetheless, the comparison between the EV and ICEV is useful for the purpose of illustrating application of the GPSR method.

4.2: Case Study 2 – Dental X-ray System

To further demonstrate the relevance and applicability of the GPSR characterization model, this section presents a second case study – a dental x-ray system. This common medical diagnostic product is not well understood from an environmental or criticality perspective. In contrast to the first case study, in which supply risk assessment is based on data from a widely cited LCA study (Hawkins et al., 2012), this case required construction of a new bill of materials (BOM). As a consequence of the GPSR method "cancelling out" amounts of material inputs, the BOM in some ways requires a greater level of detail than typical of environmental LCA. In this case, unit processes in the Ecoinvent 2.2, ELCD, and United States Life Cycle Inventory (US LCI) databases in SimaPro 7.3.0 are used to conduct environmental LCA. The same unit processes are traced through the databases to input commodities (for example, minerals, metals, and petroleum) with corresponding Harmonized System (HS) codes used to collect commodity trade data from the United Nations (UN) Comtrade database. Thus, this case study contributes a novel application of GPSR assessment along with environmental LCA.

4.2.1: Methods

This LCA study follows the requirements and guidelines of ISO 14044 (ISO, 2006b). The goal is to assess environmental performance of a common intraoral dental x-ray system over the "production" and "use" stages of its life cycle, along with supply risk of the product system based on its material composition. Although the system boundary does not cover a full life cycle, it nonetheless provides valuable information for product designers and manufacturers looking to improve environmental performance while managing supply risks associated with "critical" materials. The functional unit is defined as 37,000 x-ray images based on assumptions of 3,700 patients per year, one image per patient, and a time period of 10 years. While most components of a dental x-ray system are expected to last 10 years, the digital imaging sensor, which is degraded by exposure to x-rays, may only last 5 years. Therefore, reference flows include one (1) x-ray system with two (2) sensors.

As illustrated in Figure 12, the product system boundary includes production of the x-ray "head" assembly, arm assembly, main power unit, control unit, and digital x-ray sensor (×2), as well as the electricity required to operate the x-ray system. Excluded, however, is any computer/monitor used to *view* images, as that would arguably constitute another product system. Moreover, inclusion of a computer/monitor would create unnecessary allocation problems, as a computer/monitor is likely to be used for numerous other functions in addition to displaying x-ray images.

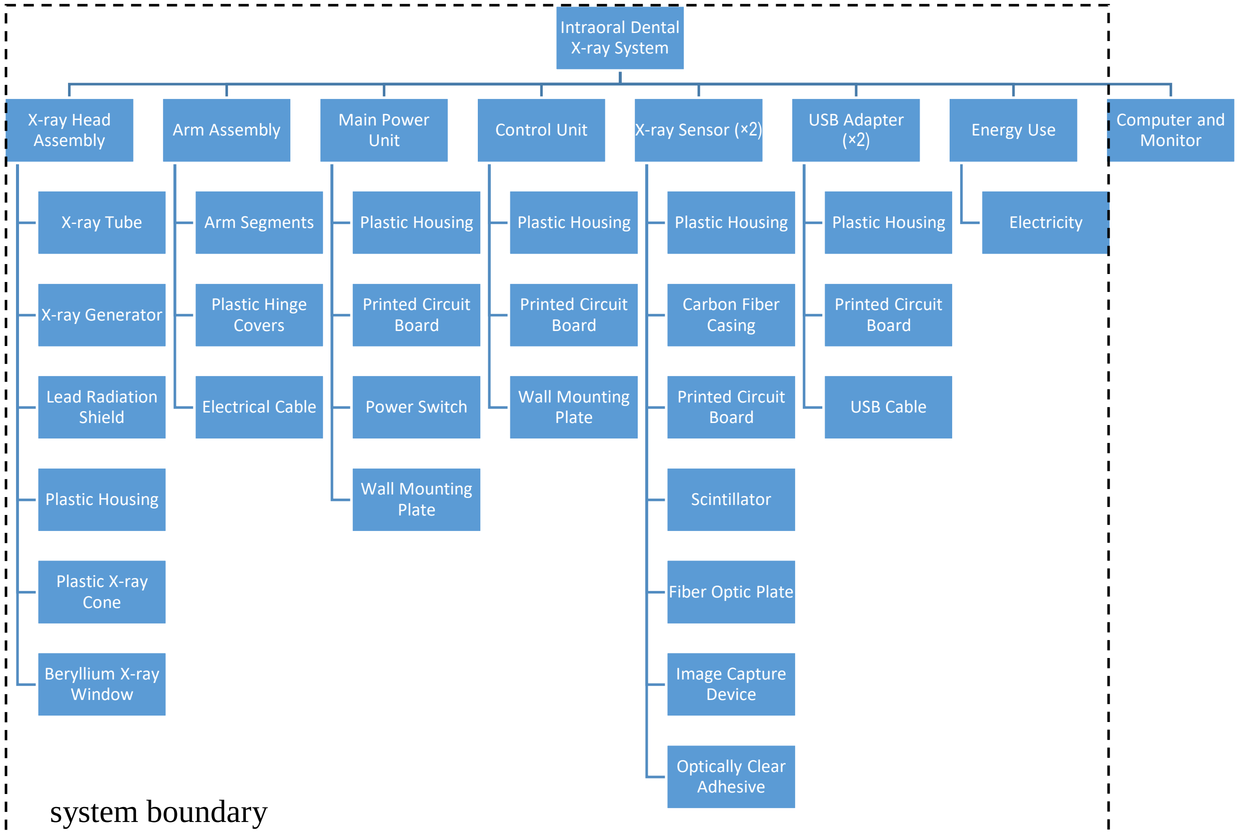


Figure 12: Boundary for intraoral dental x-ray system

As seen in Figure 12, the x-ray head assembly is comprised of an x-ray tube, x-ray generator, and lead radiation shield within a plastic housing. A plastic x-ray cone with a beryllium "window" maintains the source-to-skin distance (SSD) between the x-ray head and the patient. The arm assembly is comprised of rigid arm segments, plastic hinge covers, and an electrical cable that connects the x-ray head to the main power unit. The main power unit consists of a printed circuit board (PCB), plastic housing cover, power switch, and wall mounting plate. The control unit consists of a PCB, plastic housing, and wall mounting plate. The x-ray sensor consists of a scintillator, fiber optic plate (FOP), image capture device, PCB, and carbon fiber reinforced polymer (CFRP) casing inside a plastic housing. Attached to the sensor is a USB adapter that is comprised of a PCB, plastic housing, and USB cable. For the purpose of supply risk assessment, three scenarios are considered for the location of final manufacturing and assembly of the x-ray system: the USA, Japan, and the European Union (EU-27). For environmental LCA, three scenarios are considered for the electricity supply mix of the location where the x-ray system is installed: the Canadian average (baseline assumption), USA average, and EU-27 average.

To assess environmental performance of the x-ray system over the “production” and “use” stages of its life cycle, “foreground” data for material composition and power consumption are obtained from manufacturer specifications (at the time of writing) supplemented with assumptions informed by the technical expertise of one of the authors.[ix] Gaps in foreground data are filled by estimations and calculations – for example, mass calculations based on approximate dimensions of product components along with densities of different materials. “Background” data for production processes are primarily obtained from the Ecoinvent 2.2, ELCD, and US LCI databases in SimaPro 7.3.0. Data gaps are filled via references to relevant literature and/or using a “proxy” for the actual material or process.

Data collected for supply risk assessment include country production volumes from the United States Geological Survey (USGS), import-export trade volumes from the United Nations (UN) Comtrade database, and political stability of producing countries according to the Worldwide Governance Indicator (WGI) – Political Stability and Absence of Violence/Terrorism. All of these data are on an annual basis for the year 2015. As described earlier, material substitutability indicators from Graedel et al. (2015) are applied as a supplementary measure of vulnerability to supply disruption. As detailed in Appendix C, assumptions are made to estimate substitutability of commodities not covered by Graedel et al. (2015).

[ix] Karim S. Karim is a professor of Electrical and Computer Engineering at the University of Waterloo and Chief Technical Officer (CTO) of KA Imaging. His research interests include developing improved digital x-ray imaging technologies, such as a patented pixel design aimed at providing a higher performing and lower cost alternative to conventional imagers.

Based on the functional unit of 37,000 x-ray images over the assumed 10-year lifespan of the x-ray system, an overview of material and energy inputs is provided in Table 3. Further details regarding data sources, calculations, estimations, and assumptions are provided in Appendix B.

Table 3: Overview of material and energy inputs for 37,000 x-ray images over 10 years

Input	Unit	Amount per FU
X-ray head assembly		
Pyrex (borosilicate) glass	kg	0.03
Copper anode core (incl. metal working)	kg	0.03
Tungsten anode target (incl. metal working)	kg	0.02
Nickel-molybdenum cathode (incl. metal working)	kg	0.02
Aluminum x-ray tube housing (incl. metal working)	kg	0.03
Dielectric oil	kg	0.01
X-ray generator (high voltage power supply)	p	1
Capacitor(s)	kg	0.1
Lead radiation shield	kg	3
Plastic (ABS) housing (injection molded)	kg	0.45
Plastic (ABS) x-ray cone (extruded)	kg	0.04
Arm assembly		
Extruded aluminum arm segments	kg	3
Powder coating of arm segments	m^2	0.4
Plastic (ABS) hinge covers (injection molded)	kg	0.3
Electrical cable	m	3
Main power unit		
Plastic (ABS) housing (injection molded)	kg	1
Printed circuit board (PCB)	kg	0.4
Power switch	kg	0.05
Wall mounting plate (steel)	kg	1.4
Control unit		
Plastic (ABS) housing (injection molded)	kg	0.2
Printed circuit board (PCB)	kg	0.07
Wall mounting plate (steel)	kg	0.1
X-ray sensor[b]		
Scintillator, thallium “doped” cesium iodide (CsI:Tl)[a]	kg	0.0048
Scintillator, gadolinium oxysulfide (GOS)[a]	kg	0.0028
Fiber optic plate (FOP)	kg	0.002
Complementary metal oxide semiconductor (CMOS)	m^2	0.00184
Optically clear adhesive (OCA)	kg	0.00028
Printed circuit board (PCB)	kg	0.01
Carbon fiber reinforced polymer (CFRP) casing	kg	0.02
Plastic (ABS) housing (injection molded)	kg	0.02
USB adapter[b]		
Printed circuit board (PCB)	kg	0.02
Plastic (ABS) housing (injection molded)	kg	0.04

Input	Unit	Amount per FU
USB cable	m	2
Plugs	p	2
Electricity for system operation (modified from unit processes in Ecoinvent 2.2)		
Canadian average grid, 2013 (baseline assumption)[c] • Hydro: 62% • Nuclear: 15% • Steam: 16% • Internal combustion: 1% • Combustion turbine: 5% • Tidal: 0% • Wind: 2% • Solar: 0%	kWh	40
USA average grid, 2015[c] • Hydro: 6% • Wind: 5% • Biomass, wood: 1% • Solar: 1% • Biomass, waste: 0% • Nuclear: 20% • Natural gas: 33% • Coal: 33%	kWh	40
EU-27 average grid, 2014[c] • Combustible fuels: 48% • Nuclear: 27% • Hydro: 13% • Wind: 8% • Solar: 3% • Geothermal: 0% • Other: 0%	kWh	40

[a]The scintillator in the x-ray sensor may be comprised of thallium “doped” cesium iodide (CsI:Tl) or gadolinium oxysulfide (GOS).
[b]This table includes two (2) x-ray sensors and two (2) USB adapters in accordance with the functional unit of 37,000 x-ray images over 10 years.
[c]If this scenario applies

For supply risk assessment, unit processes in SimaPro are traced through the databases to input commodities (for example, minerals, metals, and petroleum) with corresponding HS codes used to collect import-export trade data from the UN Comtrade database. An overview of input commodities with corresponding HS codes and values of the Herfindahl-Hirschman Index (HHI) – used to measure production concentration – is provided in Table 4. More detailed information about data sources and assumptions, along with illustrations of supply chain stages, is provided in Appendix B.

Table 4: Overview of commodities and HHI values for dental x-ray system

Commodity (A)	HS Code	HS Code Description	HHI_A
Ag	7106	Silver, unwrought or semi-manufactured, silver powder	0.133
Al metal	7601	Unwrought aluminium	0.327
Al oxide	2818	Aluminium oxide, hydroxide and artificial corundum	0.285
Ar[b]	280421	Argon	0.422
As	280480	Arsenic	0.538
Au	7108	Gold, unwrought, semi-manufactured, powder form	0.144
B	280450	Boron, tellurium	0.517
Barite	283327	Barium sulphate	0.210
Be	811219	Beryllium, articles thereof, nes	0.856
Ca	280521	Calcium	0.741
Cl[c]	280110	Chlorine	0.164
Clay	2507	Kaolin and other kaolinic clays	0.159
Coconut oil (crude)[d]	151311	Coconut (copra) oil crude	0.167
Cr	811220	Chromium, articles thereof, waste or scrap/powders	0.307
CsI[a,e]	282760	Iodides and iodide oxides of metals	1.000
Cu + brass	7403	Refined copper and copper alloys, unwrought	0.172
Fe + steel	7206	Iron and non-alloy steel in primary forms, ingots	0.295
Feldspar	252910	Feldspar	0.178
Fluorspar	252922	Fluorspar, >97% calcium fluoride	0.409
Gadolinium oxysulfide (GOS)[a]	280530	Rare-earth metals, scandium and yttrium	0.728
H[c]	280410	Hydrogen	0.164
He	280429	Rare gases other than argon	0.422
Kraft paper[f]	4804	Uncoated kraft paper and paperboard	0.393
Limestone	2521	Limestone materials for manufacture of lime or cement	0.441
Mg metal	810411	Magnesium unwrought > 99.8% pure	0.772
Mn	8111	Manganese, articles thereof, waste or scrap	0.168
Mo	810294	Unwrought molybdenum, incl. bars & rods obt. simply by sintering	0.246
N and ammonia	280430	Nitrogen	0.151
NaOH[g]	281511	Sodium hydroxide (caustic soda) solid	0.164
Ni	7502	Unwrought nickel	0.115
P	280470	Phosphorus	0.242
Palm oil[h]	151110	Palm oil, crude	0.395
Pb	7801	Unwrought lead	0.275
Pd	711021	Palladium unwrought or in powder form	0.307

Commodity (A)	HS Code	HS Code Description	HHI_A
Petroleum[i]	2709	Petroleum oils, oils from bituminous minerals, crude	0.080
Potassium nitrate	283421	Potassium nitrate	0.185
S	2503	Sulphur, except sublimated, precipitated, colloidal	0.108
Salt (NaCl)	2501	Salt (sodium chloride) including solution, salt water	0.164
Si, electronics grade	280461	Silicon, >99.99% pure	0.477
Silica sand	250510	Silica sands and quartz sands	0.350
Sn	8001	Unwrought tin	0.202
Ta	810310	Tantalum unwrought, bars, rods simply sintered, scrap	0.311
Ti oxide	2823	Titanium oxides	0.252
Tl[a]	811251	Thallium, unwrought; powders	0.333
Vegetable oil[h]	151590	Veg fats, oils nes, fractions, not chemically modified	0.167
W	810194	Unwrought tungsten (wolfram), incl. bars & rods obt. simply by sintering	0.667
Zeolite	2839	Silicates	0.542
Zn metal	7901	Unwrought zinc	0.194
Zn oxide	2817	Zinc oxide and peroxide	0.194

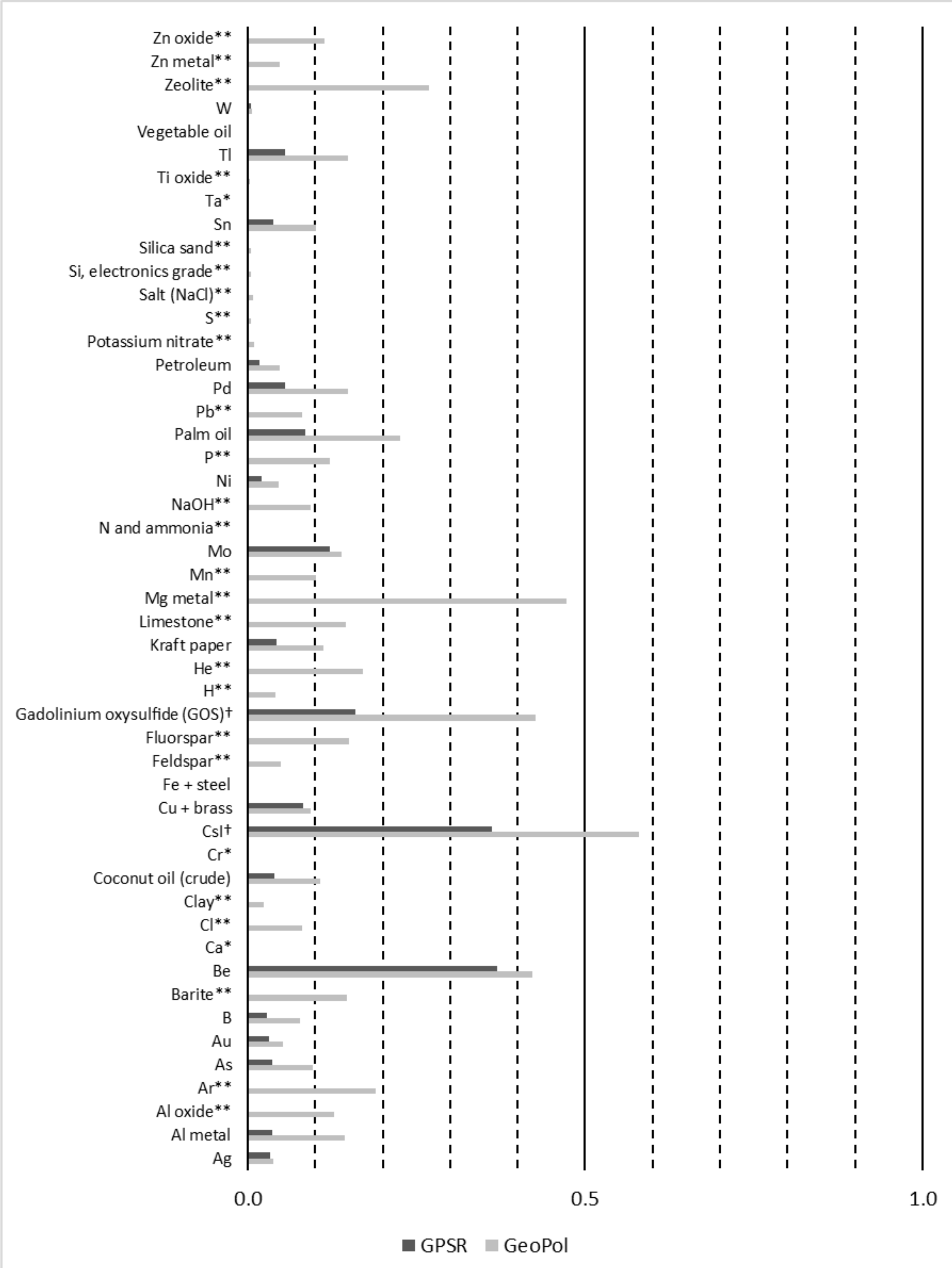
[a]The scintillator in the x-ray sensor may be comprised of thallium “doped” cesium iodide (CsI:Tl) or gadolinium oxysulfide (GOS).
[b]HHI based on helium (elemental symbol He)
[c]HHI based on sodium hydroxide co-product
[d]HHI based on vegetable oil
[e]Maximum HHI value assumed
[f]HHI based on data from United Nations (UN) Food and Agriculture Organization (FAO, 2016)
[g]HHI based on salt (NaCl)
[h]HHI based on data from United States Department of Agriculture (USDA, 2017)
[i]HHI based on data from BP Statistical Review (BP, 2016)

To address the AoPs “human health” and “ecosystem quality,” this study applies the Tool for the Reduction and Assessment of Chemical and other environmental Impacts (TRACI 2 version 4.00) impact assessment method for the categories of global warming, acidification, eutrophication, smog formation, ozone depletion, carcinogenic effects, non-carcinogenic effects, respiratory effects, and ecotoxicity. Developed by the United States Environmental Protection Agency (EPA), TRACI is an LCIA method developed for a North American context (Bare, 2011; Bare et al., 2003).

Regarding the “natural resources” AoP, the GPSR method complements the Abiotic Depletion Potential (ADP) method (Guinée and Heijungs, 1995; van Oers et al., 2002; van Oers and Guinée, 2016) commonly used in LCA and contained within the CML method in SimaPro. Water intake is calculated according to ReCiPe 1.06. Although this method does not account for regional and temporal variations in water availability and scarcity, and thus is technically not an impact assessment, it does account for the volume of water intake across unit processes in the system boundary.

4.2.2: Results – Dental X-ray System

Figure 13 presents GPSR results for a dental x-ray system manufactured in the EU-27. Supply risk "hotspots" include beryllium (elemental symbol Be), cesium iodide (chemical formula CsI), gadolinium oxysulfide (GOS), and magnesium (elemental symbol Mg).

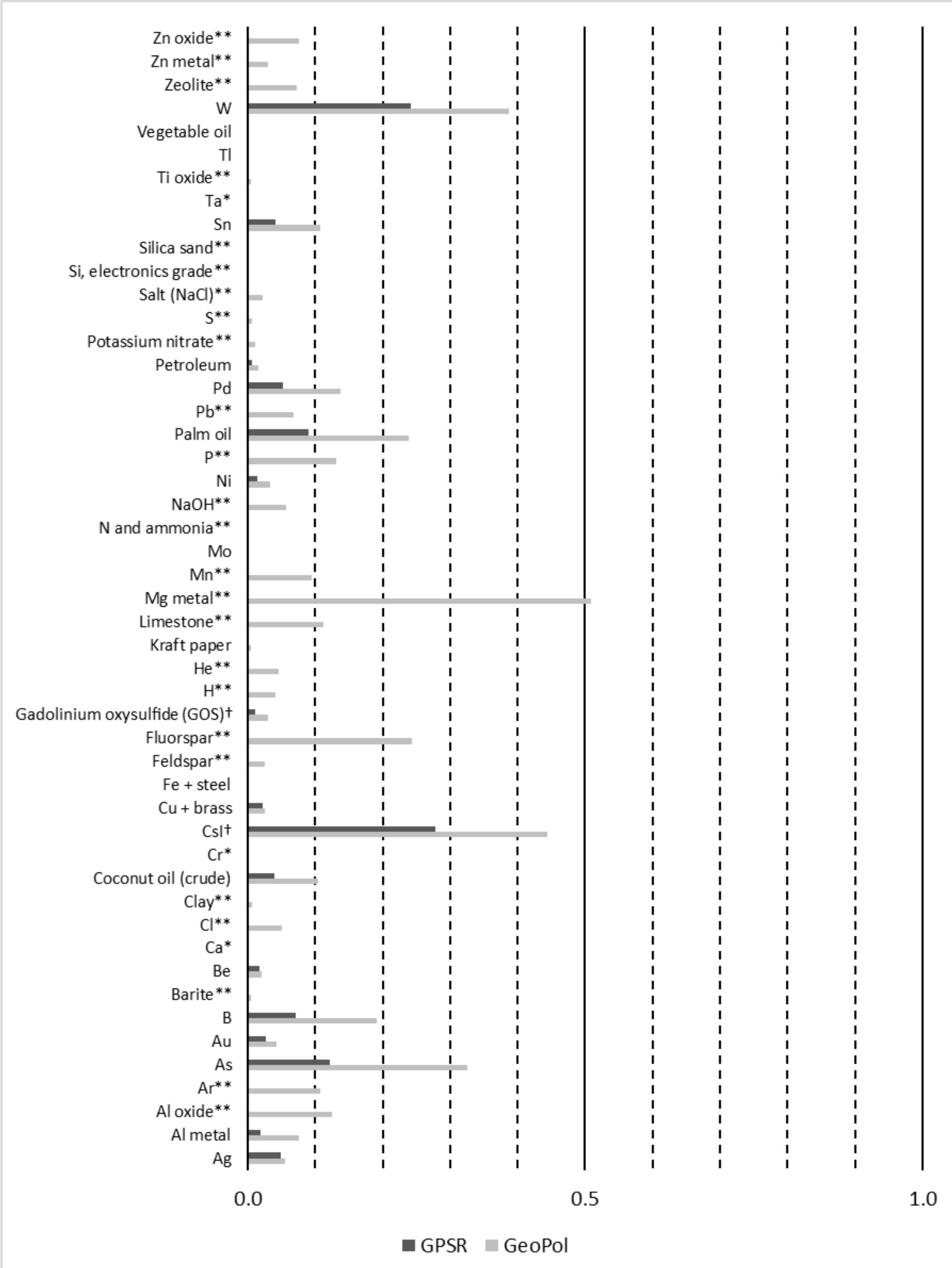


*No data **No data for substitutability †Scintillator may be CsI or GOS

Figure 13: Geopolitical Supply Risk (GPSR) for dental x-ray system manufactured in EU-27

Beryllium’s high probability of supply disruption is largely a consequence of its concentrated production outside the EU-27, as evidenced by its HHI value in Table 4. Moreover, it has limited substitutability for its specialized application in dental x-ray equipment. Cesium iodide also has high probability of supply disruption, as the EU-27 imports this commodity from high-risk countries like Brazil, Chile, China, and India. Cesium production is believed to be highly concentrated, though much of it is sourced in Canada – suggesting an opportunity for the EU-27 to reduce supply risk associated with this commodity. Moreover, thallium “doped” cesium iodide (CsI:Tl) can be substituted with GOS, though performance (particularly image resolution) may be inferior. Both scintillator materials present high probability of supply disruption for the EU-27, but their GPSR values are significantly lower due to their mutual substitutability. Magnesium presents high probability of supply disruption – due in part to production concentration – and has no known substitute for its application in the x-ray system. Despite being classified as “critical” by the EC (2014), tungsten (elemental symbol W) is assessed with minimal supply risk in Figure 13. This result can be attributed to domestic European production, though it should be recognized that the supply risk assessment in this thesis chapter only covers a single stage of the supply chain (for example, production of unwrought metallic commodities like bars and rods). In reality, other supply chain stages also contribute to overall supply risk.

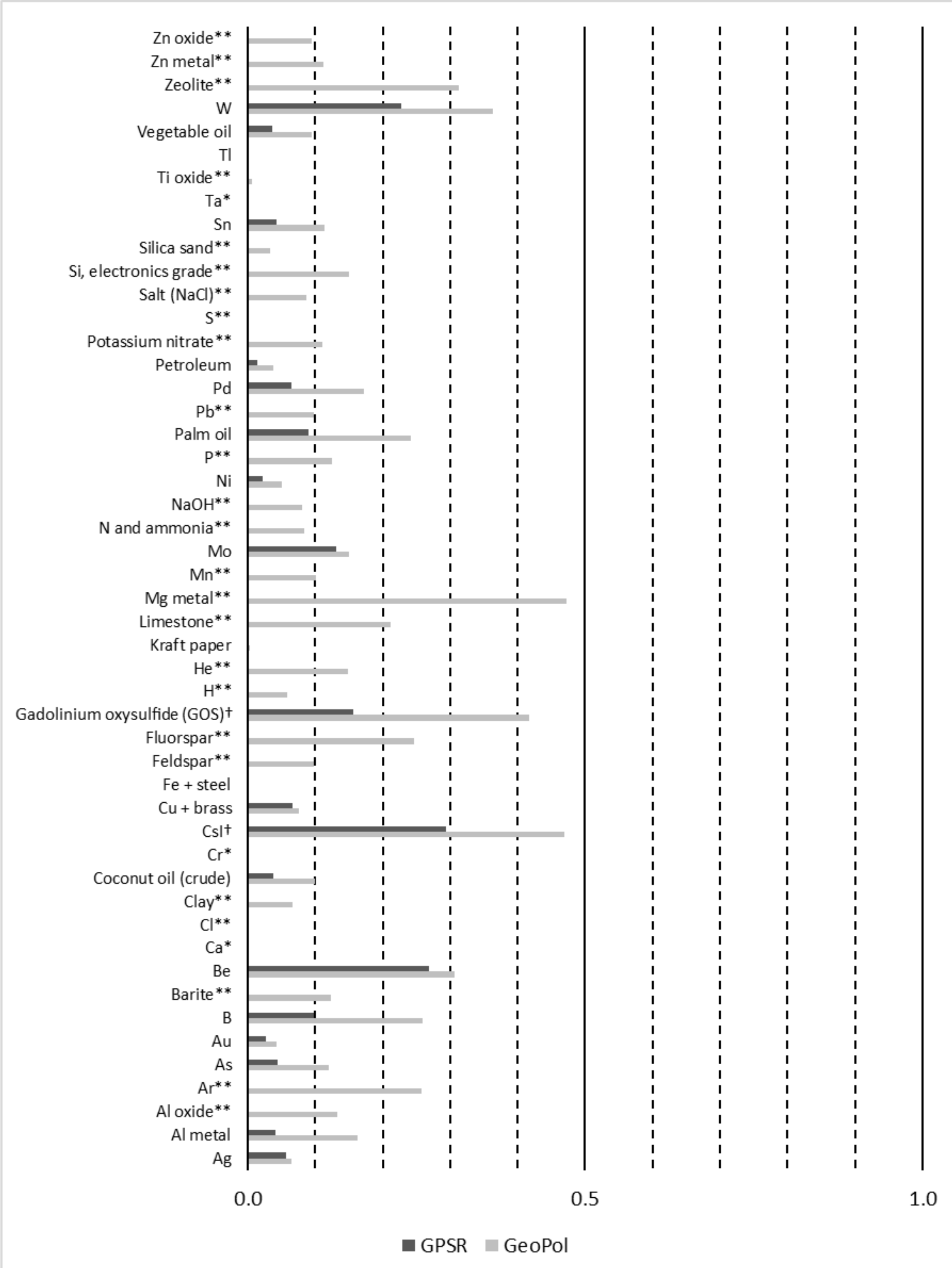
In contrast to a European-manufactured x-ray system, one manufactured in the USA (Figure 14) has very low supply risk associated with beryllium and GOS – due in part to domestic production. However, gadolinium is considered a rare earth element, and in 2015 (the year represented by the data used for this case study), the USA had only one company mining rare earths – a company that went bankrupt in 2017 (subsequent to the 2015 dataset). Domestic beryllium was also mined by only one company (USGS, 2016). This illustrates that supply risks are always changing – GPSR represents a snapshot in time – and that there are some *intra*-country risk factors not presently captured in the method.



*No data **No data for substitutability †Scintillator may be CsI or GOS

Figure 14: Geopolitical Supply Risk (GPSR) for dental x-ray system manufactured in USA

Compared to an x-ray system manufactured in the USA, one manufactured in Japan has similar supply risk for tungsten, cesium iodide, and magnesium, but higher risk for beryllium and GOS (Figure 15).



*No data **No data for substitutability †Scintillator may be CsI or GOS

Figure 15: Geopolitical Supply Risk (GPSR) for dental x-ray system manufactured in Japan

Table 5 presents environmental loads of the x-ray system, assuming the x-ray sensor features CsI:Tl scintillator technology and the system is powered by the Canadian electricity supply mix in the use stage.

Table 5: Environmental loads of dental x-ray system with Canadian electricity supply mix

Impact category	**Unit**	**TOTAL**	**Production**	**Use**
Ozone Depletion Potential (ODP)[a]	kg CFC-11 eq	5.E-05	5.E-05	7.E-07
Global Warming Potential (GWP)[a]	kg CO_2 eq	3.E+02	3.E+02	1.E+01
Smog Formation Potential[a]	kg O_3 eq	2.E+01	2.E+01	5.E-01
Acidification Potential (AP)[a]	mol H^+ eq	1.E+02	1.E+02	4.E+00
Eutrophication Potential (EP)[a]	kg N eq	6.E+00	6.E+00	4.E-02
Carcinogenic Effects[a]	CTUh	6.E-05	6.E-05	1.E-06
Non Carcinogenic Effects[a]	CTUh	4.E-04	4.E-04	3.E-06
Respiratory Effects[a]	kg PM_{10} eq	5.E-01	5.E-01	1.E-02
Ecotoxicity[a]	CTUe	2.E+03	2.E+03	2.E+01
Abiotic Depletion Potential (ADP)[b]	kg Sb eq	2.E+00	2.E+00	8.E-02
Water Depletion[c]	m^3	4.E+00	4.E+00	4.E-02

[a]TRACI 2 version 4.00
[b]CML baseline 2001
[c]ReCiPe 1.06

As illustrated in Figure 16, environmental loads from production of the x-ray system dominate over the "use" stage. Changing the electricity supply mix from the Canadian average to the USA average or EU-27 average has minimal effect on this result.

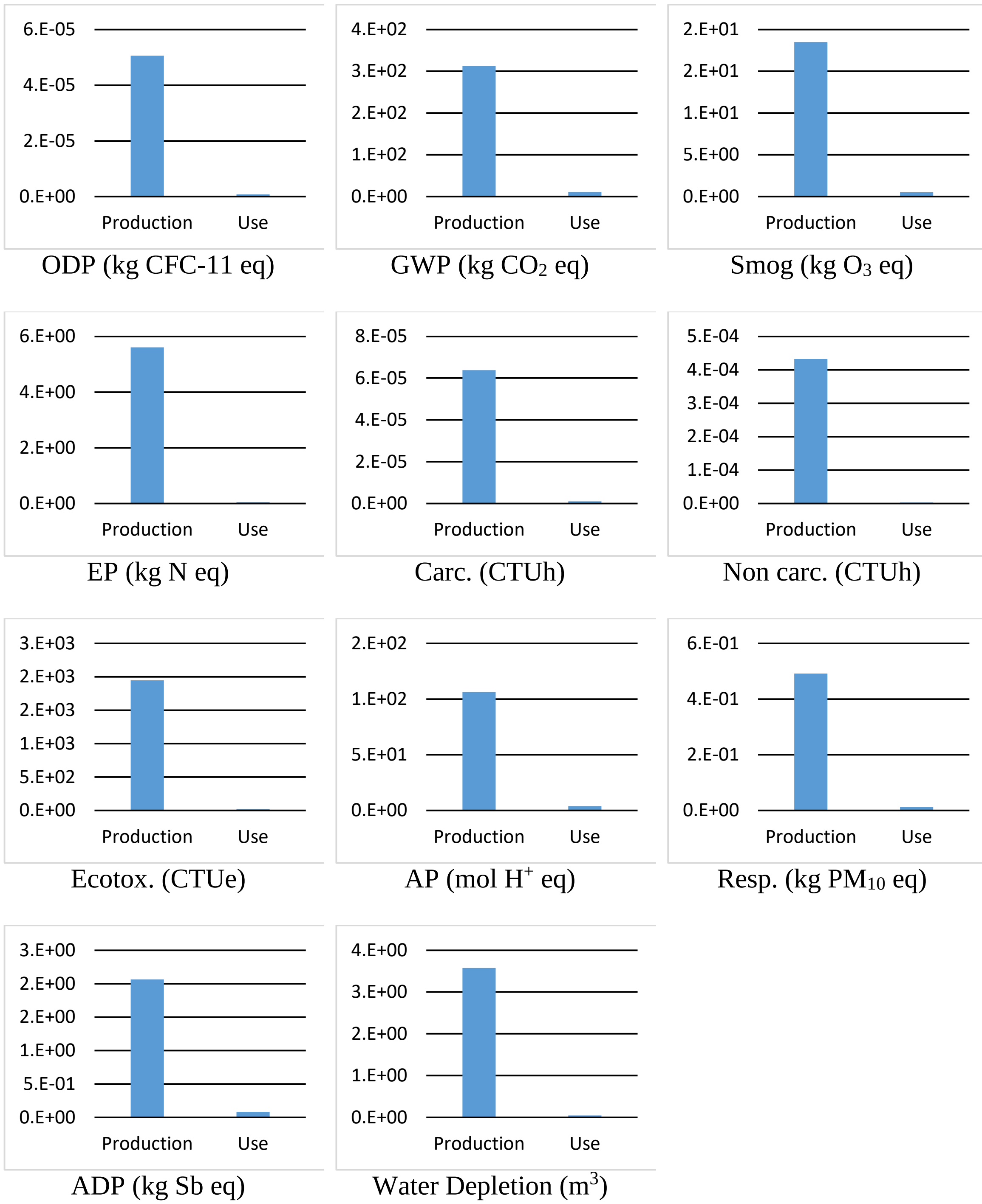


Figure 16: Contributions of “production” and “use” stages to environmental loads of dental x-ray system

More specifically, environmental "hotspots" in production of the x-ray system include the x-ray sensor, x-ray head assembly, and main power unit (Figure 17). As can be seen in Figure 18, environmental loads from production of the x-ray sensor are dominated by the complementary metal oxide semiconductor (CMOS). With the exception of ODP, the x-ray tube makes a small contribution to the environmental loads of the x-ray head assembly (Figure 19). "Hotspots" include the x-ray generator and capacitors. Environmental loads of the main power unit are dominated by its PCB (Figure 20). According to process data from Ecoinvent 2.2 (modified to partially reflect updates in version 3.3), electricity consumption accounts for over 60% of "embodied" GWP of PCBs.

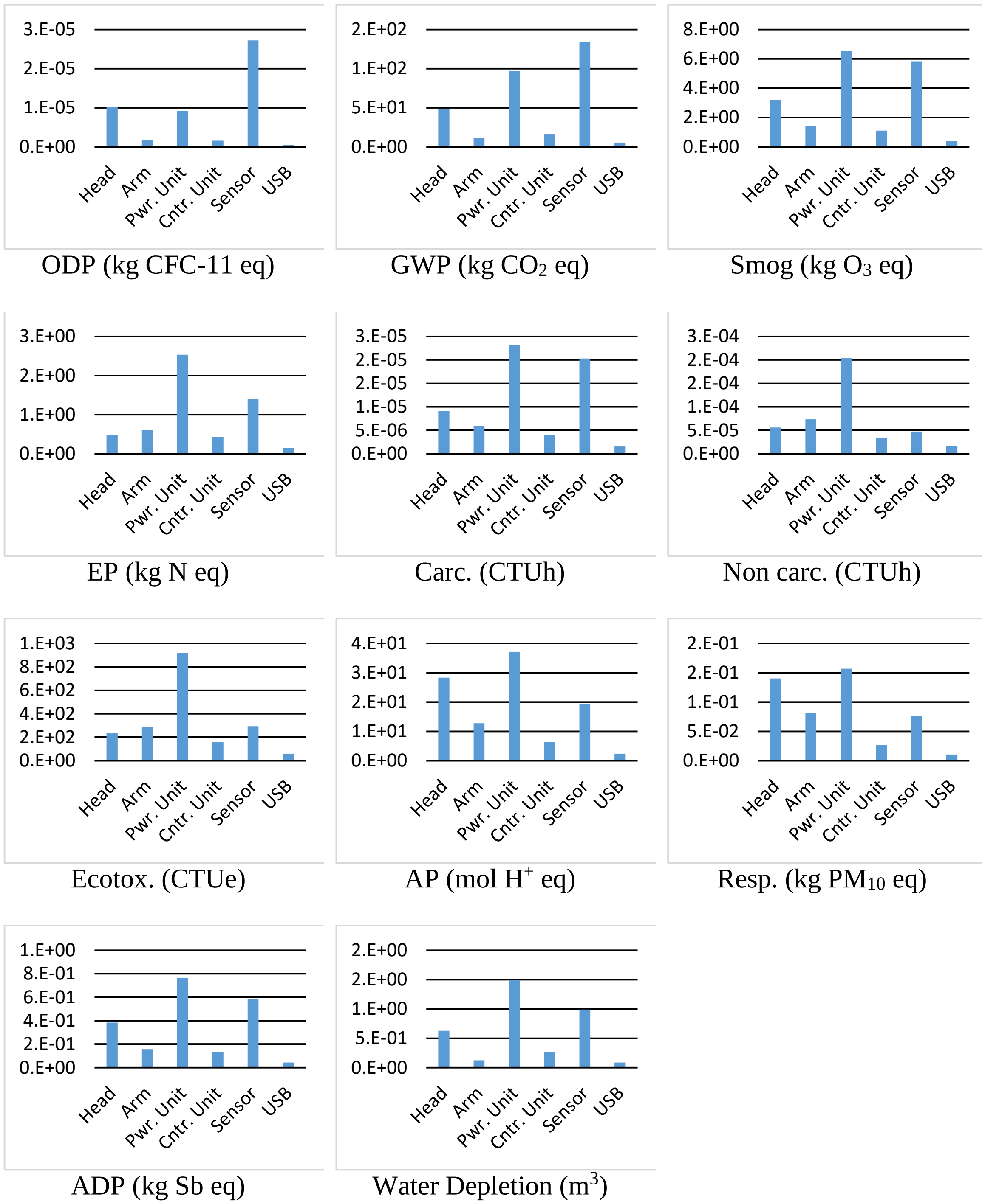


Figure 17: Contributions of major components to environmental loads of dental x-ray system

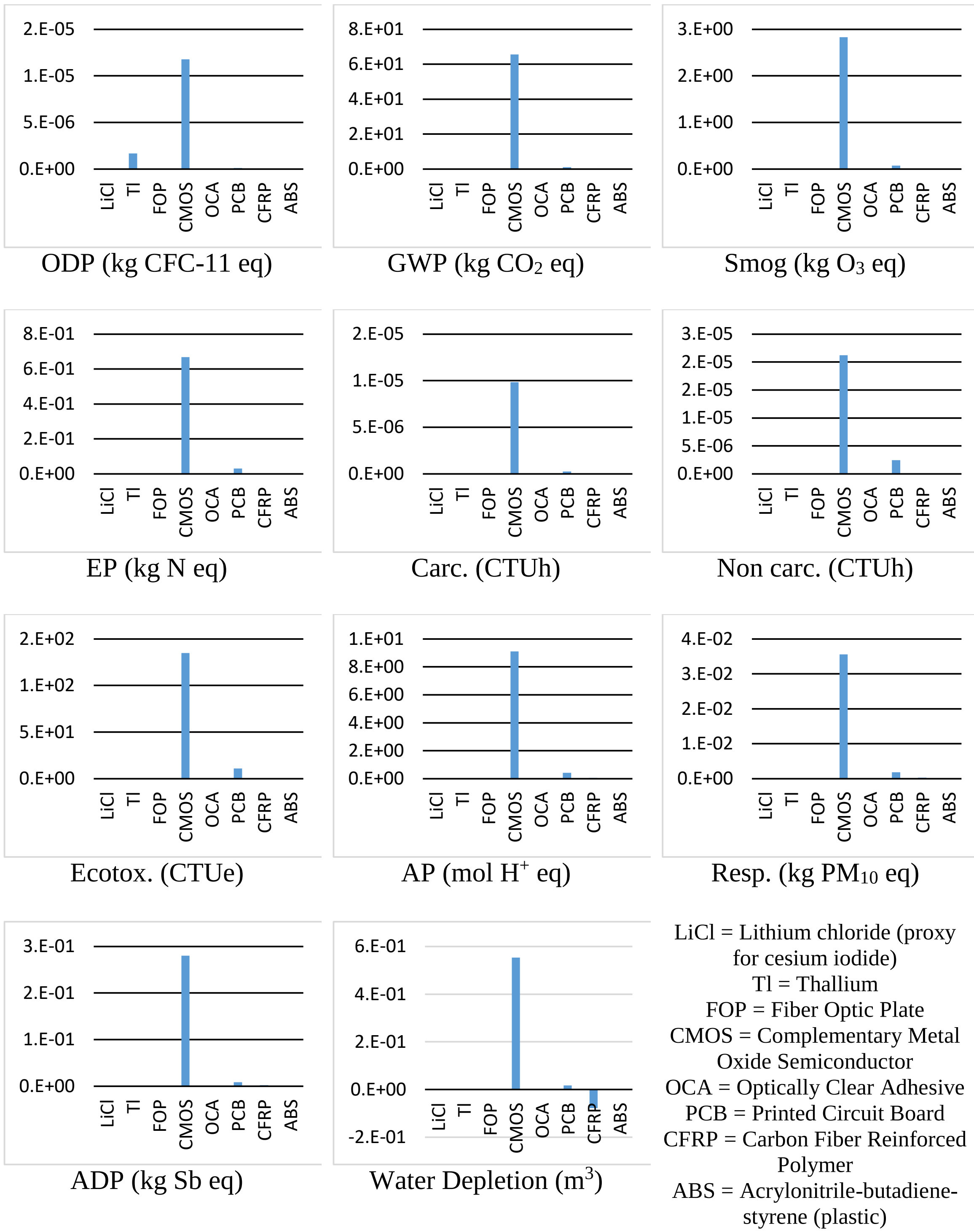


Figure 18: Contribution analysis of x-ray sensor

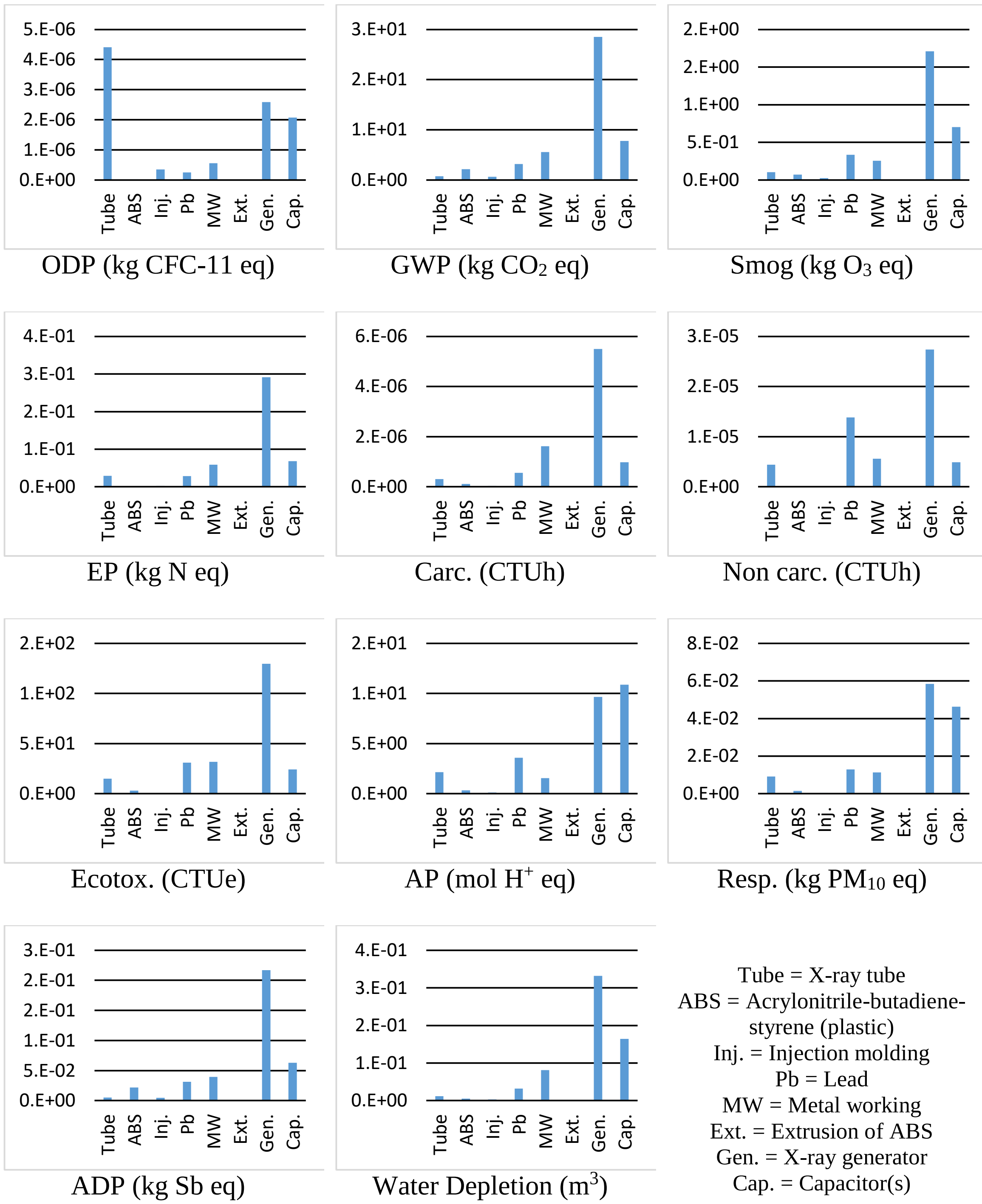


Figure 19: Contribution analysis of x-ray head assembly

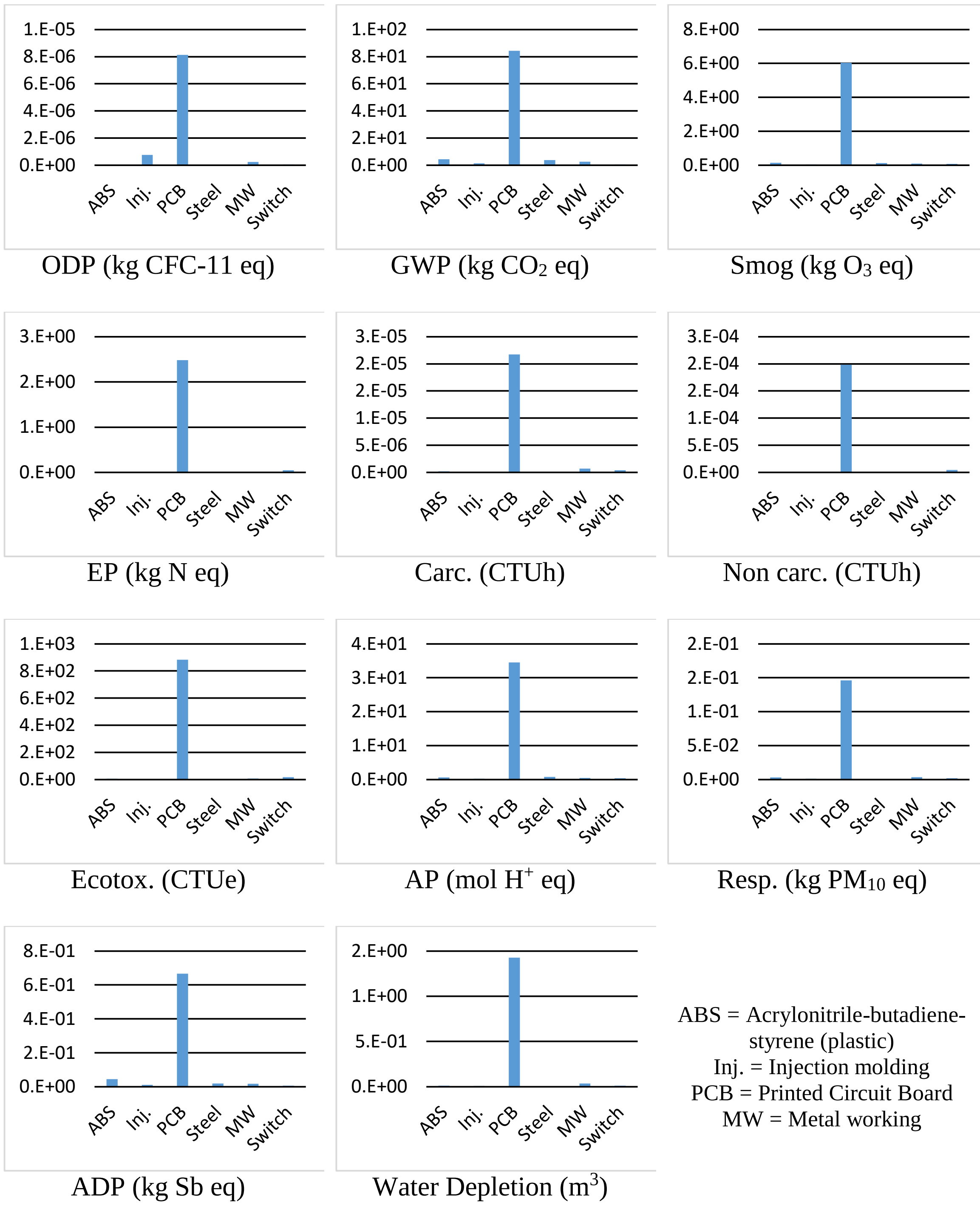


Figure 20: Contribution analysis of main power unit

4.3: Discussion

This thesis chapter advances integration of resource “criticality” assessment into LCSA by extending and demonstrating the Geopolitical Supply Risk (GPSR) characterization model presented in Chapter 3. The GPSR method brings criticality assessment to a product-level by measuring supply risk in relation to a *functional unit* – thus providing information relevant for product design. Supply risk is defined as the multiple of *probability* of supply disruption and *vulnerability* to supply disruption. The former is represented by the GeoPol indicator in the original GPSR method, while the latter can be conceptualized as the multiple of “importance” and “substitutability” of a commodity. The “product-level importance” factor proposed in Chapter 3 and applied to the case studies in this chapter “cancels out” the *amounts* of commodity inputs to the product system, as every input is equally necessary for product performance (i.e., the *functional unit*) based on the product design. Further, this chapter incorporates measures of material “substitutability” as a potential risk mitigation factor. The proposed characterization model incorporating these methodological extensions is demonstrated by updating a comparative case study of a European-manufactured electric vehicle (EV) and internal combustion engine vehicle (ICEV) presented in Chapter 3. Additionally, this chapter presents a novel case study of a common medical diagnostic product: a dental x-ray system.

While the GPSR characterization model brings resource “criticality” assessment to a product-level, it also represents a new approach to the “natural resources” AoP in LCA. Whereas conventional approaches to the “natural resources” AoP – such as the commonly applied Abiotic Depletion Potential (ADP) method – concern the “inside-out” impact of resource depletion *in the long-run*, the GPSR method – along with other “criticality” assessment methods – concerns the “outside-in” impact of *short-run* supply disruptions on a given product.

While the ADP calculation is very sensitive to the *amounts* of resource inputs to the product system, the GPSR method "cancels out" these amounts. Further, the "elementary flow" is redefined as a given commodity (or "intermediate product" per ISO (2006b)) input to a given unit process. The total supply risk associated with a product depends not only on resource extractions, but on *all* upstream stages of the supply chain. Moreover, from a supply risk perspective, it does not matter whether a tonne or a gram of material is needed to produce a product. If supply of even the smallest input is disrupted, a completed product cannot be produced. "Critical" materials – like beryllium in x-ray "windows" – are often used in small amounts and thus may be overlooked in environmental LCA. Such "cut-offs" are not permissible in the GPSR characterization model – indeed, this assessment suggests beryllium presents high probability of supply disruption for a dental x-ray system manufactured in the EU-27 or Japan.

As a consequence of "cancelling out" amounts of commodity inputs, a comprehensive bill of materials (BOM) is required for GPSR calculation. In the case of the dental x-ray system, for example, unit processes are traced through LCI databases in SimaPro so that commodity inputs can be matched with identification codes for collecting trade data needed for supply risk assessment. On the other hand, it is convenient that the *amounts* of commodity inputs need not be known. Nonetheless, it is still good practice to estimate the amounts where possible, as they *are* needed for environmental LCA and may be useful for further extensions of the GPSR method – for example, to account for the risk mitigation effect of commodity stockpiles or "safety stocks" as suggested by Sprecher et al. (2015).

While difficult to quantify, "substitutability" is the most commonly applied notion of vulnerability in resource criticality assessment (Helbig et al., 2016b). Substitutability could theoretically be measured using economic concepts like price elasticity of demand (Nassar, 2015) or material science concepts (Ashby, 2013; Nassar, 2015), but due to practical limitations of those approaches, this thesis chapter applies the "expert judgement" approach proposed by Graedel et al. (2015). Their study provides broad and detailed coverage of material substitutability. Broad, in that it covers all metals and metalloids in the periodic table (62 were assessed), and detailed, in that the supplementary information provides *application-specific* substitutability scores for each metal. Substitutability indicators used in product-level supply risk assessment need to be application-specific to account for the "outside-in" mechanism of supply disruption. Even within a given product system, there can be different substitutability factors for similar materials used in different components of the product. In a dental x-ray system, for example, aluminum is used in the arm assembly and in capacitors. Therefore, aluminum is assigned a substitutability score of 0.25 – the equally-weighted average of its substitutability scores for "building and construction" applications (i.e., the arm assembly) and "electrical and electronics" (i.e., capacitors in the x-ray system). Equal weighting reflects the equal "importance" of each component for product performance as previously argued.

Similarly, different components could be made of similar materials from different suppliers. With regard to a dental x-ray system, for example, the sourcing of aluminum for capacitors could differ from that for the arm assembly. Compounding this complexity is the reality that supply chains actually consist of multiple stages (corresponding to unit processes in LCA), including for example mining, smelting, refining, fabrication, and assembly. As a practical simplification for this thesis chapter, the GPSR method implicitly assumes a single-stage supply chain from upstream commodities (for example, metal bars and rods) to final manufacturing and assembly. In principle, however, different probability and vulnerability factors would be needed for each input to each unit process – an enormous exercise in data collection and computation. This limitation of the GPSR method is analogous to classical environmental LCA, which often "lumps together" emissions from different unit processes without regard for spatial and temporal variability in environmental impact mechanisms.

The case studies presented in this thesis chapter also illustrate how the probability and vulnerability dimensions can be used as “filters” in supply risk assessment. By construction, the probability (i.e., GeoPol) factor for a given commodity ranges from 0 to 1. The substitutability scores also range from 0 (highly substitutable) to 1 (non-substitutable). Therefore, substitutability serves as a mitigation factor that can lower the risk but not increase it. Consequently, for commodities assessed with low probability of supply disruption – such as tungsten for the EU-27 or beryllium for the USA – there is little added value in assessing substitutability or other measures of vulnerability. Vulnerability is most significant for commodities with high probability of supply disruption. On the other hand, commodities with limited substitutability – such as beryllium and magnesium – can be prioritized for assessing probability of supply disruption.

Along with further extending the GPSR method to incorporate material substitutability, this thesis chapter contributes a novel case study of dental x-ray equipment. Except for a few recent studies (for example, Campion et al., (2015, 2012) and Thiel et al. (2015)), the health care sector has been largely overlooked by the LCA community. The dental x-ray system considered in this thesis chapter is essentially comprised of three types of product components: structural and mechanical components (for example, the arm assembly), electronic components (for example, PCBs and capacitors), and components unique to the x-ray system (namely the x-ray tube and x-ray sensor). In contrast to the typical environmental “profile” of long-lived, energy-consuming products, environmental loads from production of a *dental* x-ray system dominate over the “use” stage of the life cycle. This curious finding is a result of the low energy consumption of this type of x-ray system – estimated at 40 kWh over 10 years – due to the short time for taking dental x-ray images. For comparison, an average Canadian household consumes about 10,000 kWh of electricity per year (Statistics Canada, 2011). Other types of x-ray systems – in hospitals, for example – may be used more intensively and thus have a different “profile” with a greater contribution from the use stage.

Compared to an automobile (as in the first case study), the amount of major industrial metals like steel, aluminum, and copper in a dental x-ray system is relatively small. For example, while a typical car body contains hundreds of kilograms of steel, a dental x-ray system has only a few small steel parts, such as wall mounting plates for the control unit and main power unit. A dental x-ray arm assembly contains about 3 kg of aluminum (own estimation), compared to roughly 200 kg in an EV (Hawkins et al., 2012). Consequently, environmental loads from production of a dental x-ray system are dominated not by major industrial metals used in large amounts, but rather by specialized functional components in the x-ray head, main power unit, and x-ray sensor. Specialized functional components like printed circuit boards (PCBs) have complex manufacturing stages requiring inputs of extremely high-purity materials and chemicals, and thus are far more environmentally intensive per unit of mass than common structural and mechanical components (Williams et al., 2002).[x] Despite considerable data limitations in this LCA study, the conclusion that production stages – particularly for specialized functional components – are "hotspots" of environmental loads is quite strong. If anything, environmental loads from components with the poorest data quality – particularly the x-ray sensor – are likely underestimated. Thus, the results illustrate how "precise judgments can be drawn from imprecise data" (Ashby, 2013, p. 68). The environmental "profile" of a dental x-ray system is likely similar to that of products like microwave ovens, (consumer-use) power drills, and automatic garage door openers – ubiquitous products that are used for short time intervals and are primarily comprised of specialized functional components with relatively small amounts of common structural and mechanical components.

[x] It is possible that process improvements have been made in recent years. Background data for the x-ray case study are primarily obtained from the Ecoinvent 2.2 database, which is not the most recent version at the time of writing. Regarding PCBs, unit processes from version 2.2 have been modified to partially reflect updates in version 3.3. These changes result in slight reductions in environmental loads, but do not substantially change the conclusions of this study.

There are several opportunities to improve environmental performance of a dental x-ray system. The CMOS substrate – a major "hotspot" in the x-ray sensor – can be substituted with an amorphous silicon semiconductor on glass substrate, which is cheaper and likely less environmentally intensive to produce. Further, it is less susceptible to x-ray damage and can thus extend the lifespan of the x-ray sensor and reduce the need for replacement sensors. However, a potential trade-off is lower image resolution, but this is application-dependent. Embodied burdens of PCBs can be reduced by sourcing these components, and their sub-components, from regions with low-carbon electricity. Carbon nanotube (CNT) cold cathode x-ray tubes are an emerging technology with potential to extend product lifetimes and reduce energy consumption. This technology could also negate the need for critical metals like tungsten used in x-ray targets. From an LCA perspective, however, such "indirect substitution" creates a new product system and should therefore be addressed in the LCI phase rather than in impact assessment methods like GPSR. Finally, there is an established market for remanufacturing of x-ray systems.

Supply risk "hotspots" for a dental x-ray system include beryllium (for the EU-27 and Japan), cesium iodide, GOS (for the EU-27 and Japan), magnesium, and tungsten (for Japan and the USA) – all used in relatively small amounts (less than 100 g). Thus, the dental x-ray system illustrates how small components can "pack a punch" from both a supply risk and environmental perspective.

Although the GPSR method shows promise as a product-level decision support tool, there are several limitations to be addressed in future research. Except for a case study of polyacrylonitrile-based carbon fibers (Helbig et al., 2016a), the few applications of the method thus far – including those presented in this thesis – only cover a single stage of the product supply chain. The assessment is conducted on the level of material commodities like minerals and metals, which in themselves have multiple supply chain stages (for example, mining, smelting, and refining). Further, production of end products like automobiles and x-ray systems involves many other supply chain stages for processing, fabrication, assembly, and transportation. While Helbig et al. (2016a) proposed an extension of the GPSR method for multi-stage supply chains, the extended method is not explicitly connected to a functional unit under the LCSA framework. It is also unclear how the concept of "vulnerability" can be applied to fabrication, assembly, and transportation processes, as notions like "substitutability" are more readily applicable to tangible material commodities.

Moreover, whereas the GPSR method models product supply chains based on commodity trading between *countries*, supply chains actually consist of market relationships between *firms*. As illustrated with the case of GOS used in dental x-ray scintillators, supply risks can emerge from *domestic* production concentration, particularly if domestic production comes from unstable *companies*. Thus, the *level of analysis* needs careful consideration when calculating and interpreting supply risk estimates. It could also be argued that the risk mitigation effect of substitutability may be overestimated; for example, cesium iodide and GOS (which are substitutes for each other) both have high probability of supply disruption. However, unless production of these materials is related (for example, through geographical location and/or co-production), the probability of a *simultaneous* disruption of both materials would presumably be lower than that of supply disruption of either one by itself. Co-production is another risk factor to consider in future extensions of the GPSR method.

Though secondary material sources are relevant to supply risk assessment, the role of recycling is not presently captured in the GPSR method. Commodity stockpiles, or "safety stocks," are another potential risk mitigation factor to consider in future work. Finally, greater computational power is needed to facilitate further operationalization of the GPSR method. Application is presently burdensome, requiring large amounts of manual data entry and construction of calculation steps. Even the limited applications to date push the limits of common software programs. For example, the Microsoft Excel file for the case study of dental x-ray equipment is nearly 80 MB, despite being a simplified “single-stage” calculation.

Chapter 5: Conclusion

Growth in global population and living standards, along with the transition to a low-carbon economy, require increasing supply of an unprecedented variety of material commodities. Consequently, securing availability of “natural resources” is a key priority for sustainable development. Life Cycle Assessment (LCA) serves as a decision support tool for policy and product design by providing information about potential environmental impacts of products from the “cradle” where resources are extracted to the “grave” where the product arrives at the end of its useful life. More recently, the term Life Cycle Sustainability Assessment (LCSA) has emerged to incorporate socio-economic dimensions of sustainable development alongside environmental impact categories covered in the traditional LCA framework.

There is broad consensus in the LCA community regarding three “areas of protection” (AoPs) for sustainable development: “human health,” “ecosystem quality,” and “natural resources.” While the first two are addressed via relatively well developed impact assessment methods, the “natural resources” AoP has long been controversial in the LCA community. Moreover, while conventional approaches towards the “natural resources” AoP are concerned with physical exhaustion or “dilution” of resource availability *in the long-run*, resource availability can also be constrained by geopolitical and socio-economic factors *in the short-run*. In that regard, newer approaches for assessing “criticality” of resources and commodities have emerged outside the LCA community. In accordance with a classical risk assessment framework, criticality can be defined in terms of *probability* of supply disruption and *vulnerability* to supply disruption. Methods for criticality assessment, however, have had limited applicability on a product-level because they have lacked a clear connection to a *functional unit* of a given product – a central concept in LCA.

Therefore, recent efforts have been made to integrate resource criticality assessment into LCSA as a complement to conventional environmental LCA. For example, the Geopolitical Supply Risk (GPSR) method aims to quantify risks of supply disruption arising from international commodity trading. However, early iterations of the method arguably measure *probability* of supply disruption due to geopolitical factors. Nonetheless, the method has been demonstrated with an LCSA case study of a European-manufactured electric vehicle (EV) and subsequently extended for multi-stage global supply chains with a case study of polyacrylonitrile-based carbon fibers. This thesis further extends the method by linking criticality to a *functional unit* while incorporating measures of material "substitutability" to reflect the vulnerability dimension of supply risk. These contributions are demonstrated with an update of the previous EV case study along with a novel case study of dental x-ray equipment.

A characterization model for GPSR is constructed based on a classical risk assessment framework and supply chain resilience concepts. Accordingly, the characterization factor is defined as the multiple of *probability* of supply disruption and *vulnerability* to supply disruption. Several novel features of the characterization model are worth highlighting. First, the "elementary flow" is defined not as a resource extraction from the environment (as in conventional LCA methods), but as a commodity (or "intermediate product") input to a given unit process. The total supply risk associated with a product depends not only on resource extractions, but on *all* upstream stages of the supply chain. Second, the socio-economic cause-effect mechanism of supply risk is mainly "outside-in." That is, while conventional LCA is concerned with potential impacts of a product system on the environment, the GPSR characterization model is concerned with potential impacts of supply disruptions on a given product. Whereas characterization factors in conventional LCA (for example, global warming potentials) are independent of the studied product, the "outside-in" impact mechanism of supply risk implies that the characterization factor depends on the product *itself*.

Third, as every commodity input to a product system is equally important to performance (i.e., the *functional unit*) of the product – regardless of the *amounts* of the inputs – the most promising embodiment of the GPSR characterization model "cancels out" these amounts. As a consequence, comprehensive data are required for product material composition; no "cut-offs" are permissible in the Life Cycle Inventory (LCI). For example, the case study of dental x-ray equipment presented in this thesis involves tracing unit processes through LCI databases so that commodity inputs can be matched with identification codes for collecting commodity trade data. On the other hand, it is convenient that the *amounts* of commodity inputs need not be known.

While minor commodities are often neglected in conventional (environmental) LCA, the case studies presented in this thesis illustrate how small components can "pack a punch" from both a supply risk and environmental perspective. In the case of a European-manufactured EV, for example, neodymium, magnesium, and boron have disproportionately high supply risk despite constituting a small fraction of the vehicle mass. In the case of a dental x-ray system, small parts like the x-ray sensor have large contributions to environmental loads and may also present significant supply risk. The case studies also illustrate the significance and complexity of material substitutability in supply risk assessment.

Several complications have arisen in this thesis. These include the multi-stage nature of globalized product supply chains, the level of analysis, and the role of recycling, co-production, and commodity "stockpiling." Future research will need to address these limitations, while streamlining supply risk calculations (for example, through integration in LCA software) to facilitate practical application. The overall research direction is promising as a means of enhancing consideration of "natural resources" in LCSA to better inform design and management decisions on a product-level.

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Appendix A: Details of Electric Vehicle Case Study[xi]

Table A1: Bill of Materials for EV and ICEV based on Hawkins et al. (2012)

Commodity	**Mass in EV (kg)**	**Mass in ICEV (kg)**	**GeoPol EU-27 (dimensionless)** according to Gemechu et al. (2015) and Helbig et al. (2016)
Aluminum	2.06E+02	7.13E+01	0.0820
Iron + Steel	8.35E+02	9.97E+02	0.0947
Copper	1.26E+02	2.23E+01	0.0713
Lead	3.10E-01	3.00E-01	0.1134
Magnesium	2.00E-01	2.00E-01	0.4435
Nickel	1.20E-03	0.00E+00	0.0505
Tin	1.32E-02	0.00E+00	0.1691
Neodymium	1.70E+00	0.00E+00	0.5181
Brass	2.31E-01	0.00E+00	0.0961
Gold	1.20E-04	0.00E+00	0.0198
Boron	6.25E-02	0.00E+00	0.2318
PGMs	0.00E+00	1.00E-02	0.1777
Silver	1.20E-04	0.00E+00	0.0401
Zinc	1.00E-01	1.00E-01	0.0707

EV = electric vehicle

ICEV = internal combustion engine vehicle

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Table A2: Economic importance of commodities for EU-27

Commodity	**Economic Importance (€B)** as calculated by Oakdene Hollins (2013)	**Total Imports (kg)** according to UN Comtrade (for 2012)	**Economic Importance (€ / kg)**	**Economic Importance (kg W eq. / kg)**
Tungsten	165	4.52E+06	36,477	1.00E+00
REEs (light)*	95	2.27E+07	4,189	1.15E-01
Magnesium	100	5.26E+08	190.0	5.21E-03
Tin	123	8.23E+08	149.4	4.10E-03
Zinc	158	1.77E+09	89.4	2.45E-03
PGMs	120	3.95E+09	30.4	8.34E-04
Nickel	161	5.54E+09	29.1	7.97E-04
Silver	87	3.33E+09	26.1	7.16E-04
Copper	105	1.50E+10	7.01	1.92E-04
Aluminum	138	1.98E+10	6.96	1.91E-04
Iron	135	5.15E+10	2.62	7.18E-05
Gold	69	6.23E+10	1.11	3.04E-05
Lead	No data available	N/A	N/A	N/A
Brass**	105	5.82E+07	1,805	4.95E-02
Boron	No data available	N/A	N/A	N/A

*Economic importance (€B) is for *all* "light" REEs (including neodymium) as defined by Oakdene Hollins and Fraunhofer ISI (2013). However, the total imports in this table only include neodymium.
**Copper used as proxy
N/A = not applicable

One way of deriving a *product-level* vulnerability indicator is to calculate the "product consumption" in relation to a reference commodity (Equation A1).

Equation A1

$$Product\ Consumption_{APc} = \left(\frac{1}{M_{Ac}}\right)\left(\frac{M_{Rc}}{m_{RPc}}\right)$$

Where

- M_{Ac} = apparent consumption of commodity A in country c
- M_{Rc} = apparent consumption of reference commodity (R) in country c
- m_{RPc} = amount of reference commodity (R) needed to produce product P in country c (from LCI)

Importantly, the reference commodity must be present in the LCI of the studied product system. Note that when product consumption is multiplied by the elementary flow (m_{APc}), the result is the ratio of the commodity input to the product (per functional unit) to (economy-wide) apparent consumption of the commodity, normalized to the reference commodity. This approach is not employed in any proposed embodiment of the GPSR characterization model, as testing revealed it produces very similar results compared to using the economy-wide economic importance indicator.

Appendix B: Details of Dental X-ray Case Study[xii]

The dental x-ray system under study includes an x-ray "head" assembly, arm assembly, main power unit, control unit, and digital x-ray sensor with attached USB adapter. The system employs multiple capacitors and printed circuit boards (PCBs). Figure B1 provides a simplified representation of supply chain stages in production of capacitors (according to Ecoinvent 2.2 unit processes).

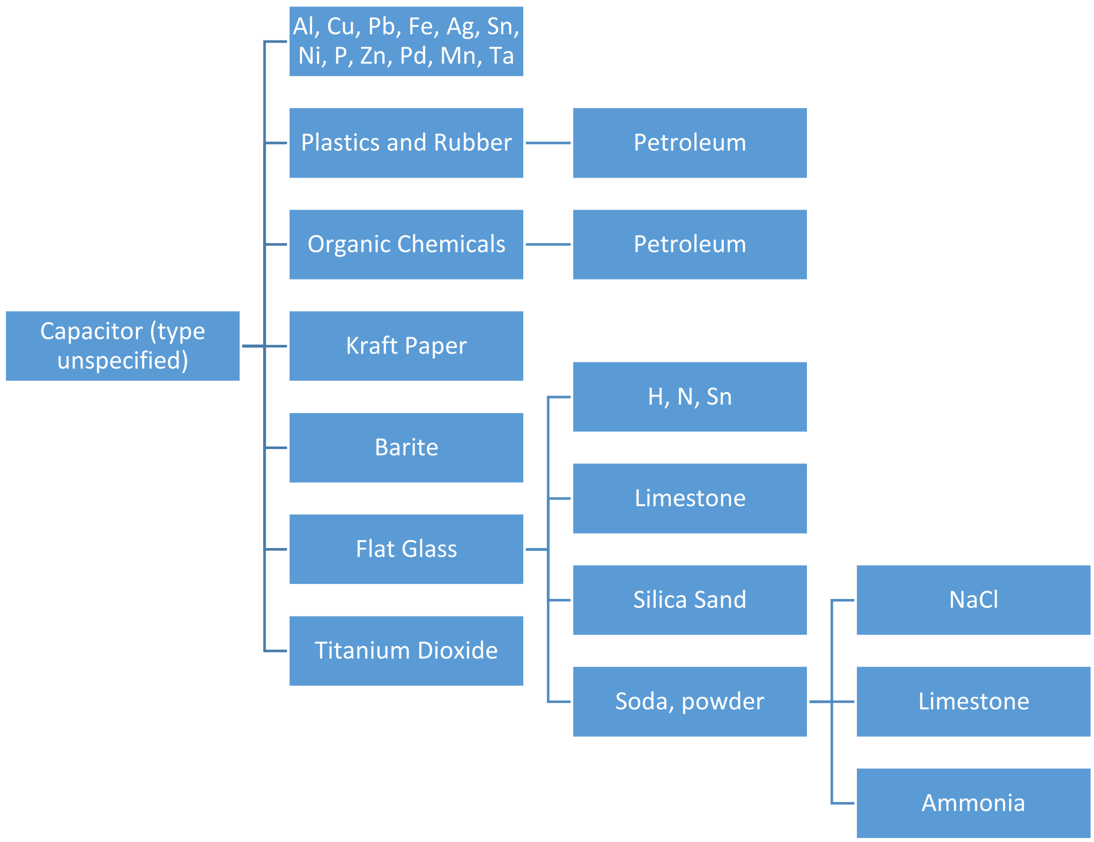

Figure B1: Simplified supply chain for capacitors (based on Ecoinvent 2.2 unit processes)

All PCBs in the x-ray system are assumed to be lead-free and similar in composition to a laptop PC mainboard. Therefore, the unit process "printed wiring board, mounted, Laptop

[xii] The contents of this appendix have been submitted for publication in the International Journal of Life Cycle Assessment: http://www.springer.com/environment/journal/11367

PC mainboard, Pb free, at plant" is selected from Ecoinvent 2.2. Supply chain stages in production of a laptop PC mainboard are illustrated in Figure B2.

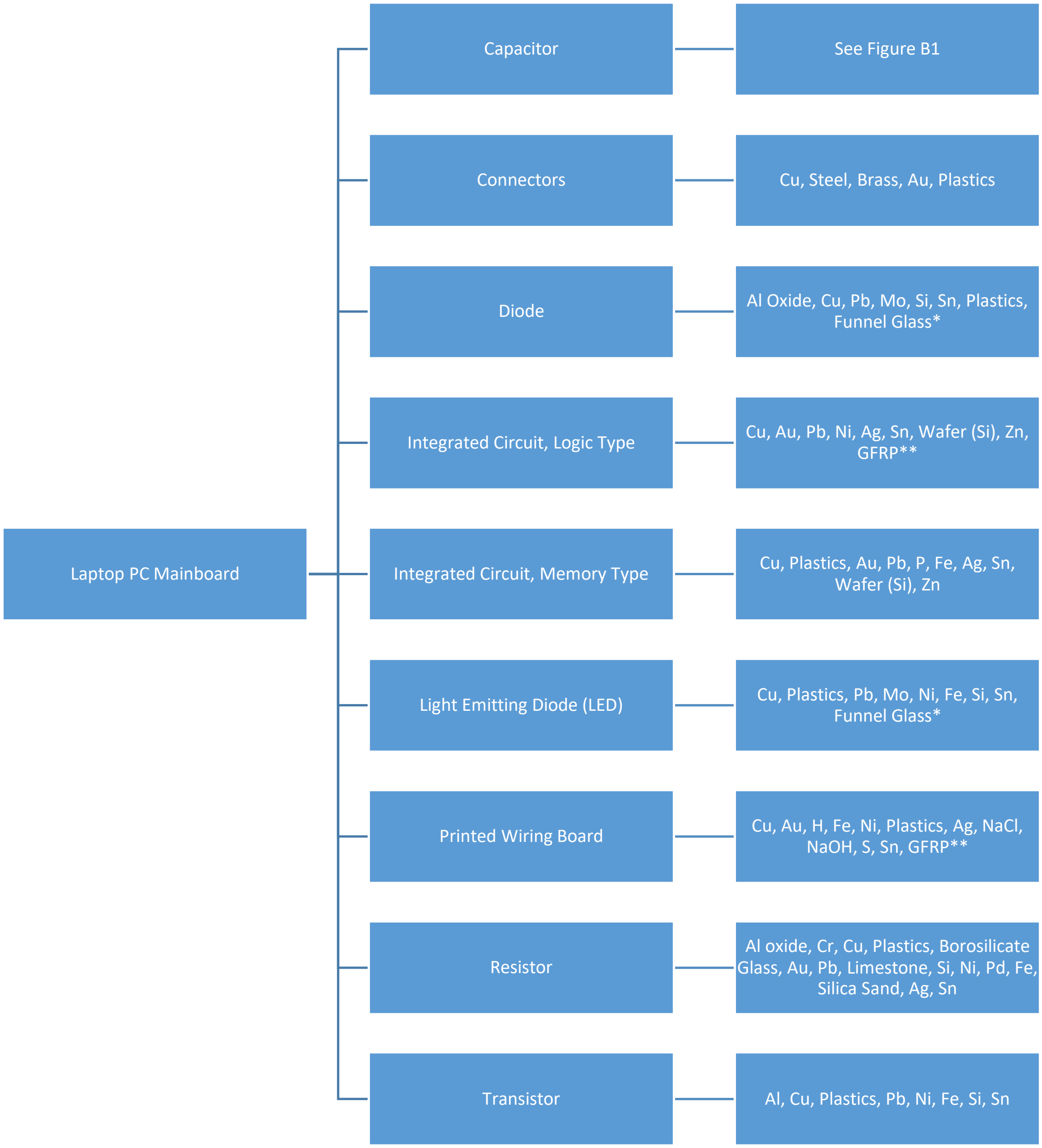

Figure B2: Simplified supply chain for a laptop PC mainboard (based on Ecoinvent 2.2 unit processes)

*Ecoinvent 2.2: "Funnel glass, CRT screen, at plant" includes inputs of barite, Ca, organic chemicals, Mg, feldspar, Pb, limestone, potassium nitrate, silica sand, and "soda, powder"

**Glass Fiber Reinforced Polymer: inputs of Al oxide, B, clay, silica sand, fluorspar, and limestone

An approximate bill of materials (BOM) for each component of the x-ray system is constructed based on manufacturer specifications (such as component dimensions and operational power consumption) supplemented with assumptions informed by the technical expertise of one of the authors.[xiii]

Based on dimensions specified by Belmont (2015a), and assuming the x-ray head housing is constructed of 3 mm thick injection molded ABS plastic with a density of approximately 1,100 kg/m^3, the mass of the housing is estimated at 450 g. The x-ray head is fitted with an x-ray "cone" having an estimated length of 80 mm and diameter of 50 mm. Therefore, the x-ray cone, which is assumed to be made of 3 mm thick extruded ABS plastic, has an estimated mass of 40 g. Given data limitations and the very small amount of beryllium in the x-ray window, the beryllium window is not considered for environmental LCA. However, beryllium *is* included in supply risk assessment of the x-ray system.

The x-ray head contains an x-ray generator and stationary anode x-ray tube. The x-ray tube consists of a cathode and anode inside a Pyrex (borosilicate) glass envelope. The anode is assumed to consist of a copper core and tungsten target, while the cathode is assumed to be made of a nickel-molybdenum "super alloy." Based on dimensions provided by Toshiba (2015), and assuming the glass envelope is 2 mm thick with a density of about 2,300 kg/m^3, the mass of the glass envelope is estimated at 30 g. The copper anode core, with a density of about 9,000 kg/m^3, has an estimated mass of 30 g. The mass of the cathode is estimated at 20 g. Given its relatively high density, the tungsten anode target also has an estimated mass of 20 g, despite its relatively small size. The x-ray tube is immersed in dielectric insulating oil and sealed inside a protective housing. While the total mass of the x-ray tube, oil, and housing is approximately 140 g, the x-ray tube itself weighs about 100

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g (Toshiba, 2015). Therefore, the housing is assumed to be made of an aluminum alloy (due to its low density) with an estimated mass of 30 g, while the oil is estimated at 10 g. The approximate BOM for the x-ray tube is summarized in Table B1.

Table B1: Bill of materials for x-ray tube

Input	**Unit**	**Amount**	**Process name(s)**
Pyrex (borosilicate) glass envelope	kg	0.03	Ecoinvent 2.2: Glass tube, borosilicate, at plant
Copper anode core	kg	0.03	Ecoinvent 2.2: Copper, at regional storage Ecoinvent 2.2: Copper product manufacturing, average metal working
Tungsten anode target	kg	0.02	Tungsten production: Nuss and Eckelman (2014) Ecoinvent 2.2: Metal product manufacturing, average metal working
Nickel-molybdenum cathode* *Assumption of 90% Ni and 10% Mo, by mass	kg	0.02	Ecoinvent 2.2: Nickel, 99.5%, at plant Ecoinvent 2.2: Molybdenum, at regional storage Ecoinvent 2.2: Metal product manufacturing, average metal working
Aluminum x-ray tube housing	kg	0.03	Ecoinvent 2.2: Aluminium, production mix, cast alloy, at plant Ecoinvent 2.2: Aluminium product manufacturing, average metal working
Dielectric insulating oil	kg	0.01	Ecoinvent 2.2: Lubricating oil, at plant (used as proxy for dielectric oil)

Supply chain stages in production of the x-ray tube are illustrated in Figure B3.

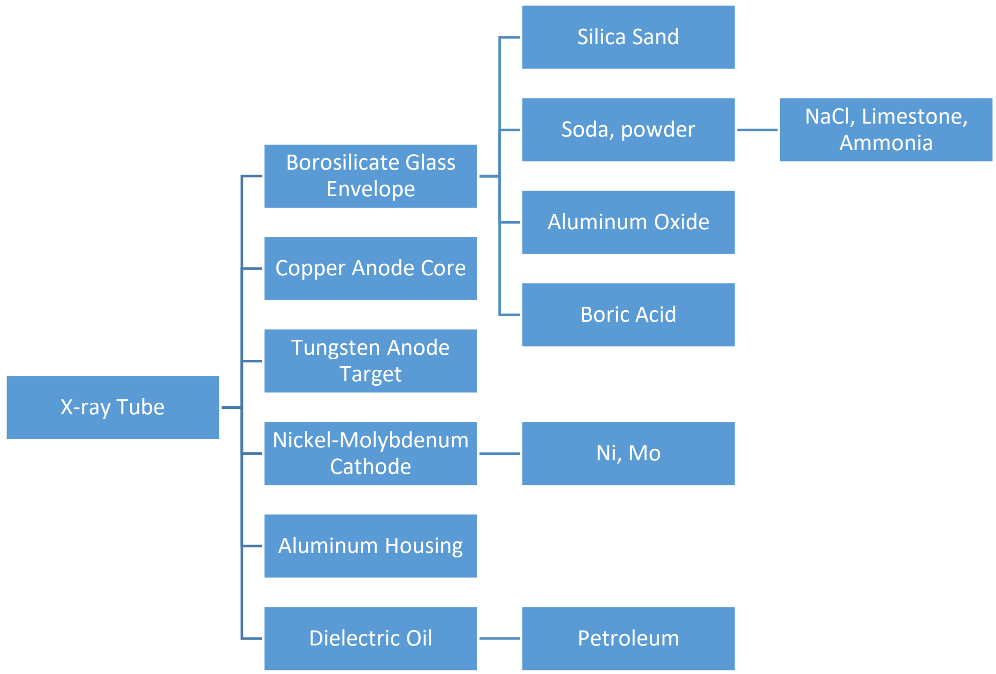

Figure B3: Simplified supply chain for x-ray tube (based on Ecoinvent 2.2 unit processes)

To minimize excess radiation, the x-ray tube and generator are placed inside a lead radiation shield. The radiation shield is assumed to have approximately the same surface area as the x-ray head housing, and is assumed to be 2 mm thick. As the density of lead is approximately 11,000 kg/m^3, the mass of the lead radiation shield is estimated at 3 kg. A desktop PC power supply is used as a proxy for the high-voltage power supply (i.e., x-ray generator). To better represent a high-voltage power supply, a capacitor is added. The mass of the capacitor is estimated at 100 g based on the size of the x-ray tube and head assembly. The approximate BOM for the x-ray head assembly is summarized in Table B2.

Table B2: Bill of materials for x-ray head assembly

Input	Unit	Amount	Process name(s)
X-ray tube	p	1	See Table B1
X-ray generator	p	1	Ecoinvent 2.2: Power supply unit, at plant
Capacitor(s)	kg	0.1	Ecoinvent 2.2: Capacitor, unspecified, at plant
Lead radiation shield	kg	3	Ecoinvent 2.2: Lead, at regional storage Ecoinvent 2.2: Metal product manufacturing, average metal working/kg
ABS plastic housing	kg	0.45	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Injection moulding
X-ray cone	kg	0.04	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Extrusion, plastic pipes
Beryllium window	N/A*	N/A*	N/A*

*Included in GPSR assessment but not in environmental LCA

Supply chain stages in production of the x-ray head assembly are illustrated in Figure B4.

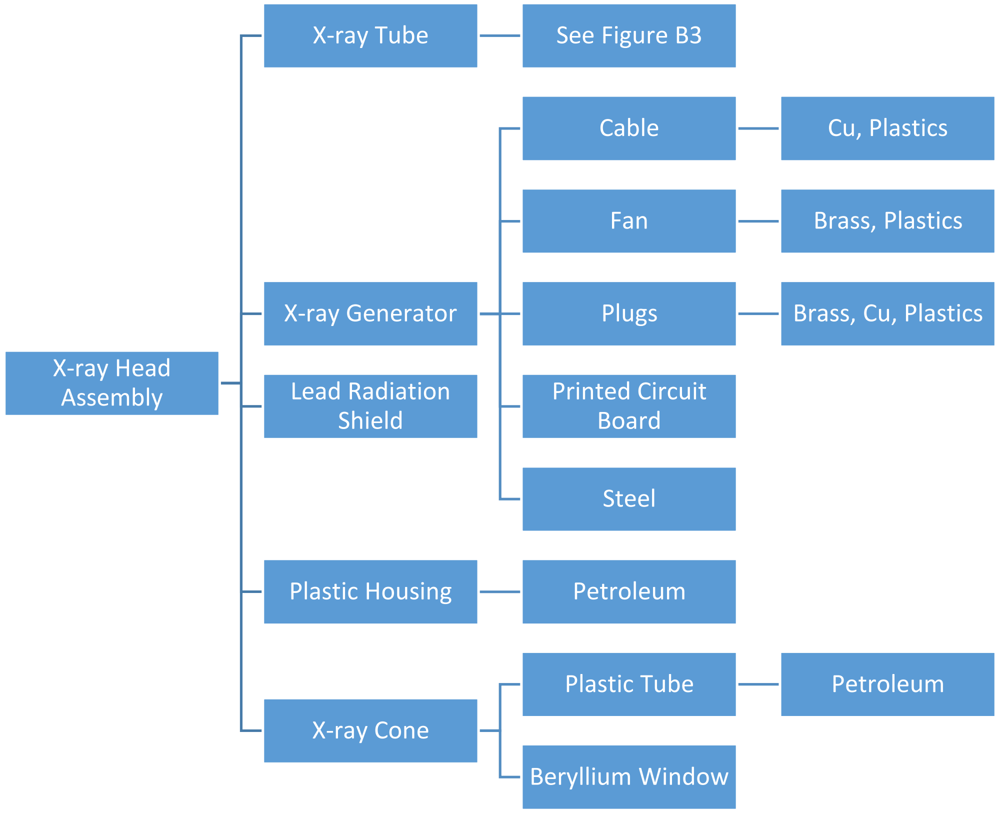

Figure B4: Simplified supply chain for x-ray head assembly (based on Ecoinvent 2.2 unit processes)

The arm assembly consists of rigid arm segments that are assumed to be constructed of 2 mm thick extruded aluminum alloy with a powder coated finish, and to have a cross section of 50 mm by 50 mm. Given dimensions from Belmont (2015a) and a density of approximately 2,700 kg/m^3, the mass of the aluminum arm segments is estimated at 3 kg. The arm assembly also includes three (3) plastic hinge covers, which are assumed to be made of injection molded ABS with a mass of roughly 300 g in total. The electrical cable routed through the arm assembly is estimated to be 3 m long. The approximate BOM for the arm assembly is summarized in Table B3.

Table B3: Bill of materials for arm assembly

Input	Unit	Amount	Process name(s)
Arm segments	kg	3	ELCD: Aluminium extrusion profile, primary prod., prod. mix, aluminium semi-finished extrusion product
Powder coating of arm segments	m^2	0.4	Ecoinvent 2.2: Powder coating, aluminium sheet
Hinge covers	kg	0.3	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Injection moulding
Electrical cable	m	3	Ecoinvent 2.2: Cable, three-conductor cable, at plant

Supply chain stages in production of the arm assembly are illustrated in Figure B5.

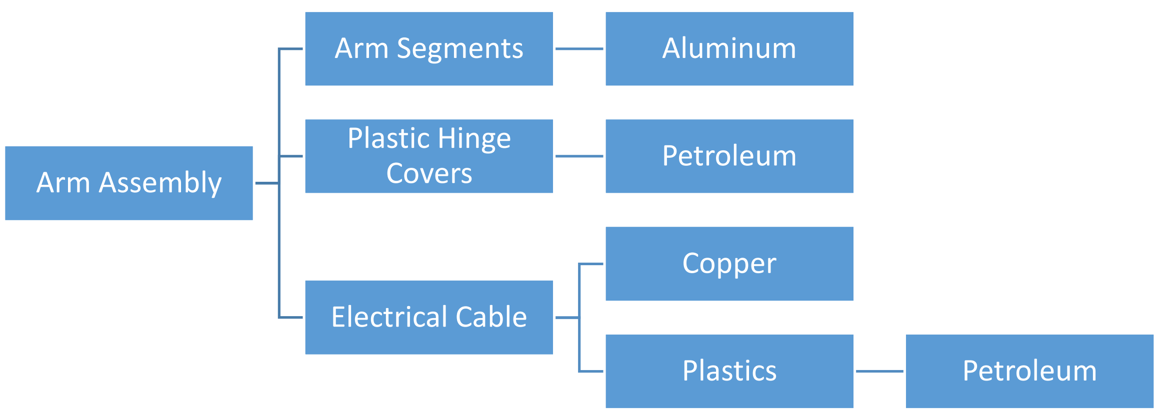

Figure B5: Simplified supply chain for arm assembly

The main power unit consists of a wall mounting plate, power switch, PCB, and housing cover. Based on dimensions from Belmont (2015a), and assuming the housing cover is made of 3 mm thick injection molded ABS plastic, the mass of the housing cover is estimated at 1 kg. Based on an investigation by Kahhat et al. (2011), a laptop PC mainboard has an estimated mass of 400 g and dimensions of 30 cm by 25 cm. These assumptions imply a mass of 5.3 kg per m^2 on average. Accordingly, the mass of the PCB in the main power unit is estimated at 400 g. Given dimensions from Belmont (2015a), the surface area of the wall mounting plate is estimated at 0.1 m^2. The material is assumed to be 14 gauge (0.07 inch thick) galvanized steel. The density of steel is about 7,900 kg/m^3. Therefore, the mass of the wall mounting plate is estimated at 1.4 kg. The approximate BOM for the main power unit is summarized in Table B4.

Table B4: Bill of materials for main power unit

Input	**Unit**	**Amount**	**Process name(s)**
Housing cover	kg	1	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Injection moulding
Printed circuit board (PCB)	kg	0.4	Ecoinvent 2.2: Printed wiring board, mounted, Laptop PC mainboard, Pb free, at plant (modified based on Ecoinvent 3.3)
Switch	kg	0.05	Ecoinvent 2.2: Switch, toggle type, at plant
Wall mounting plate	kg	1.4	US LCI: Galvanized steel sheet, at plant Ecoinvent 2.2: Steel product manufacturing, average metal working

Similarly, the control unit also consists of a PCB, housing cover, and wall mounting plate. Based on dimensions from Belmont (2015a), and assuming the housing cover is made of 3 mm thick injection molded ABS plastic, the mass of the housing cover is estimated at 200 g. The PCB is assumed to be 130 mm by 100 mm, for an estimated mass of 70 g. The wall mounting plate is assumed to have dimensions of 150 mm by 100 mm, and to be made of 20 gauge (0.0336 inch thick) galvanized steel. Therefore, it has an estimated mass of 100 g. The approximate BOM for the control unit is summarized in Table B5.

Table B5: Bill of materials for control unit

Input	Unit	Amount	Process name(s)
Housing cover	kg	0.2	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Injection moulding
Printed circuit board (PCB)	kg	0.07	Ecoinvent 2.2: Printed wiring board, mounted, Laptop PC mainboard, Pb free, at plant (modified based on Ecoinvent 3.3)
Wall mounting plate	kg	0.1	US LCI: Galvanized steel sheet, at plant Ecoinvent 2.2: Steel product manufacturing, average metal working

Supply chain stages in production of the main power unit and control unit are illustrated in Figure B6.

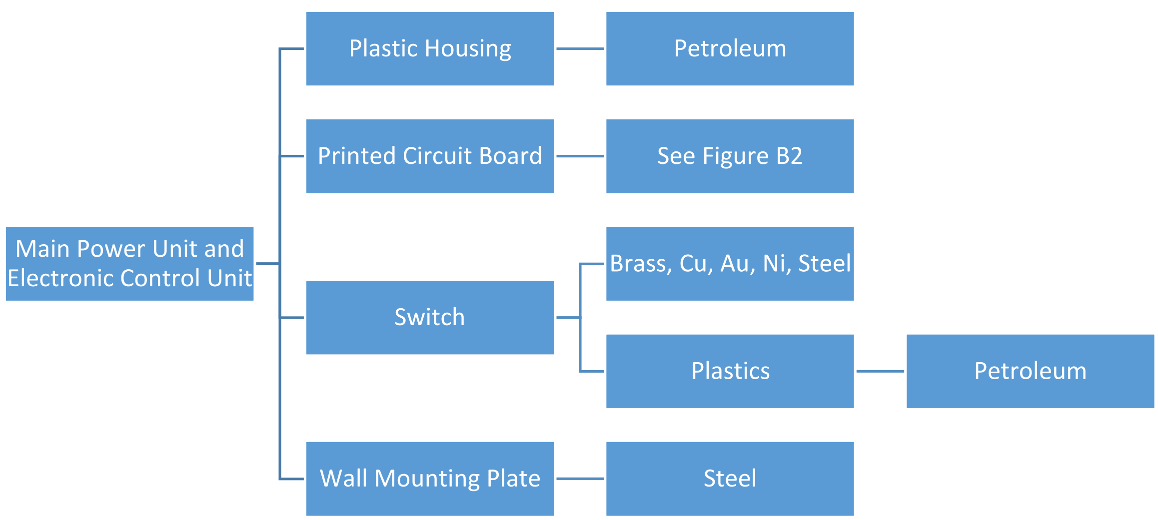

Figure B6: Simplified supply chain for main power unit and control unit

Based on specifications from Belmont (2015b), the x-ray sensor has external dimensions of 43.5 mm by 31.5 mm, with an "active area" of 35.2 mm by 26.2 mm. The scintillator has an estimated thickness of 120 µm and may be comprised of either thallium "doped" (5%

by mass) cesium iodide (CsI:Tl) or gadolinium oxysulfide (GOS). Assuming 60% yield, a 500 μm thick, 43 cm × 43 cm scintillator requires input of 2 kg of CsI:Tl. Based on linear extrapolation of this assumption, the dental x-ray sensor would require input of 2.4 g of CsI:Tl. Alternatively, the scintillator could be composed of GOS with a density of 7.44 g/cm^3. Assuming 60% yield and a thickness of 120 μm, the scintillator would require input of 1.4 g of GOS.

Based on information from Scintacor (2015), the FOP is estimated to be 0.6 mm thick. The FOP is essentially comprised of borosilicate glass with a density of about 2,300 kg/m^3. Therefore, the mass of the FOP is estimated at 1 g. The FOP is bonded to an image capture device using optically clear adhesive (OCA). According to Belmont (2015b), the image capture device is comprised of a complementary metal oxide semiconductor (CMOS) – which is essentially a digital camera. The CMOS is assumed to occupy the "active area" of the sensor. Assuming the OCA is applied at a thickness of 120 μm and has a density of approximately 1,300 kg/m^3, the mass of OCA is estimated at 0.14 g. The PCB is assumed to occupy the "active area" of the sensor, for an estimated mass of 5 g.

The scintillator, FOP, image capture device, and PCB are protected by a carbon fiber reinforced polymer (CFRP) casing with estimated dimensions of 35.2 mm by 26.2 mm by 10 mm. The thickness of CFRP is estimated at 2 mm. Given a density of about 1,600 kg/m^3, it follows that the mass of the CFRP casing is approximately 10 g. Unit processes from the Ecoinvent 2.2 and ELCD databases are combined with assumptions from Das (2011). Production of the CFRP casing begins with processing of polyacrylonitrile (PAN) precursor (Table B6).

Table B6: Carbon fibers (1 lb), production, from polyacrylonitrile (PAN) precursor, based on Das (2011)

Input	Unit	Amount	Process name(s)
PAN precursor	lb	2	ELCD: Polyacrylonitrile fibres (PAN), from acrylonitrile and methacrylate, prod. mix, PAN w/o additives EU-27 S
Energy (natural gas)	BTU	42,000	Ecoinvent 2.2: Natural gas, burned in industrial furnace >100kW
Energy (electricity)	kWh	9.1	Ecoinvent 2.2: Electricity, high voltage, consumer mix, at grid

The next step is production of CFRP from polyester resin and carbon fibers (Table B7).

Table B7: CFRP (1 lb), production, from polyacrylonitrile (PAN), based on Das (2011)

Input	Unit	Amount	Process name(s)
Carbon fibers	lb	0.302	See Table B6
Polyester resin	lb	0.656	Ecoinvent 2.2: Polyester resin, unsaturated, at plant
Low shrink additive	lb	0.0278	Ecoinvent 2.2: Vinyl acetate, at plant
Mold release agent	lb	0.0278	Zinc stearate • (90% by mass*) Ecoinvent 2.2: Zinc oxide, at plant • (10% by mass*) Ecoinvent 2.2: Soap, at plant *own assumption
Thickener	lb	0.0278	Ecoinvent 2.2: Magnesium oxide, at plant
Energy (electricity)	kWh	0.48	Ecoinvent 2.2: Electricity, low voltage, consumer mix, at grid

Finally, the CFRP is compression molded into the desired shape (Table B8).

Table B8: CFRP, compression molded (1 lb), based on Das (2011)

Input	Unit	Amount	Process name(s)
CFRP	lb	1.03	See Table B7
Energy (electricity)	kWh	62.8	Ecoinvent 2.2: Electricity, medium voltage, consumer mix, at grid

Supply chain stages in production of the CFRP casing are illustrated in Figure B7.

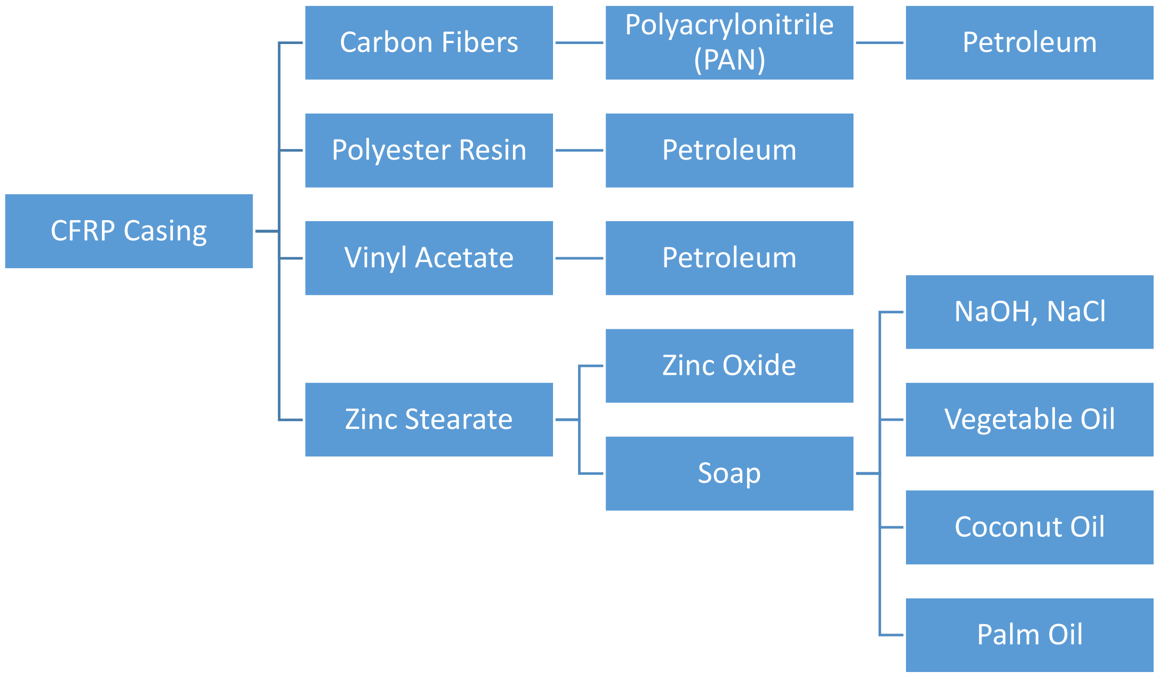

Figure B7: Simplified supply chain for carbon fiber reinforced polymer (CFRP) casing (based on Ecoinvent 2.2 unit processes)

The contents of the x-ray sensor are contained within a plastic housing. The housing is assumed to have dimensions of 43.5 mm by 31.5 mm by 12 mm, and to be made of 2 mm thick injection molded ABS plastic with a density of about 1,100 kg/m^3. From these assumptions, the mass of the ABS housing is estimated at 10 g. The approximate BOM for one (1) x-ray sensor is summarized in Table B9. Two (2) sensors are required based on the functional unit of 37,000 x-ray images over 10 years.

Table B9: Bill of materials for x-ray sensor

Input	Unit	Amount	Process name(s)
Cesium iodide (CsI:Tl*) scintillator (if so equipped) *doped with 5% Tl, by mass	g	2.4	Ecoinvent 2.2: Lithium chloride, at plant (used as proxy for cesium iodide) Thallium production: Nuss and Eckelman (2014)
Gadolinium oxysulfide (GOS) scintillator (if so equipped)	g	1.4	Ecoinvent 2.2: Rare earth concentrate, 70% REO, from bastnasite, at beneficiation
Fiber optic plate (FOP)	g	1	Ecoinvent 2.2: Glass tube, borosilicate, at plant
Complementary metal oxide semiconductor (CMOS)	m^2	9.22E-04	Ecoinvent 2.2: Wafer, fabricated, for integrated circuit, at plant
Optically clear adhesive (OCA)	g	0.14	Ecoinvent 2.2: Epoxy resin, liquid, at plant
Printed circuit board (PCB)	g	5	Ecoinvent 2.2: Printed wiring board, mounted, Laptop PC mainboard, Pb free, at plant (modified based on Ecoinvent 3.3)
CFRP casing	g	10	See Tables B6, B7, and B8
Plastic (ABS) housing	g	10	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Injection moulding

Supply chain stages in production of x-ray sensors are illustrated in Figure B8.

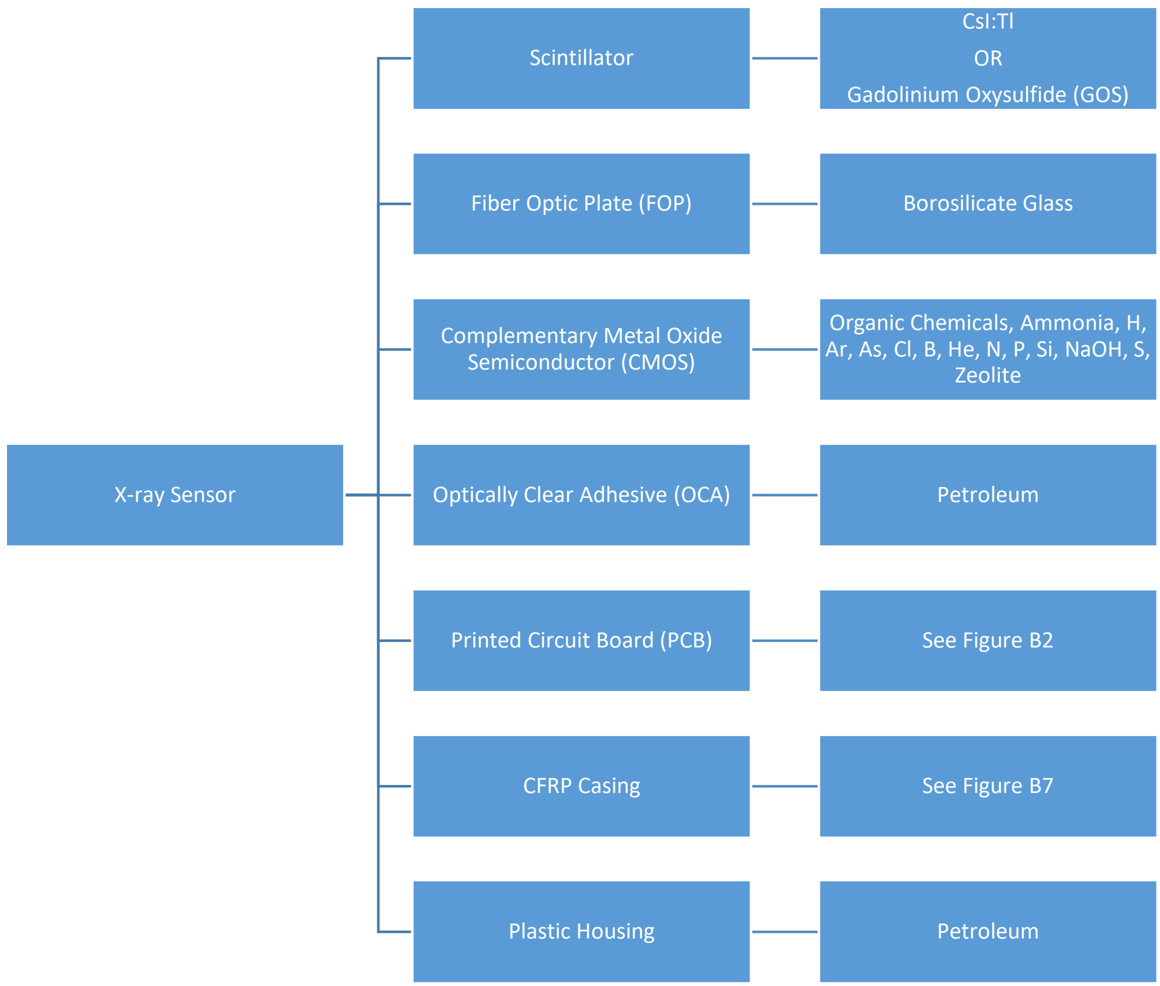

Figure B8: Simplified supply chain for x-ray sensor (based on Ecoinvent 2.2 unit processes)

Attached to the x-ray sensor is a USB cable that connects to a USB adapter with estimated dimensions of 30 mm by 100 mm by 20 mm. The housing for the USB adapter is assumed to be made of 2 mm thick injection molded ABS plastic. From these assumptions, the mass of the ABS housing is estimated at 20 g. Inside the USB adapter is a PCB with estimated dimensions of 90 mm by 25 mm. Thus, the mass of the PCB is estimated at 10 g. The USB cable is approximately 1 m in length (Belmont, 2015b). The approximate BOM for one (1) USB adapter and cable is summarized in Table B10. Two (2) USB adapters are required based on the functional unit of 37,000 x-ray images over 10 years.

Table B10: Bill of materials for USB adapter

Input	**Unit**	**Amount**	**Process name(s)**
Printed circuit board (PCB)	g	10	Ecoinvent 2.2: Printed wiring board, mounted, Laptop PC mainboard, Pb free, at plant (modified based on Ecoinvent 3.3)
Plastic (ABS) housing	g	20	Ecoinvent 2.2: Acrylonitrile-butadiene-styrene copolymer, ABS, at plant Ecoinvent 2.2: Injection moulding
USB cable	m	1	Ecoinvent 2.2: Cable, network cable, category 5, without plugs, at plant
Plugs for USB cable (inlet and outlet)	p	1	Ecoinvent 2.2: Plugs, inlet and outlet, for network cable, at plant

Supply chain stages in production of a USB adapter and cable are illustrated in Figure B9.

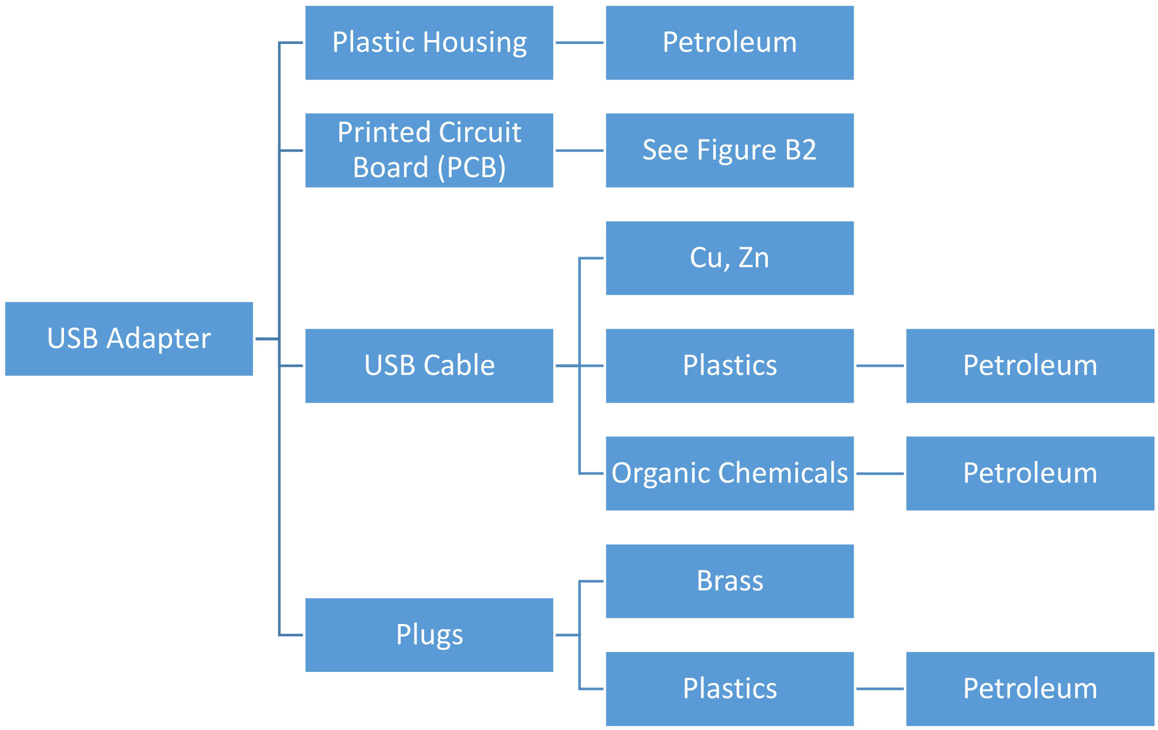

Figure B9: Simplified supply chain for USB adapter (based on Ecoinvent 2.2 unit processes)

Additionally, electricity is required to operate the x-ray system. The average power consumption for an x-ray image is derived from voltage and current settings from manufacturer specifications, as given in Table B11.

Table B11: Voltage and current settings of dental x-ray systems

Setting	**Voltage (kV)**	**Current (A)**	**Power (kW)**
Phot-XII, setting 1 (Belmont, 2015a)	60	0.004	0.24
Phot-XII, setting 2 (Belmont, 2015a)	60	0.007	0.42
Phot-XII, setting 3 (Belmont, 2015a)	70	0.004	0.28

Setting	Voltage (kV)	Current (A)	Power (kW)
Phot-XII, setting 4 (Belmont, 2015a)	70	0.007	0.49
Expert® DC (Gendex Dental Systems, 2011)	65	0.007	0.46
ProX, setting 1 (Planmeca, 2016)	50	0.002	0.10
ProX, setting 2 (Planmeca, 2016)	50	0.008	0.40
ProX, setting 3 (Planmeca, 2016)	60	0.002	0.12
ProX, setting 4 (Planmeca, 2016)	60	0.008	0.48
ProX, setting 5 (Planmeca, 2016)	70	0.002	0.14
ProX, setting 6 (Planmeca, 2016)	70	0.008	0.56
ProVecta® HD, setting 1 (Air Techniques, 2016)	60	0.004	0.24
ProVecta® HD, setting 2 (Air Techniques, 2016)	60	0.007	0.42
ProVecta® HD, setting 3 (Air Techniques, 2016)	70	0.004	0.28
ProVecta® HD, setting 4 (Air Techniques, 2016)	70	0.007	0.49
Minray™, setting 1 (Soredex, 2015)	60	0.007	0.42
Minray™, setting 2 (Soredex, 2015)	70	0.007	0.49
AVERAGE	**N/A**	**N/A**	**0.35**

The exposure time ranges from 0.01 to 3.2 seconds (Air Techniques, 2016; Belmont, 2015a; Gendex Dental Systems, 2011; Planmeca, 2016; Soredex, 2015), for an estimated average of 1.6 seconds. It follows that 37,000 images would take approximately 16 h. At the average power consumption of 0.35 kW, this amounts to approximately 6 kWh of energy consumption. The electronic controls of the machine may also continue to consume "standby" power even when no images are being taken. Although the operator manual recommends shutting off the main power switch when the machine is not in use (Belmont, 2015c), this study considers the energy that would be consumed if this advice is not followed and the machine is left in "standby" mode for 8 hours per day, 5 days per week (20,800 hours over 10 years). The standby power consumption is estimated to be 1.7 W based on the average standby power requirement for a laptop computer according to a study by Fung et al. (2003). These assumptions imply an additional 35 kWh of energy consumption over the assumed lifespan of the x-ray system. The total operational energy consumption over the lifetime of the product system is thus estimated at 40 kWh.

Appendix C: Direct Substitution Potential of Commodities for Various Applications[xiv]

For the purpose of this study, direct substitution is defined as the replacement of a commodity with a different commodity having similar properties (with respect to the intended application). Indirect substitution (not considered here) refers to product design changes that negate the need for particular commodity inputs. For each application of each commodity, the primary (i.e., best performing) substitute is identified, and its performance is scored per Table C1. Substitute performance rankings for most commodities are from Graedel et al. (2015), unless otherwise noted.

Table C1: Substitutability rankings and scores based on Graedel et al. (2015)

Ranking	**Score (out of 1*)**
Exemplary	0.125
Good	0.375
Adequate	0.625
Poor	0.875
No data	No data

*A score of 0 indicates perfect substitutability, whereas a score of 1 indicates perfect non-substitutability. Therefore, the higher the substitution potential, the lower the supply risk associated with a given commodity. Commodities without an identified substitute are assigned a substitute ranking of "poor."

Primary substitutes and substitute rankings for each application of each commodity are listed in Table C2.

[xiv] The contents of this appendix have been submitted for publication in the International Journal of Life Cycle Assessment: http://www.springer.com/environment/journal/11367

Table C2: Commodity substitutes by application, based on Graedel et al. (2015)

Commodity	Application	Primary Substitute	Substitute Ranking
Ag	Electrical and electronics	Cu	Poor
Ag	Investment	Au	Exemplary
Ag	Jewelry	Au	Exemplary
Ag	Photography	Paper	Adequate
Ag	Silverware	Stainless steel	Exemplary
Al metal	Building and construction	Steel	Good
Al metal	Cooking utensils	Cu	Good
Al metal	Electrical and electronics	Cu	Exemplary
Al metal	Machinery	Steel	Adequate
Al metal	Packaging	Steel	Good
Al metal	Transportation	Steel	Adequate
Al oxide*	Abrasives	Silicon carbide	Adequate
Al oxide**	Ceramics and glasses	Zr	Good
Al oxide**	Refractories	Zr	Good
Al oxide	Automotive	Unknown	No data
Al oxide	Ceramics and glasses	Unknown	No data
Al oxide	Electrical and electronics	Unknown	No data
Ar	Semiconductors	Unknown	No data
As	Cu alloys	Sb	Good
As	Semiconductors	Si	Good
As	Wood preservatives and pesticides	Cu	Good
Au	Dental fillings	Ag	Adequate
Au	Electrical and electronics	Ag	Adequate
Au	Investment	Ag	Good
Au	Jewelry	Ag	Good
B	Agriculture	None	Poor
B	Bleaches	Cl	Good
B	Ceramics and glasses	Na	Good
B	Soaps and detergents	Enzymes	Good
Ba	Oil and gas	Hematite	Adequate
Barite	Capacitors	Unknown	No data
Be	Medical	Unknown	No data
Be*	X-ray windows	Al alloys	Poor
Be	Aerospace	Polymers	Adequate
Be	Electrical and electronics	Cu-Ni-Si alloys	Adequate

Commodity	**Application**	**Primary Substitute**	**Substitute Ranking**
Bi	Chemicals	Mg compounds	Good
Bi	Fusible alloys, solders, and ammunition cartridges	Pb	Good
Bi	Metallurgy	Pb	Adequate
Bi	Pharmaceuticals	Mg compounds	Good
Ca	Ceramics and glasses	Unknown	No data
Cd	Batteries, consumer	Li	Exemplary
Cd	Batteries, industrial	None	Poor
Cd	Coatings	None	Poor
Cd	Pigments	Cerium sulfide	Adequate
Ce	Automotive catalysts	La	Adequate
Ce	Batteries	Li	Good
Ce	Ceramics and glasses	Se	Adequate
Ce	Glass polishing	Fe oxide	Adequate
Ce	Metallurgy, excl. batteries	Mg	Adequate
Cl	Semiconductors	Unknown	No data
Clay	Ceramics and glasses	Unknown	No data
Co	Batteries	Mn	Good
Co	Catalysts	Ni	Good
Co	Cemented carbides	Ni + Cr	Adequate
Co	Magnets	Nd	Good
Co	Pigments	None	Poor
Co	Superalloys	Ni	Adequate
Coconut oil (crude)*	Soaps and detergents	Other fats and oils	Good
Cr	Appliances and electronics	Al	Adequate
Cr	Building and construction	Mn	Adequate
Cr	Machinery	None	Poor
Cr	Transportation	Al	Adequate
CsI*	CsI:Tl scintillators	Gadolinium Oxysulfide (GOS) scintillators	Adequate
Cu + brass	Cooling equipment	Al	Adequate
Cu + brass	Electrical and electronics	Al	Poor
Cu + brass	Machinery	Steel	Adequate
Cu + brass	Mechanical fasteners	Steel	Adequate
Cu + brass	Plumbing	PVC	Good
Cu + brass	Roofing and gutter systems	Al	Good
Cu + brass	Telecommunications	Optical fibers (Si)	Exemplary

Commodity	**Application**	**Primary Substitute**	**Substitute Ranking**
Cu + brass	Transportation	Al	Poor
Dy	Nd magnets	None	Poor
Er	Phosphors	Tb	Adequate
Eu	Phosphors	None	Poor
Fe + steel	Appliances and electronics	Al	Good
Fe + steel	Building and construction	Wood	Adequate
Fe + steel	Machinery	Fiber reinforced polymers	Adequate
Fe + steel	Packaging	Al	Good
Fe + steel	Transportation	Al	Good
Feldspar	Ceramics and glasses	Unknown	No data
Fluorspar	Ceramics and glasses	Unknown	No data
Ga	Integrated circuits	Si	Good
Ga	Optoelectronic devices	InP	Good
Gadolinium oxysulfide (GOS)*	Gadolinium Oxysulfide (GOS) scintillators	CsI:Tl scintillators	Good
Gd	Nd magnets	Nd	Adequate
Gd	Phosphors	Y	Adequate
Ge	Electronics and solar electric applications	Si	Good
Ge	Fiber optic systems	Al oxide	Good
Ge	Infrared optics	ZnSe	Good
Ge	Polymerization catalysts	Ti alkoxides	Adequate
H	Electrical and electronics	Unknown	No data
He	Semiconductors	Unknown	No data
Hf	Aerospace	Zr	Good
Hf	Electrical and electronics	Zr	Good
Hf	Nuclear energy control rods	Ag-Cd-In alloy	Good
Hf	Plasma cutting tools	Zr	Good
Hf	Refractories	Zr	Good
Hf	Superalloys	Zr	Good
Hg	Artisanal and small-scale gold mining	Borax	Adequate
Hg	Batteries	Li	Exemplary
Hg	Cl production	Membrane cells	Good
Hg	Dental equipment	Ceramic composites	Exemplary
Hg	Electrical and electronics	Ga-In alloys	Adequate

Commodity	Application	Primary Substitute	Substitute Ranking
Hg	Fluorescent lamps	None	Poor
Hg	Thermometers and thermostats	Galinstan	Exemplary
Hg	Vinyl Chloride Monomer (VCM) production	Precious metal salts	Adequate
Ho	Magnets	Nd magnets	Adequate
In	Electrical and electronics	GaAs	Good
In	In-Sn oxide thin film coatings	Al-doped Zn oxide	Adequate
In	Solders and alloys	Ga	Good
Ir	Chemicals	Rh	Adequate
Ir	Electrical and electronics	Mo	Poor
Ir	Electrochemical	Ru	Adequate
Kraft paper*	Capacitors	Polymers	Good
La	Batteries	Li	Good
La	Ceramics and glasses	Ce	Good
La	Fluid cracking catalysts	None	Poor
La	Glass polishing	Fe oxide	Adequate
La	Metallurgy, excl. batteries	Mg	Adequate
Li	Air conditioning	Ammonia/water systems	Poor
Li	Batteries, disposable	Zn	Good
Li	Batteries, rechargable	NiMH	Good
Li	Ceramics and glasses	Na	Exemplary
Li	Continuous casting	Na	Good
Li	Lubricating greases	Ca	Good
Li	Pharmaceuticals	None	Poor
Li	Polymers	None	Poor
Li	Primary aluminum production	Na	Good
Limestone	Ceramics and glasses	Unknown	No data
Lu	Medical	Bi	Adequate
Mg metal	Agriculture	None	Poor
Mg metal	Refractories	None	Poor
Mg metal	Stack-gas scrubbing	Lime	Exemplary
Mg metal	Water treatment	Lime	Exemplary
Mg metal	Ceramics and glasses	Unknown	No data
Mn	Batteries, dry cell	Li	Exemplary
Mn	Metallurgy	None	Poor

Commodity	**Application**	**Primary Substitute**	**Substitute Ranking**
Mn	Non-steel alloys	Polymers	Adequate
Mn	Capacitors	Unknown	No data
Mo	Cast iron	Mo-free cast iron	Adequate
Mo	Chemicals	None	Poor
Mo	Stainless steel	Mo-free stainless steel	Adequate
Mo	Steel alloys	Mo-free steel	Adequate
Mo	Superalloys	Nb	Poor
N and ammonia	Electronics + glass manufacturing	Unknown	No data
NaOH	Electronics + soaps	Unknown	No data
Nb	Building and construction	V	Good
Nb	Capacitors	Mo	Adequate
Nb	Jet engines	Mo	Adequate
Nb	Magnetic Resonance Imaging (MRI)	Mo	Adequate
Nb	Oil and gas	V	Good
Nb	Particle accelerators	Mo	Adequate
Nb	Stainless steel	Ta	Adequate
Nb	Transportation	V	Good
Nb	Turbines	Mo	Adequate
Nd	Automotive catalysts	Ce	Good
Nd	Ceramics and glasses	Ce	Adequate
Nd	Metallurgy, excl. batteries	Mg	Adequate
Nd	Nd magnets	Sm-Co magnets	Good
Ni	Aerospace	None	Poor
Ni	Appliances and electronics	Ni-free stainless steels	Good
Ni	Building and construction	Ni-free stainless steels	Good
Ni	Electrical and electronics	None	Poor
Ni	Machinery	Ni-free stainless steels	Poor
Ni	Transportation (excl. aerospace)	Al	Adequate
Os	Chemicals	Ru	Good
Os	Electron microscopy	Ru	Good
P	Electrical and electronics	Unknown	No data
Palm oil*	Soaps and detergents	Other fats and oils	Good
Pb	Batteries	None	Poor
Pb	Radiation shielding	Unknown	No data
Pd	Automotive catalysts	Pt	Good

Commodity	Application	Primary Substitute	Substitute Ranking
Pd	Chemicals	Ni	Adequate
Pd	Dental	Ni	Good
Pd	Electrical and electronics	Ni	Good
Pd	Investment	Au	Good
Pd	Jewelry	Pt	Good
Petroleum*	Polymers	Natural gas	Good
Potassium nitrate	Ceramics and glasses	Unknown	No data
Pr	Automotive catalysts	Ce	Good
Pr	Batteries	Li	Good
Pr	Glass polishing	Fe oxide	Adequate
Pr	Metallurgy, excl. batteries	Mg	Adequate
Pr	Nd magnets	Sm-Co magnets	Good
Pt	Automotive catalysts, diesel	None	Poor
Pt	Automotive catalysts, gasoline	Pd	Good
Pt	Ceramics and glasses	Ir	Poor
Pt	Chemicals	Co	Adequate
Pt	Electrical and electronics	Pd	Adequate
Pt	Investment	Au	Good
Pt	Jewelry	Pd	Good
Pt	Medical	Pd	Adequate
Pt	Petroleum refining	Mo	Poor
Re	Catalysts	Pt	Good
Re	Superalloys	None	Poor
Rh	Automotive catalysts	None	Poor
Rh	Ceramics and glasses	Pt	Adequate
Rh	Chemicals	Co	Adequate
Rh	Electrical and electronics	Ni	Adequate
Ru	Chemicals	Magnetite	Adequate
Ru	Electrical and electronics	Ir	Adequate
Ru	Electrochemical	Ir	Adequate
S	Electrical and electronics	Unknown	No data
Salt (NaCl)	Electronics + glass manufacturing	Unknown	No data
Sb	Ceramics and glasses	Sn oxide	Adequate
Sb	Chemicals	Ti	Poor
Sb	Flame retardents	Hydrated Al oxide	Adequate
Sb	Pb-acid batteries	Ca alloy	Good

Commodity	Application	Primary Substitute	Substitute Ranking
Sc	Aerospace	Al (not alloyed with Sc)	Adequate
Sc	Lighting	None	Poor
Sc	Sports equipment	Ti	Good
Se	Agriculture	None	Poor
Se	Ceramics and glasses	Cerium oxide	Good
Se	Chemicals and pigments	Te	Good
Se	Electrical and electronics	Si	Good
Se	Metallurgy	Bi	Good
Si, electronics grade	Electrical and electronics	Unknown	No data
Silica sand	Electronics + glass manufacturing	Unknown	No data
Sm	Batteries	Li	Good
Sn	Brass and bronze	Cu alloys	Good
Sn	Chemicals	Pb	Adequate
Sn	Solders	Epoxy resin	Good
Sn	Tinplate	Al	Exemplary
Sr	Ferrite ceramic magnets	Ba	Adequate
Sr	Master alloys	Na	Adequate
Sr	Pigments and fillers	Ba	Poor
Sr	Pyrotechnics and signals	None	Poor
Sr	Zn production, electrolytic	Ba	Adequate
Ta	Alloys	Nb	Good
Ta	Sputtering targets	Zr	Adequate
Ta	Ta carbide	Nb	Good
Ta	Capacitors	Al	Good
Tb	Nd magnets	Dy	Adequate
Tb	Phosphors	Er	Adequate
Te	Chemicals and catalysts	Se	Good
Te	Metallurgy, ferrous	Bi	Good
Te	Metallurgy, nonferrous	Pb	Good
Te	Photoreceptor and thermoelectric devices	Si	Good
Th	Lighting	Y compounds	Good
Th	Nuclear applications	None	Poor
Th	Refractories	Yittrium oxide	Exemplary
Th	Welding electrodes	Ce	Good
Ti	Pigments	Talc	Adequate

Commodity	**Application**	**Primary Substitute**	**Substitute Ranking**
Ti oxide	Capacitors	Unknown	No data
Tl*	CsI:Tl scintillators	Gadolinium Oxysulfide (GOS) scintillators	Good
Tl	Electrical and electronics	None	Poor
Tm	X-rays	Ba	Poor
U	Nuclear energy	Th	Adequate
V	Carbon steel	Nb	Adequate
V	Full alloy steel	Nb	Adequate
V	High strength steel	Nb	Adequate
Vegetable oil*	Soaps and detergents	Other fats and oils	Good
W	Filaments	Ni-Mo alloys	Adequate
W	Cemented carbides	BN	Adequate
W	Mill products	Mo	Good
W	Steel alloys	Mo	Good
W	Superalloys	Ni-Mo alloys	Good
Y	Ceramics and glasses	Ca	Poor
Y	Phosphors	None	Poor
Yb	X-rays	Th	Poor
Zeolite	Semiconductors	Unknown	No data
Zn metal	Brass and bronze	Al alloys	Good
Zn metal	Galvanizing	Al-Si alloy	Good
Zn metal	Zn alloys	Al alloys	Good
Zn metal	Electrical and electronics	Unknown	No data
Zn oxide	Zinc stearate	Unknown	No data
Zr	Ceramics and glasses	Alumina	Adequate
Zr	Foundry molds	Chromite	Poor
Zr	Refractories	Alumina spinels	Adequate

*Own assumption

**Own assumption based on Zr according to Graedel et al. (2015)