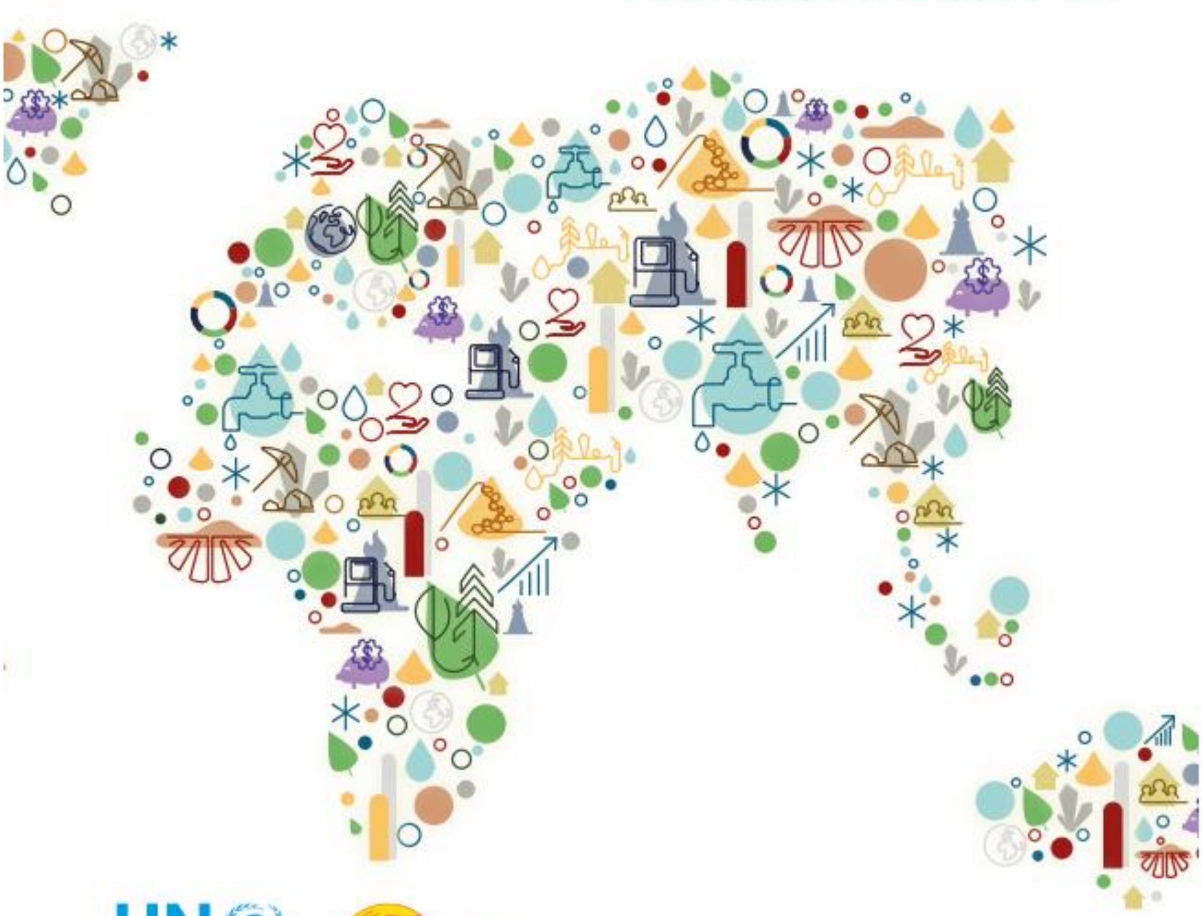
GLOBAL RESOURCES OUTLOOK 2019

NATURAL RESOURCES FOR THE FUTURE WE WANT



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METHODS ANNEX

Acknowledgements

This Methods Annex is only online. It should be read in conjunction with the full International Resource Panel report *Global Resources Outlook 2019: Natural Resources for the Future We Want*. That report includes some preliminary information about the scientific methodology used to reach the report findings. The Methods Annex builds on that information to provide the reader with a more nuanced understanding of the scientific methodology used throughout the various report chapters when needed. The Methods Annex as well as the full report can be found at: www.resourcepanel.org/reports/global-resources-outlook.

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METHODS ANNEX

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Chapters 2.4 and 4.2.4 - Methods annex

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A.1 Overview

In this chapter the methodological procedure of Chapter 2.4 to assess historical land-use change between 2000 and 2010 and to simulate land-use change under the *Historical Trends* scenario until 2060 is explained.

A.2 Historical land-use maps (chapter 2.4)

Global land-use change was calculated for the time period between 2000 and 2010 by fusing remote sensing land-cover data with statistical data from FAO for cropland and rangeland on country level. Furthermore, forest was sub-divided into three intensity classes.

A.2.1 Land-cover data

For global land-cover the CCI Version 2.0.7 data set was used (Bontemps et al. 2012). The data has a spatial resolution of 300 m and differentiates between 22 primary and 15 secondary land-cover classes based on the standardized LCCS classification system of the United Nations (Di Gregorio 2016). Secondary classes were assigned to their primary classes. For the analysis the data set was rescaled to 5 arc-minute resolution using the majority resampling filter of GRASS GIS – Geographic Resources Analysis Support System – version 7.2 (GRASS Development Team 2017; Neteler et al. 2012). The majority resampling determines the value that occurs most often of all cells in the value raster (300m) that belong to the same zone as the output cell (5 arc-minute).

A.2.2 Agricultural land-use data

Data on agricultural land use was derived from the FAO data base. It includes area and production information of the 36 most important crops cultivated, grazing area, livestock numbers of three ruminants and human population on a per country basis of the 181 countries relevant to their size (FAOSTAT 2016). The 36 crops are aggregated to the 12 crop type classes (called crop types further on) that are used by the global land-use model LandSHIFT (Schaldach et al. 2011). Crop specific area is only available as harvested area. The crop specific harvested area is recalculated to physical crop area using FAOs physical area given as total per country.

A.2.3 Fusion of land-cover maps and agricultural land-use data

Land-use maps were generated for the years 2000, 2005 and 2010. For each year the respective land-cover map was combined with FAO data on crop and pasture area (5-year means). Land use allocation introduces additional information of the spatial location of specific crop types, grazing areas and artificial surfaces onto the global land-cover data sets. It is based on the multi criteria analysis (MCA) allocation process utilized by LandSHIFT to translate country area data into spatial patterns for each of the three activities. The process produces a gridded land-cover/land-use map that is consistent with the agricultural FAO statistics.

Urban areas were updated by using spatial population information from HYDE 3.1 (Klein Goldewijk et al. 2011). Cells with a population density of more than 2000 inhabitants/km² were defined as urban cells. The cropland and grassland areas from the FAO were allocated according to the MCA allocation process by their preference values and for crop types before grazing. Therefore, the most probable and potential regions were identified by the MCA. The preference value of a certain cell is further weighted by its land-cover type to ensure land use is allocated primarily to the corresponding land cover (e.g. grazing is more likely to be allocated to grassland than to forest). The rank order is for crop types: (1) Cropland, (2) shrubland/grassland/wetlands, (3) forest and (4) barren; and for grazing: (1) Grassland (2) cropland (unused), (3) shrubland/wetlands, (4) forest and (5) barren. The rank order is based on a land-cover transition analysis between the datasets of 2000 and 2010. Urban, snow and ice, water bodies and protected areas (if not already associated with the cropland or pastures) are not considered. The statistical land use census data is allocated either until all area is allocated or no usable grid cells are available anymore.

A.2.4 Calculation of forest use intensity maps

The land-use type forest is subdivided in three new classes of forest-use intensity: intact forests, extensively used forests and intensively used forests. The spatial extent of forest is provided by the LandSHIFT land-use maps for the years 2000, 2005 and 2010 (see previous section). Two additional map products contribute information about forest use in order to allocate use intensities on the forest cells. The class intact forests is based on the intact forest landscapes maps (IFL) for the year 2000 (Patapov et al. 2008) and 2013 (Patapov et al. 2017). This intact forest landscape maps have been compared with the CCI LC map products to identify the cells with intact, mostly undisturbed forests. The IFL maps for the year 2000 were used for the "Intact Forest Map" of 2000 and 2005 and compared with the LandSHIFT land-use type maps for 2000 and 2005, respectively. The intact forest use map for 2010 was produced using the IFL map for 2013 and the CCI map product for the year 2010. The class intensively used forests is mapped on cells that meet one of two conditions: extensive forest loss or forest stock loss on these cells in the 5-year period before the mapped year. A LandSHIFT map forest cell is considered as being affected by extensive forest loss, if 25% of the area of the 5 arc-min cell is classified as lost. The information about lost forest area is taken from the 300mx300m CCI LC maps (Di Gregorio 2016). The second condition, depletion of forest stock, is evaluated with the Global Biomass Maps (Hengeveld et al. 2015). If according to these maps the loss of forest stock in the 5-year period before the mapped year is greater than 50% the area is classified as having been degraded through forest stock loss. The remaining class, extensively used forests is assigned to the forest cells, which are either not intensively used or part of an intact forest system.

A.3 Historical Trends outlook for land use (chapter 4.2.4)

A future projection of land-use change until 2060 was calculated for the Historical Trends scenario, using the global land-use model LandSHIFT (Schaldach et al. 2011). Scenario data on agricultural development was provided by the GLOBIOM model (Havlik et al. 2011).

A.2.1Model input

Model drivers on the macro level were specified until the year 2060. They were derived from a simulation study conducted with the GLOBIOM model (Havlik et al. 2011) for a scenario that follows the Shared Socio Economic Pathway 2 (SSP2). This SSP describes a world that "follows a path in which social, economic, and technological trends do not shift markedly from historical patterns" (Riahi et al., 2017; p. 5).

A.2.2 Model framework

Land-use change was calculated with the spatially explicit LandSHIFT model (Schaldach et al., 2011) which has been applied and validated in case studies for Brazil (Lapola et al., 2010; Göpel et al. 2018), Africa (Alcamo et al. 2011; Van Soesbergen et al. 2017), Europe (Humpenöder et al. 2013) as well as for analyses on the global level (Alexander et al., 2017). LandSHIFT operates on two spatial scale levels. The macro level comprises 30 world regions (derived from GLOBIOM) and is used to define drivers of land-use change. In this study these drivers concentrate on agricultural development and include information on crop and livestock production as well as on crop yield changes due to climate change and technological change. Changing land-use patterns were calculated on a global raster with a cell size of 5 arc-minutes (~ 9 km x 9 km at the Equator).

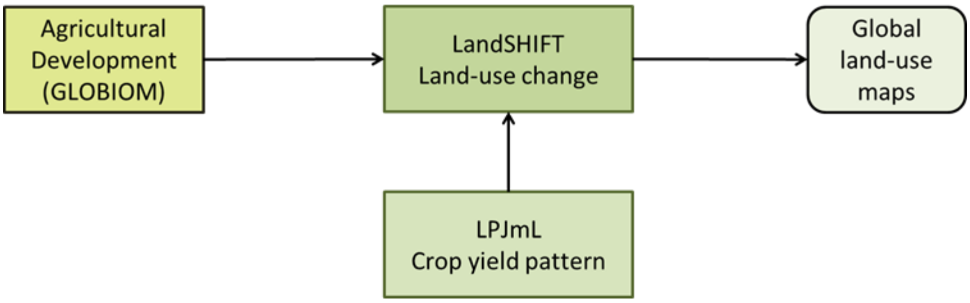

Figure A1: Modelling framework used for the calculation of the TREND scenario.

As our study concentrates on agriculture, LandSHIFT consists of sub-modules that represent the land-use activities crop cultivation (AGRO) and livestock grazing (GRAZE). An additional sub-module (BIOPROD) provides data on potential rain-fed and irrigated yields for 12 crop types or groups of crop types as well as on net primary productivity (NPP) for pasture. This data was calculated with the global vegetation model LPJmL (Bondeau et al. 2007). It serves as input to the AGRO and GRAZE sub-modules where it is used for suitability assessment and to define the amount of crop production and livestock that can be allocated to each cell (Figure A1).

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Chapter 2.3 Method Annex

Author: Martina Flörke

A.1 Water scarcity: Withdrawals-to-Availability Relation

Water stress as shown in Figure 2.35 measures the amount of pressure put on water resources and aquatic ecosystems by the users of these resources (households, industries, and agricultural users) and can easily be compared across river basins. For calculating today's water stress, the withdrawals-to-availability ratio is used (w.t.a.). This indicator has the advantage of being transparent and computable for all river basins and has been used in several studies (e.g. Alcamo et al. 2007). The larger the volume of water withdrawn, used, and discharged back into a river, the more river flow is depleted and/or degraded for users downstream, and thus the higher the water stress Increasing water stress results in stronger competition between society's users and between society and ecosystem requirements. A river basin is assumed to be under low water stress if w.t.a. ≤ 0.2; under medium water stress if 0.2 < w.t.a. ≤ 0.4, and under severe water stress if w.t.a. > 0.4 (Cosgrove and Rijsberman 2000, Vorösmarty et al. 2000, Alcamo et al. 2007). Water withdrawals and availability were computed by WaterGAP3 on 5x5 arc minute grid cells and aggregated to river basin scale.

Using a time series of climatic data as input, the hydrological model of WaterGAP3 (Eisner et al., 2016) calculates the daily water balance for each grid cell, taking into account physiographic characteristics such as soil type, vegetation, slope, and aquifer type. Runoff generated on the grid cells is routed to the catchment outlet on the basis of a global drainage direction map (Lehner et al., 2008), taking into account the extent and hydrological influence of lakes, reservoirs, dams, and wetlands. The climate input for the hydrology model consists of precipitation, air temperature, and solar radiation. These data come from the WATCH data set (Water and Global Change) applied to ERA-Interim data (WFDEI) for the time period 1979-2010 (Weedon et al. 2014). The climate data have a temporal resolution of one day and a spatial resolution of 0.5° by 0.5° (latitude and longitude, respectively) downscaled to the 5 arc minute grid cells. Water withdrawals were simulated for the year 2010 for the agriculture i.e., (irrigation and livestock), industry (i.e., manufacturing and thermal electricity production), and domestic sectors as described in aus der Beek et al. (2010) and Flörke et al. (2013).

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Chapter 3 – Methods Annex

Authors of this annex: Livia Cabernard, Stefanie Hellweg, Jonas Mehr, Christopher Oberschelp, Stephan Pfister, Emile Piccoli, Akshat Sudheshwar

Contents

A.1 Overview of methodological approach

In this chapter the methodological procedure of Chapter 3 is explained. Based on the resource extraction and material use information provided in Chapter 2, emissions and resource consumptions of resource extraction and processing were inventoried and environmental impacts assessed.

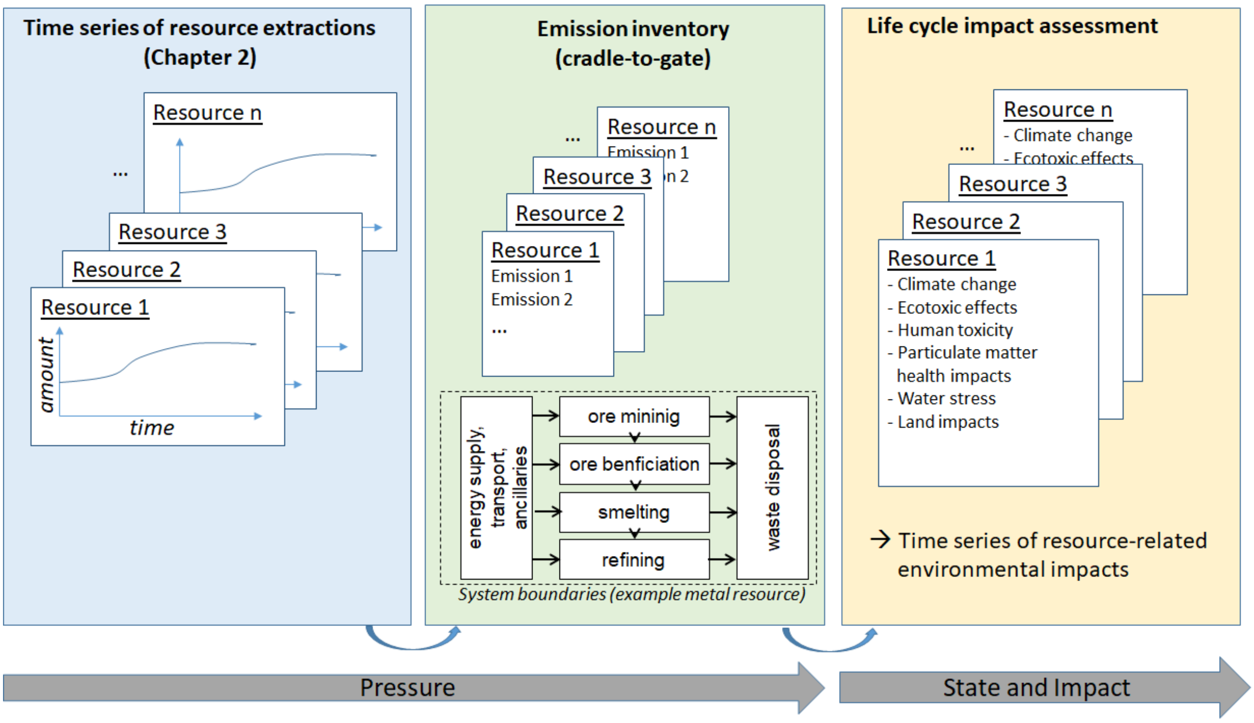

Figure A.1: Overview of methodological procedure to assess the health and environmental impacts of resource extraction and processing. For some resources a complete life cycle perspective (cradle to grave) was adopted (these cases are marked with a box).

Two perspectives were adopted: a domestic extraction and resource processing (production) perspective as well as a consumption footprint point of view. The former quantifies the impacts at the location of extraction and resource/material processing. The latter quantifies the environmental impacts of resource consumption throughout the supply chain, in a manner similar to the material footprint, but in terms of environmental impacts.

A.2 System boundaries

The focus lies on resource extraction and processing up to “ready-to-use” materials and fuels.
The input-output system Exiobase 3.4 was used for assessing impacts of all resource types of the whole economy (macro-analysis). In addition to the Exiobase “macro-analysis”, we used data from ecoinvent v3.4 to study single resources and materials in depth in a bottom-up analysis. Due to the system boundaries, both analyses allow to study the total impact and the improvements that can be reached by changing the end use of materials (e.g. steel).

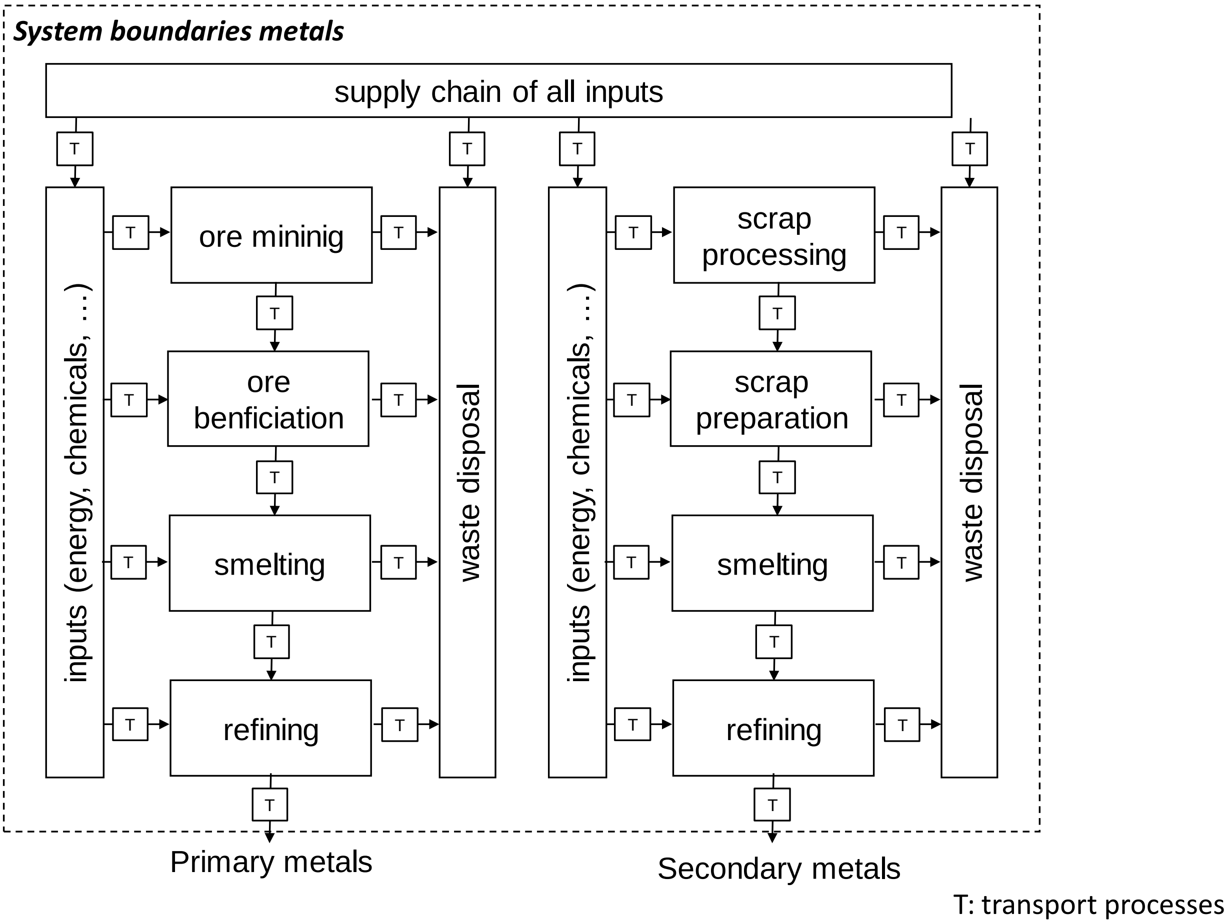

Figure A.2: Example of system boundaries for metallic minerals in the bottom-up analysis (system boundaries for other resource groups have been established in an analogous way). The complete supply chain is considered to do a comprehensive analysis per resource type. The graph is only indicative of some exemplary processes (e.g. infrastructure of factories, such as buildings and equipment, was considered but is not shown for visibility reasons). Emissions (e.g. CO_2, NO_x, PM, metals, etc.) and resource extractions (e.g. land use) are assessed for all processes included in the system boundaries.

A.3 Life Cycle Impact Assessment

In the impact assessment step, the best-practice guidelines of the UNEP-SETAC Life Cycle Initiative for use in Life Cycle Assessment were followed (UNEP SETAC 2016).

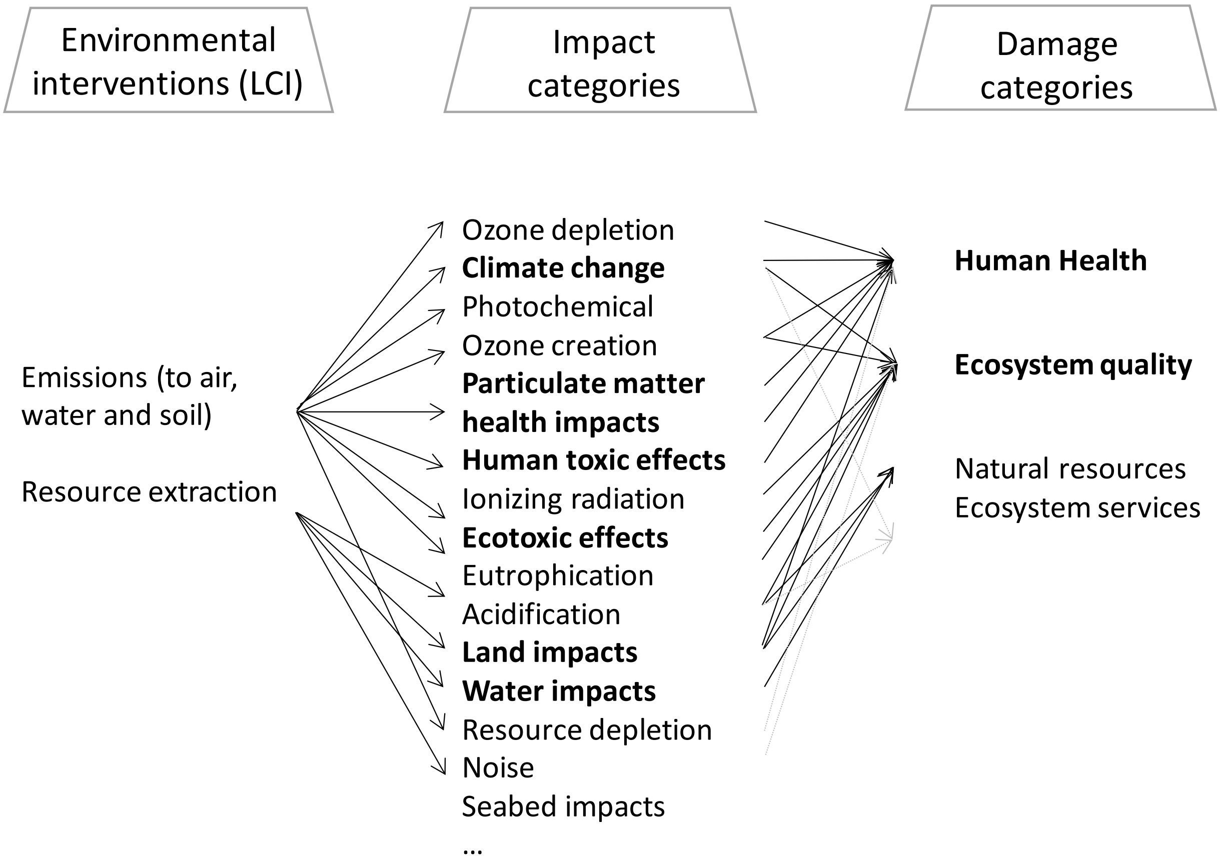

Figure A.3: Excerpt of framework of Life Cycle Impact Assessment. All impact categories quantified in this report are printed in bold. (figure adapted from UNEP-SETAC 2016) (UNEP SETAC 2016)

Recommended methods exist to calculate impacts of climate change, eco-toxicity, water stress, biodiversity loss from land use, human toxicity, and human health impacts from particulate matter exposure. This selection fits well with the "core planetary boundaries" (Steffen et al. 2015; Dao, Peduzzi, and Friot 2018) of climate change and biodiversity loss, and additionally includes human health impacts. Furthermore, all of these impacts are relevant for resource use, and some of them have been shown to correlate with (and therefore represent) other impacts as well. In particular, climate change impacts associated with resource extraction and processing have been demonstrated to correlate with ozone depletion, acidification and eutrophication (Steinmann et al. 2018). Therefore, these impact categories are not shown separately unless they diverge from the development of climate change impacts and are predominant with regard to resources, such as in the case of phosphorous use as fertilizer and its relation to eutrophication, which is extensively discussed.

Table A.1: Overview and description of environmental impacts assessed in the report (UNEP SETAC 2016)

Impact category	Impact pathway (simplified)	Impact unit	Primary reference
Climate change	Greenhouse gas emissions (CO_2, CH_4, N_2O, CO, VOC, halocarbons, nitrogen fluorides, sulfur hexafluoride etc.; in the ecoinvent analysis >600 emissions were assessed; in the EXIOBASE3 analysis CO_2, CH_4, N_2O, hydrofluorocarbons and perfluorocarbons were considered) affect the atmospheric radiation absorption properties and thereby they change global temperature. Temperature change can lead to various impacts to humans and ecosystems, like heat stress, extreme weather events, sea level rise, species extinctions. In this report, the Global Warming Potentials (GWP) of IPCC were used (time horizon of 100 years). These consider the atmospheric concentration changes as a consequence of an emission and the change in radiative forcing. Hereby, the fate of the emission in the atmosphere (degradation, transformation) and substance-specific heat absorption properties are taken into account. The product of concentration and radiative efficiency is aggregated over a defined time horizon (in this case 100 years) and divided by the same product for the reference substance CO2: $GWP_i = \frac{\int_0^T c_i R_i(t)dt}{\int_0^T c_{CO_2} R_{CO_2}(t)dt}$ where ci is remaining concentration of substance i in the atmosphere at time t, R the radiative efficiency of i and T the time horizon chosen for the GWP.	All emissions are expressed as "kg CO_2-equivalents". This means that the 100-year aggregated radiative forcing effect of the emission of the particular greenhouse gas is equivalent to the radiative forcing effect of the specified amount of CO_2-emission. Note that this is not an emission value, but an impact that refers to a time horizon T, e.g. the amount of CO_2-equivalents will change if a different time horizon T is assumed, although the original emission is the same.	(IPCC 2013)
Particulate Matter (PM) health impacts	Emissions of particulates and precursor gases transformed to particulate matter (PM) in the atmosphere (SO_x, NO_x, ammonia). The fate of emissions is modeled in the atmosphere (distinguishing various archetypes of emission locations according to population density), leading to atmospheric concentration increases of particulate matter. Inhalation exposure leads to elevated risk of cardiovascular and respiratory diseases (ranging in health outcomes from diseases like aggravation of asthma to increased mortality). The full impact pathway is modeled for each substance in the impact assessment, as	DALY (disability adjusted life years); this unit expresses the years of life lost and years lived with a health impairment (the latter years are weighted with a severity factor of the disease).	(Fantke et al. 2017; UNEP SETAC 2016)

	documented in (UNEP SETAC 2016).		
Human Toxicity	Emissions of toxic substances are transported, degraded and transferred between various environmental compartments (air, water, and soil), where they may lead to direct exposure (e.g. inhalation of air with pollutants) or indirect exposure (e.g. crop uptake of pollutants from soil and ingestion of crop as food). Toxic effects may occur after human exposure. The full impact pathway is modeled for each substance in the impact assessment, as documented in (Rosenbaum et al. 2008)	The method proviedes results in terms of CTUh (Comparative Toxic Units), which were then multiplied with the following damage factors to translate these effects into the unit of DALYs: 11.5 DALYs/CTUh for carcinogenic and 2.7 DALYs/CTUh for non-carcinogenic effects (Huijbregts et al. 2005). For an explanation of DALY see previous row.	(Rosenbaum et al. 2008)
Freshwater ecotoxicity	Emissions of toxic substances are transported, degraded and transferred between various environmental compartments (air, water, and soil). The fraction that ends up in freshwater leads to exposure of aquatic species. Toxic effects may occur after exposure. To represent ecosystems, the toxic effects on a selection of indicator species are used as a proxy (species-sensitivity curves). The full impact pathway is modeled for each substance in the impact assessment, as documented in (Rosenbaum et al. 2008)	Comparative Toxic units (CTU)	(Rosenbaum et al. 2008)
Land-use related biodiversity loss	Land use reduces natural habitat size and degrades ecosystems, and thereby leads to species extinctions. Regional extinctions as a consequence of land use were quantified using ecological models (countryside species area relationship, (Pereira, Ziv, and Miranda 2014). Species-loss factors are provided on the ecoregion level (804 ecoregions) for six types of land use and four animal taxa (birds, amphibians, mammals, reptiles) and vascular plants, which were aggregated by giving equal weight to plant and animal taxa. Species loss was then weighted with a factor quantifying the risk that regional extinctions are also global (and therefore irreversible), using threat-level data from IUCN and considering species ranges. Impact factors quantify global extinctions that are "committed to extinction", i.e. the number of	Fraction of global species lost (global PDF)	(Chaudhary et al. 2015) (UNEP SETAC 2016)

	species lost in the ecoregion or globally as a consequence of land use at steady state. The reference system is natural undisturbed habitat.		
Water stress	Water stress addresses the impacts of water consumption on the water resource as a flow resource. The general concept accounts for the competition for this vital resource through a use-to-availability relation on watershed level (see also Chapter 2). Additionally, absolute water scarcity (availability per area) is considered to combine natural and human-induced water stress in a single indicator. The impacts are quantified based on water consumption, environmental water requirements (EWR) and availability data from global hydrological models for >11'000 watersheds. It is normalized to the global average condition and limited between 0.1 and 100 m^3-equivalents/m^3 consumption. This impact indicator represents a proxy for both impacts to human health and ecosystem quality, as it explicitly accounts for human water consumption and EWR	Water stress is expressed as "m^3-equivalents", which relate all m^3 of water consumption to the global average water scarcity conditions.	(Boulay et al. 2018)

A.4 Macro-analysis with EXIOBASE3 (top down analysis)

A.4.1 Methodological approach

Until recently, the accurate quantification of material-related impacts was considered as a methodical challenge due to the strong intertwining of the global material supply chain. For example, fossils are used as combustion material for metal production, and metals are used as machinery equipment for fossil production. This intertwining leads to double counting if the impacts are cumulated along the supply chain for each material category individually. Here, we applied the methodology of (Cabernard, Pfister, and Hellweg 2019), which allows to assess and track the cumulated upstream impacts of any industrial sector and region without double counting along several stages of the global supply chain. This methodology extends the method of Dente et al. (Dente et al. 2018) to global multiregional input-output analysis and was here applied to the environmentally-extended multi-regional input output database EXIOBASE3 (version 3.4, Stadler et al. 2018). The methodology is provided as a Matlab tool in (Cabernard, Pfister, and Hellweg 2019) and it can be applied to study the global supply chain impacts of any industrial sector and region. This allowed us to assess the cumulated upstream impacts of global material production without double counting from different perspectives: In Chapter 3.2 of the report, we compared the impacts of the four major material categories biomass, metals, non-metallic minerals and fossils from a *target perspective*, meaning that the cumulated upstream impacts of global material production were allocated to the final material sector that is supplied (Cabernard, Pfister, and Hellweg 2019). Exemplarily, if fossils are used for metal production, the impacts caused by fossils are allocated to metals (and are thus not accounted for in the fossils sector to avoid double counting). The *production perspective* was applied in Chapter 3.2 to assess in which region on the globe the impacts and emissions related to the production of materials are caused and take place. The *consumption perspective* was applied to allocate the material-related impacts to the region and category of final consumption (such as households, governments, capital formation etc). Note that also in the *consumption* and *target* perspective (and not only in the *production* perspective) the impacts were assessed considering the location of resource use and emissions in the supply chain. This was particularly important for regionalized impacts, such as the impacts of land and water use (See Table A.1). For the in-depth assessment of Chapter 3.3, the *production perspective* was applied to assess the direct impacts caused by key material types in accordance to the bottom-up life-cycle analysis. The categorization of the 49 regions distinguished by EXIOBASE3 into 6 world regions is shown in Table A.2.

In addition to the environmental indicators listed in Table A.1 (excluding toxicity due to incomplete emission data in EXIOBASE3), socio-economic indicators such as value added and number of workplaces were included from EXIOBASE3. Moreover, we implemented the socio-economic indicator *'risks for employment'* according to Zimdars et al (2018, further described in section A.6.2) and applied the methodology to the case of global material production.

Table A.2: Categorization of 49 regions from EXIOBASE3 (version 3.4, Stadler et al. 2018) into 6 world regions according to the GNOME3 guidelines.

	49 regions in EXIOBASE3	**6 regions in GRO**
1	Austria	Europe
2	Belgium	Europe
3	Bulgaria	Europe
4	Cyprus	West Asia
5	Czech Republic	Europe
6	Germany	Europe
7	Denmark	Europe
8	Estonia	Eastern Europe, Caucasus, and Central Asia (EECCA)
9	Spain	Europe
10	Finland	Europe
11	France	Europe
12	Greece	Europe
13	Croatia	Eastern Europe, Caucasus, and Central Asia (EECCA)
14	Hungary	Europe
15	Ireland	Europe
16	Italy	Europe
17	Lithuania	Eastern Europe, Caucasus, and Central Asia (EECCA)
18	Luxembourg	Europe
19	Latvia	Eastern Europe, Caucasus, and Central Asia (EECCA)
20	Malta	Europe

21	Netherlands	Europe
22	Poland	Europe
23	Portugal	Europe
24	Romania	Europe
25	Sweden	Europe
26	Slovenia	Europe
27	Slovak Republic	Europe
28	United Kingdom	Europe
29	United States	North America
30	Japan	Asia and Pacific
31	China	Asia and Pacific
32	Canada	North America
33	South Korea	Asia and Pacific
34	Brazil	Latin America
35	India	Asia and Pacific
36	Mexico	North America
37	Russian Federation	Eastern Europe, Caucasus, and Central Asia (EECCA)
38	Australia	Asia and Pacific
39	Switzerland	Europe
40	Turkey	West Asia
41	Taiwan	Asia and Pacific
42	Norway	Europe
43	Indonesia	Asia and Pacific
44	South Africa	Africa
45	Rest of the world Asia and Pacific	Asia and Pacific
46	Rest of the world America	Latin America
47	Rest of the world Europe	Europe
48	Rest of the world Africa	Africa
49	Rest of the world Middle East	West Asia

A.4.2 Additional results

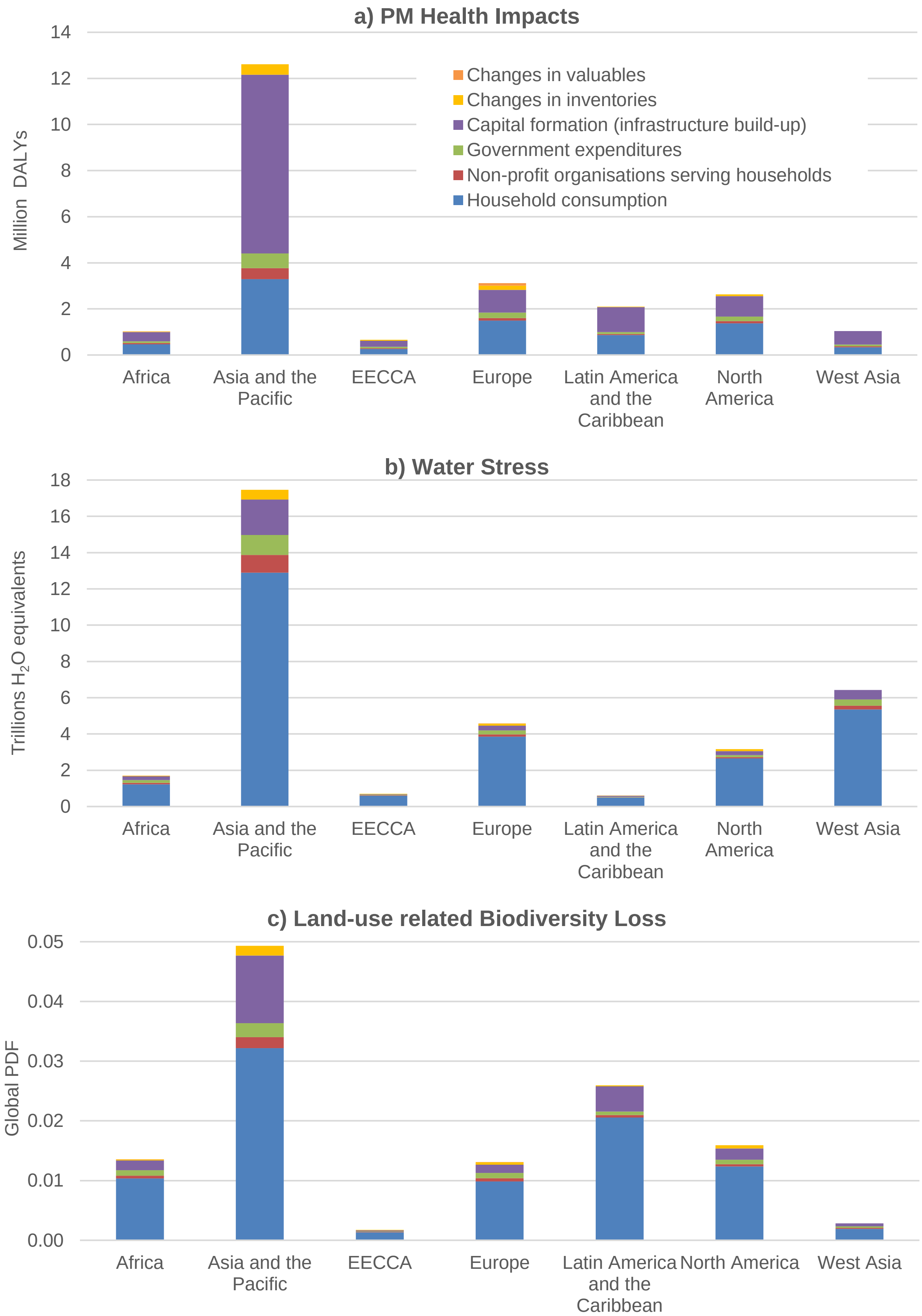

Figure A.4: Global material-related (a) PM health impacts, (b) water stress, and (c) land-use related biodiversity loss split by region and category of final consumption.

A.5 Bottom-up analysis

In addition to the macro-analysis with EXIOBASE, a more detailed bottom-up analysis was also performed, where extraction and processing data from the global MFA database and the British Geological Survey were coupled with Life Cycle Assessment data from ecoinvent v3.4. For this analysis, the whole supply chain was considered (Figure A.2). Because this analysis was specifically per resource type and did not aggregate various resource types, as was done in the macro-analysis, we did not correct for double counting. Therefore, the impacts in the bottom-up analysis tend to be larger than in the macro-analysis. A production perspective (see Section A1) was adopted for the bottom-up analysis, showing where emissions were released and impacts caused (independent of who benefits from the consumption of the materials).

A.5.1 Metal extraction and processing (method)

In general, life cycle inventories datasets as available in ecoinvent v3.4 cutoff version were used. For some metals, the ecoinvent base inventories were adapted to incorporate other available information. For example, in some cases where electricity generation was responsible for high impacts, the available inventories were further regionalised by substituting country-specific electricity mixes. This procedure is explained in detail in section A.5.1.11.

Total impacts were derived as the product of extracted/processed metal quantities by the mass-specific (per kg) environmental life cycle impacts. In general, the spatial resolution for the calculations was maintained at the finest level of detail of the data available. Therefore, the regionalized ecoinvent inventories were coupled to the extraction/processing taking place in the corresponding area and the impacts were aggregated only at a later stage.

Information on the quantities of metal extracted or processed was sourced from different agencies. When available, data on yearly total production was gathered via the World Mineral Statistics of the British Geological Survey (BGS) (Brown et al. 2018). For some metals, the U.S. Geological Survey (USGS) was used alongside the quantity data found in the BGS. These datasets were complemented by the mass of crude ore extracted for each metal, which was taken from the global MFA database (which also used BGS and USGS data as primary data sources).

A.5.1.1 Iron and steel value chain

Production data

Being the dominant metal by production volume, the iron value chain, including steel, is well reported; quantities for iron ore, pig iron production and crude steel production by country are available through the World Mineral Statistics data of the British Geological Survey (BGS), as listed in Table A.3. Global production trends taken from the BGS are shown in Figure A.5. The greater of the trend lines correspond to the mass of crude ore. The amount of crude ore is larger than the mass of metal extracted from it, which is reduced into pig iron before it can be further refined into steel. “Steel, crude” in the BGS data corresponds to all steel categories aggregated, not only including primary and secondary material, but also all other sorts of steel such as carbon steel, highly alloyed steels and special steels.

Table A.3: Iron and steel datasets taken from the British Geological Survey (BGS).

BGS commodity name	Description
iron ore	Crude iron ore, tonnes
iron, pig	Primary iron, tonnes
steel, crude	All types of steel, tonnes

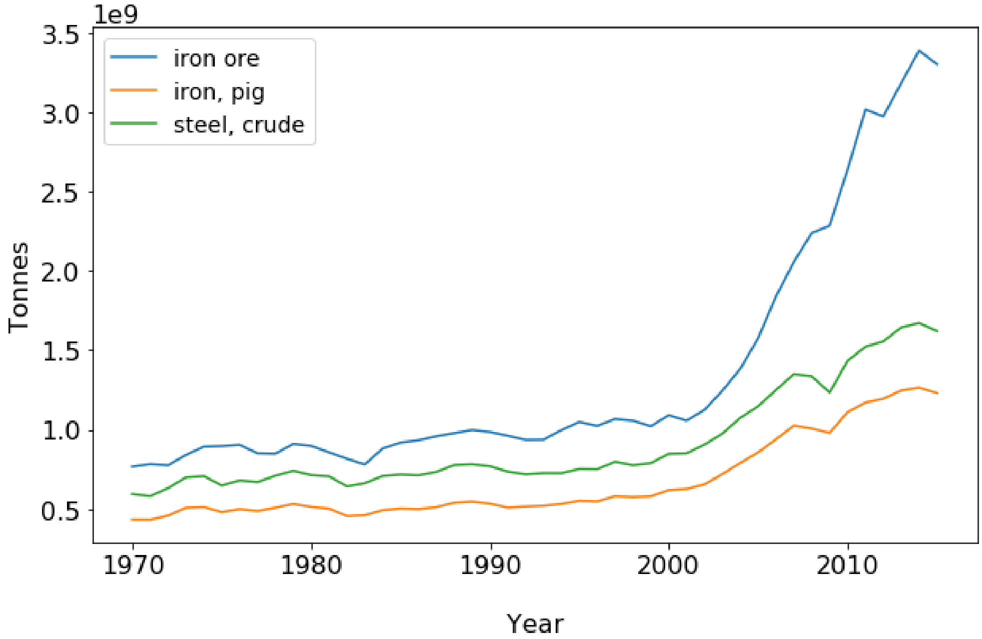

Figure A.5: Time series of global mined iron ore, pig iron and crude steel production reported by the BGS.

The Statistical Yearbook publications from the World Steel Association (Worldsteel Association 2017) were used to distinguish primary and secondary steel production. The amounts of crude steel produced in a given year with electric-arc furnaces and with oxygen-blown converters are reported at country level resolution. For countries where information on the production process (electric arc furnace or converter) was not available, but production of crude steel was reported from the BGS, all production was allocated to oxygen-blown converter technology.
In reality, both the oxygen-blown converters and the electric arc furnace processes accept a certain proportion of scrap metal, with electric arc furnaces reaching the highest values at about 90% scrap. This is taken into account by the original ecoinvent v3.4 processes, which consider a share of scrap input. For both technologies, the share of primary to secondary input material was kept the same as in the ecoinvent v3.4 database. Impacts of steel production are calculated and reported based on the subdivision by process technology, explained further below. High-alloyed steels accounted for a small proportion of world steel production and were therefore not separately assessed. For instance, while climate change impacts of stainless steel are twice as high as low-alloyed steel on a mass specific basis, stainless steel accounts for only around 2% of world steel production; thus, despite assuming that all stainless steel is of type "low-alloyed" (ignoring the exact iron content), the resulting errors are limited to 1% of total impacts.

Inventory data

Life-cycle inventory data was adapted from ecoinvent v3.4 cutoff database. Available activities were grouped around different phases of the iron and steel production chain:

- Mining of ore and its beneficiation and pelletization
- Iron fines sintering and pig iron production
- Primary steel production in oxygen-blown converter (OBC)
- Secondary production by electric-arc furnace (EAF)

Table A.4: Original ecoinvent v3.4 datasets for iron-steel value chain impact assessment

Production step	**Activity name**	**Location**
Mining	market for iron ore, beneficiated, 65% Fe	GLO
Mining	market for iron pellet	GLO
Ironmaking	sinter production, iron	GLO
Ironmaking	pig iron production	GLO
Steelmaking, primary	steel production, converter, low-alloyed	RER, RoW
Steelmaking, secondary	steel production, electric, low-alloyed	Country-specific regionalization

Original ecoinvent datasets were modified to exclude the impacts from the upstream group of processes in Figure A.6. For instance, sinter iron and pig iron production are cut-off from the impacts of iron ore beneficiation, so that emissions occurring upstream in the “mining” sector are not accounted for twice. The same was done for steel primary production, which is cut-off from the impacts occurring at the stage of pig iron production. In other words, impacts are cut-off at every boundary crossing, from mining to ironmaking and then to steelmaking, in order to be able to show them per process step.

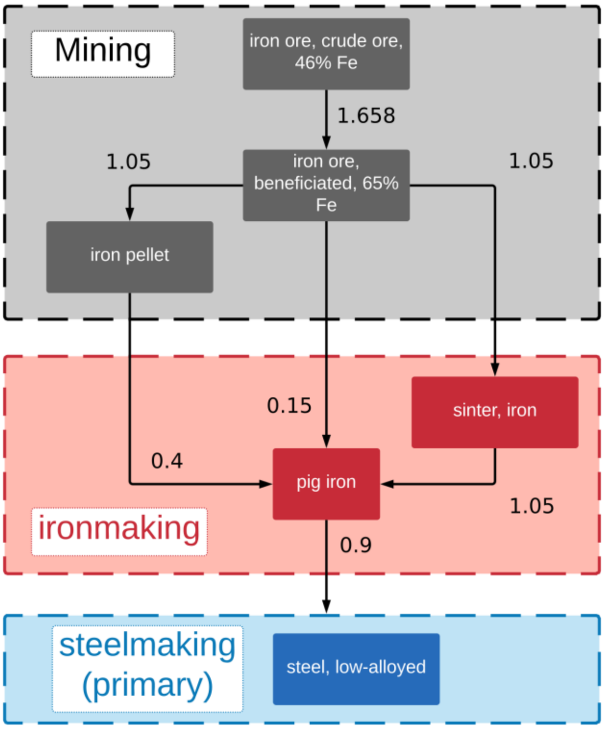

Figure A.6: Overview of the iron-steel primary production value chain and its aggregation in sectors. Values on the arrows indicate kilograms of input product for 1 kg of downstream product.

In each of the phases depicted in Figure A.6, the total impacts are calculated as the product of amounts extracted/produced (i.e. pig iron and steel) times the corresponding per-tonne impacts. 98% of iron ore extracted worldwide is fed into the production of pig iron. The share in which iron ore is transformed into iron pellet and beneficiated iron ore at the end of the mining stage is distributed according to the input requirement for pig iron production in ecoinvent v3.4 (see Figure A.6). The mining sector is lumped together as a single process that produces 0.4 kg of iron pellet and 1.2525 kg of beneficiated iron ore for each kilogram of pig iron. The global environmental burden of mining was allocated to single countries proportionally to the share of crude ore produced within them.

The impacts from ironmaking and both primary and secondary steelmaking are calculated simply as the product of mass-specific impacts and amounts produced. The geographical resolution is maintained as long as possible, in order to capture the effect of regional differences in the inventories.

For primary iron- and steelmaking, the inventories as available in ecoinvent v3.4 refer to outdated datasets and do not capture the energy efficiency improvements that the industry has implemented. These changes yield lower carbon footprints, so the climate change impacts after the year 2000 are adjusted to take into consideration the reduction in the global steel industry CO_2 intensity (Worldsteel Association 2018). The factors used are summarized in the Table A.5.

Table A.5: Carbon intensity factors applied to ironmaking and primary steelmaking based on (Worldsteel Association 2018)

Year	**2000**	**2005**	**2010**	**2015**
Factor	1	0.96	0.92	0.91

A.5.1.2 Aluminium

Production data

Primary aluminium production amounts were taken from the BGS World Mineral Statistics database. Extraction of bauxite mineral is reported along with production of alumina and primary aluminium. For secondary aluminium, regional data was taken from the International Aluminium Institute (International Aluminium Institute (IAI) 2016).

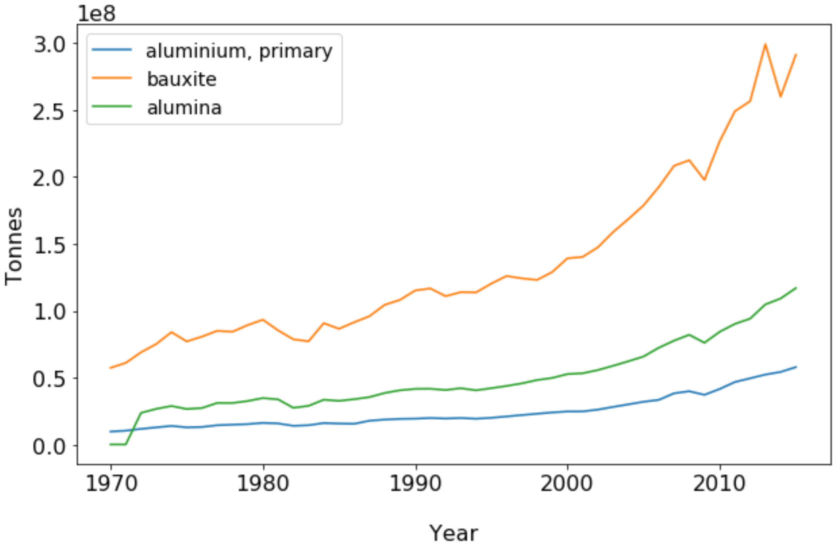

Figure A.7: Time series of global aluminium datasets available in BGS.

Inventory data

Life-cycle inventory data was adapted from Ecoinvent v3.4 cutoff database as shown in Table A.6. Inventories for primary production of aluminium were adapted with local electricity mixes where available (similar to the regionalization done for secondary steel production, as explained in section A.5.1.3).

Table A.6: Original Ecoinvent v3.4 datasets for the aluminium value chain impact assessment.

Production step	Ecoinvent v3.4 activity	Ecoinvent v3.4 product	Location
Bauxite mining	bauxite mine operation	Bauxite, without water	GLO
Alumina production	aluminium oxide production	aluminium oxide	GLO
Aluminium, primary	aluminium production, primary, liquid, prebake	aluminium, primary, liquid	Country-specific regionalization[1]
Aluminium, secondary	treatment of aluminium scrap, post-consumer, prepared for recycling, at refiner	aluminium, cast alloy	RER/RoW

The amounts data was multiplied by the mass-specific impacts for each production step. The regionalized inventories for primary production of aluminium were associated by country to the corresponding production amounts. For countries producing limited aluminium where information about the specific electricity mix was missing, the activity in ecoinvent v3.4 cutoff corresponding to the closest International Aluminium Institute region was chosen, which provides a weighted average electricity mix specific to the world region.

A.5.1.3 Copper

Production data

Table A.7: BGS data series available on copper production

BGS commodity name	Description
copper, mine	Estimated copper production from the mined ore
copper, refined	Primary + secondary copper
copper, smelter	Pyrometallurgical copper

The BGS reports three data series about copper: mined copper, refined copper, and smelter copper. The mined copper can be processed via pyrometallurgy (smelting) or hydrometallurgy (electrowinning). Prior to 1990, the mined and smelter copper data series virtually coincided, but then started diverging from each other. Hydrometallurgical processes to recover copper from lower grade copper oxide deposits are responsible for this divergence (British Geological Survey 2007), since hydrometallurgic copper is not included in the data series of smelter copper. The refined copper data includes both primary and secondary copper with purity of at least 99.5%.

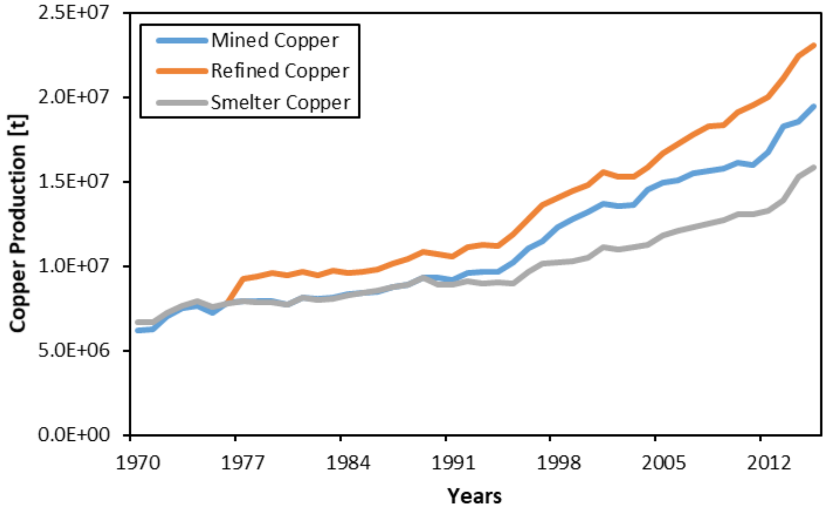

Figure A.8: Time series of global copper production datasets available in BGS (in tonnes of metal content)

The values for secondary copper reported by the USGS (Edelstein 2002, 2007; Brininstool 2012; Brininstool and Flanagan 2015) are compared to corresponding proxies for secondary copper obtained from the difference between the refined and the mined copper in the BGS database (see Table A.8).

Table A.8: Comparison of copper data from USGS and BGS and recycled content from the (United Nations Environment Programme (UNEP) 2011).

Data Source	Parameter	2000	2005	2010	2015
British Geological Survey (BGS)	Global Total	14,773,972	16,662,614	19,095,087	23,064,758
	Total Mined	13,206,324	14,958,389	16,100,975	19,422,087
	Total Recycled	1,567,648	1,704,225	2,994,112	3,642,671
	Recycled Content	10.6%	10.2%	15.7%	15.8%
United States Geological Survey (USGS)	Global Total	15,000,000	16,600,000	19,100,000	23,000,000
	Total Mined	3,390,000	14,390,000	15,800,000	18,300,000
	Total Recycled	2,030,000	2,130,000	3,280,000	4,640,000
	Recycled Content	13.5%	12.8%	17.2%	20.2%
United Nations Environment Program (UNEP)	Recycled Content	20-30%			

For the year 2000, the sum of the USGS data for the mined and recycled copper does not equal the global total. Part of the copper production for this year was listed under the “undifferentiated copper” category (not shown in the Table A.8), with no explicit primary and secondary material fractions. All undifferentiated copper was considered as primary copper; this also ensured that the amount of primary copper for the year 2000 was more consistent with that of the following years. By doing so, a share of secondary copper is potentially neglected, but based on the data in Table A.8, this share seems to be reasonably small.

Inventory Data

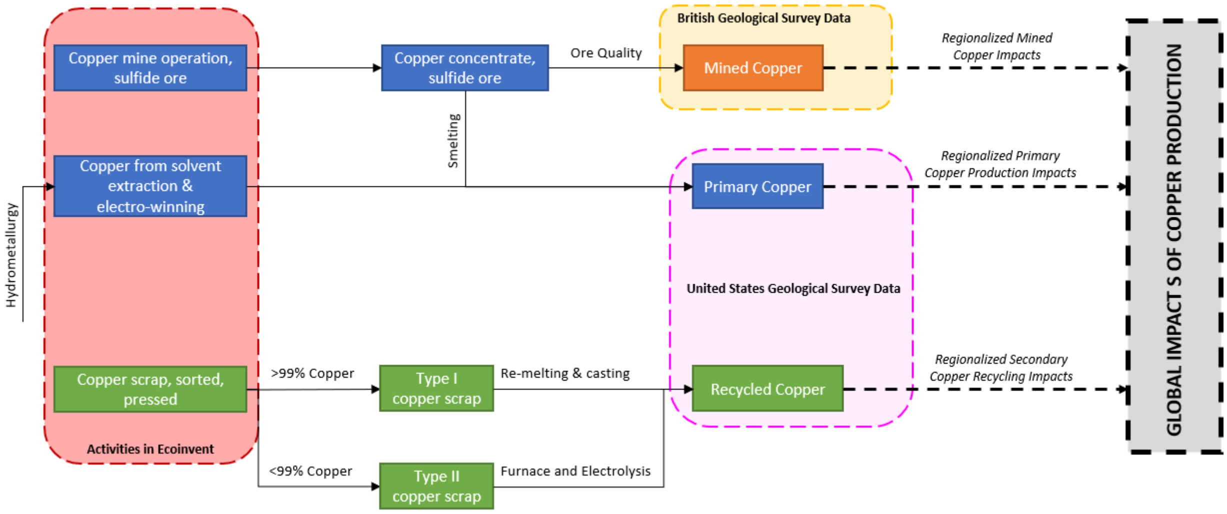

Figure A.9: Process overview linking the inventory datasets in the ecoinvent v3.4 database to the copper extraction and refining data from USGS and BGS

The reference product of the mining activities in ecoinvent v3.4. cutoff is copper concentrate (containing around 30% copper). To assess the impacts due to mining of copper, the mass of extracted copper reported from BGS was first converted into mass of copper concentrate. Regionalized conversion factors were used to account for the different percentage of metal of the copper concentrate for different locations present in Ecoinvent 3.4 (Table A.9). The impacts of copper mining were then multiplied by the amounts of copper concentrate which corresponded to the mined copper.

For primary copper production, the modified activity “copper production process only (without mining)” was used in conjunction with the data from USGS. The original activity titled “copper production, primary” was modified by removing the technosphere input of copper concentrate (derived from the mining of copper) to avoid double counting of mining impacts. Both the original and the modified activities include the process of electrowinning (hydrometallurgy) of copper. The amount of hydrometallurgic copper production differs for each location (Classen et al. 2009), and this global variation in copper extraction technology is also modelled within the ecoinvent v3.4 activities. Therefore, the current method accounts for some variation in the technology-mix (ratio between pyro- and hydro-metallurgy used to refine copper) across different regions (namely: North America, Latin America, Europe, Asia, Australia, and rest of the world) and incorporates more diversity than a single global average. However, the distribution of hydrometallurgic and pyrometallurgic copper production in these inventories is based on outdated sources and is likely to under-represent hydrometallurgic copper in recent years.

The quantities of secondary copper are reported by USGS. However, available literature shows that there is high variability in the quality of scrap, and consequentially, diverse processes are employed to extract copper from scrap. As shown in Figure A.9, depending on the percentage of copper, copper scrap can be classified into Type 1 and Type 2. The clean, unalloyed metal, corresponding to high quality Type 1 scrap, can be simply recast after melting in a furnace. A new inventory for “Type 1 copper recycling” was created with the following procedure:

1. Create an activity “Production of Copper Metal Furnace” by removing activities involving aluminium smelting and chemical organics facilities from the ecoinvent v3.4 activity named “non-ferrous metal smelter production”

2. Use the previous activity to create a “market for copper metal smelter” by replacing the respective activity in “market for non-ferrous metal smelter”, yielding a non-ferrous furnace smelter as a reference product
3. Create an activity “type 1 copper recycling” with technosphere inputs:
    a. 1.01 kg of scrap copper (assuming 99% of scrap purity)
    b. 1.2 MJ/kg of heat energy input, assuming heating from ambient temperature to fusion temperature with 0.575 as the thermal efficiency for the furnace, plus 15-20% correction for any uncertainty
    c. 1.33E-12 furnace plants per kg of copper re-melted, considering an annual output per furnace of 150 million tons and a lifetime of 50 years (based on furnace specifications in ecoinvent)

For recycling of Type 2 scrap, heating and recasting is insufficient due to contamination from other alloying or polluting elements. Therefore, purification via electrolysis is also required, which is accurately modelled in the already existing ecoinvent inventory dataset “treatment of copper scrap by electrolytic refining”. This inventory was directly applied to quantify the impacts due to type 2 scrap.

Based on (Muchova et al. 2011), it was estimated that 35% of the total recycled copper on the market was of type 1 grade and the remaining was type 2. Therefore, a weighted average (based on mass contributions) of the impact scores from “treatment of copper scrap by electrolytic refining” (65% weightage) and “Type 1 copper recycling” (35% weightage) was used to calculate impacts of copper recycling. Impacts from both recycling activities are assessed for two different heat mixes (European (RER) and other (RoW)).

Table A.9: Copper inventory datasets (column “Activity used”) and impact scores from ecoinvent v3.4

Activity used	Product	Location	IPCC 2013 | climate change | GWP 100a [kg CO2eq./kg]	USEtox | ecotoxicity [CTU/kg]	USEtox | human toxicity | weighted carcinogenic and noncarcinogenic [DALY/kg]	UNEP air pollution | average approach, average estimate [DALY/kg]	Original Ecoinvent v3.4 Activity
Regionalized Copper Mining Impacts							
copper mine operation, sulfide ore	Copper concentrate, sulfide ore (kg)	RER	0.187033787	111.0756575	2.73021E-05	2.21553E-06	copper mine operation, sulfide ore
copper mine operation, sulfide ore	Copper concentrate, sulfide ore (kg)	RLA	0.44277517	790.1791303	0.000192164	5.99547E-06	copper mine operation, sulfide ore
copper mine operation, sulfide ore	Copper concentrate, sulfide ore (kg)	RAS	1.112383128	999.1816459	0.000243702	1.169E-05	copper mine operation, sulfide ore
copper mine operation, sulfide ore	Copper concentrate, sulfide ore (kg)	AU	0.506129175	371.0418673	9.08064E-05	4.79744E-06	copper mine operation, sulfide ore
copper mine operation, sulfide ore	Copper concentrate, sulfide ore (kg)	RNA	0.916798355	1237.589797	0.000301401	1.10575E-05	copper mine operation, sulfide ore
copper mine operation, sulfide ore	Copper concentrate, sulfide ore (kg)	RoW	0.971422974	775.8511551	0.000189019	7.01993E-06	copper mine operation, sulfide ore
Regionalized Primary Copper Production Impacts							
copper production process only (without mining), primary	Copper (kg)	RER	1.080059939	17.65278343	1.43411E-05	1.54798E-06	copper production, primary
copper production process only (without mining), primary	Copper (kg)	RLA	2.754599022	1078.061801	0.000403968	1.22808E-05	copper production, primary
copper production process only (without mining), primary	Copper (kg)	RAS	1.794553042	107.5715377	0.000197495	1.39351E-05	copper production, primary
copper production process only (without mining), primary	Copper (kg)	AU	2.37763907	591.4492937	0.000300665	2.69718E-05	copper production, primary
copper production process only (without mining), primary	Copper (kg)	RNA	3.041794186	1004.813874	0.000253365	1.11232E-05	copper production, primary
copper production process only (without mining), primary	Copper (kg)	RoW	2.255658793	626.8437581	0.000307859	1.2127E-05	copper production, primary
Regionalized Secondary Copper Recycling Impacts							
Type 1 Copper Recycling	Copper (kg)	RoW	0.200460583	8.760024185	1.9179E-05	6.6179E-07	N.A.
Type 1 Copper Recycling	Copper (kg)	RER	0.127079915	8.640135192	1.91236E-05	4.4085E-07	N.A.
treatment of copper scrap by electrolytic refining	Copper (kg)	RoW	2.5324695	273.9439672	8.59071E-05	6.93985E-06	treatment of copper scrap by electrolytic refining
treatment of copper scrap by electrolytic refining	Copper (kg)	RER	1.606150357	272.9316623	8.54108E-05	4.29167E-06	treatment of copper scrap by electrolytic refining

A.5.1.4 Nickel

Production data

Nickel extraction data is available from both the BGS and USGS and is reported in the “nickel, mine” and “nickel, smelter/refinery” datasets. The BGS data shows the gradual increase in both the nickel commodities since the 1970 as depicted in Figure A.10. Mined nickel accounts for the amount of metal contained in extracted ores while neglecting the losses in the smelting and refining processes. Therefore, “nickel, mine” is found to be consistently higher than the “nickel, smelter/refinery” dataset. Additionally, there is an increase in the difference between the quantities of the two commodities along with a sharp peak in the “nickel, mine” commodity, which is not reflected in the corresponding “nickel, smelter/refinery” amounts.

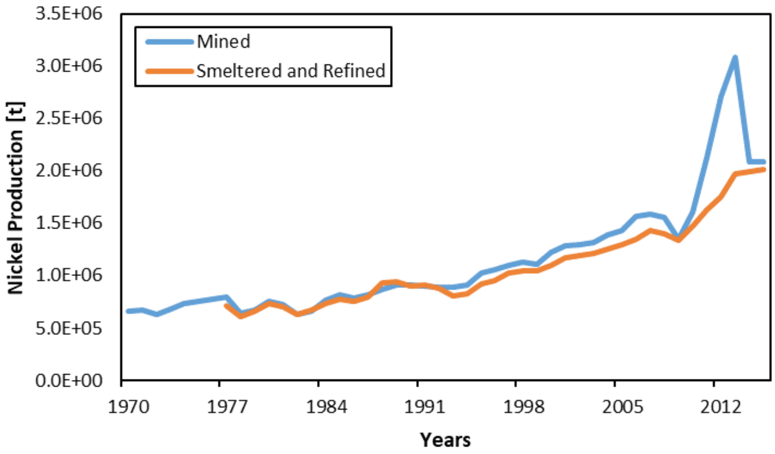

Figure A.10: Time series of global mined and smelter nickel production datasets available in BGS (in tonnes of metal content)

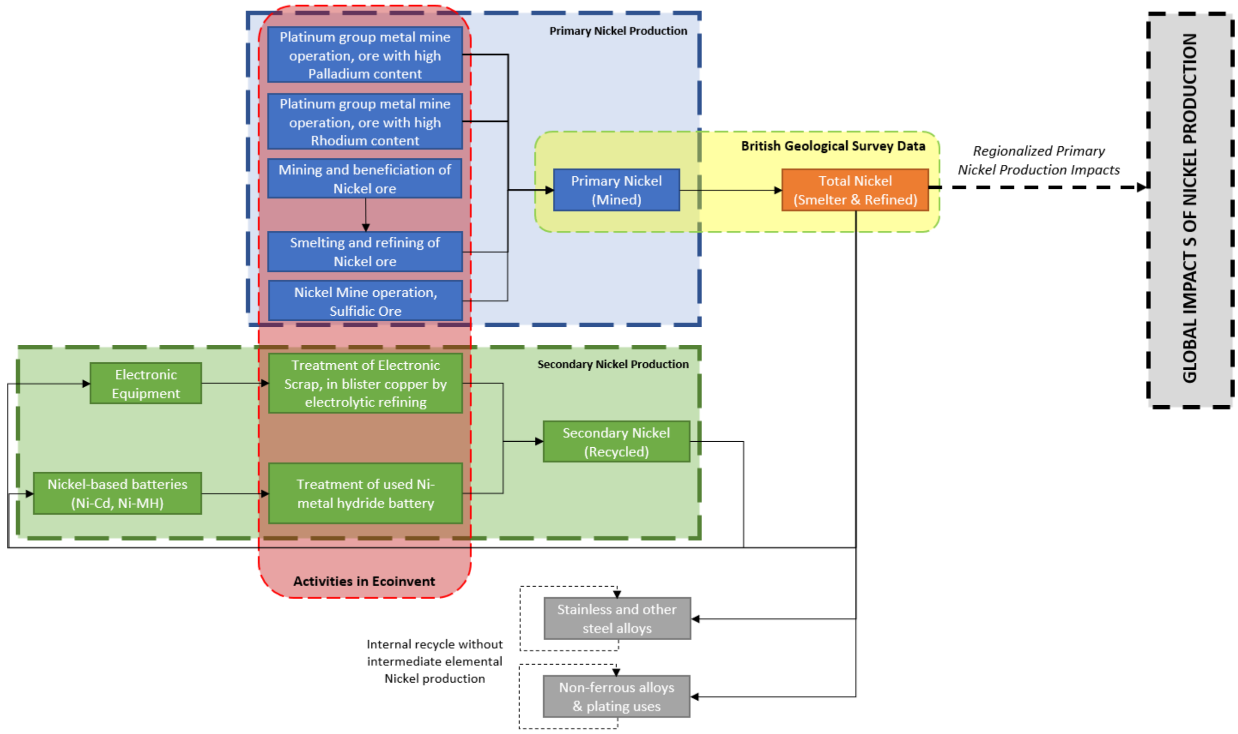

Figure A.11: Matching of metal amount data from BGS with process inventory datasets from ecoinvent v3.4.

Unlike the easily available primary nickel production data, secondary nickel production is difficult to estimate. This is mainly because nickel is used primarily as an alloying element; more than 75% of the refined nickel is used for the production of both ferrous and non-ferrous alloys. As shown in Figure A.11, the scrap alloy is recycled in the alloy form, without intermediate production of refined nickel. Other applications of nickel include foundry, plating, battery manufacturing, and electronics production. The share of nickel entering these applications is around 5% of the total, and is uncertain (United Nations Environment Programme (UNEP) 2011). Hence, for this study, only impacts of primary nickel production have been calculated based on the "smelter/refinery" nickel production reported by BGS.

Inventory data

Table A.10: Modified activity based on ecoinvent v3.4 database along with the calculated impact scores

Activity used	Product	Location	IPCC 2013 | climate change | GWP 100a [kg CO2eq./kg]	USEtox | ecotoxicity [CTU/kg]	USEtox | human toxicity | weighted carcinogenic and noncarcinogenic [DALY/kg]	UNEP air pollution | average approach, average estimate [DALY/kg]	Original Ecoinvent v3.4 Activity
Primary Nickel Production							
Primary Nickel (100%) Production	Nickel (kg)	GLO	11.91302517	713.0519409	0.000168809	7.42875E-05	Market for Nickel, 99.5%

A single activity in ecoinvent v3.4 exists for the primary production of nickel, and it includes both mining and smelting impacts. The activity “Primary Nickel (100%) Production” was created by removing transportation from the activity “market for nickel, 99.5%”. Additionally, the inputs were normalized so as to obtain 100% nickel from the activity, instead of the original 99.5%.
Following the creation of this activity, the impacts scores were calculated, which in turn were further multiplied with the reported quantities of smelted nickel from the BGS dataset.

A.5.1.5 Lead

Production data

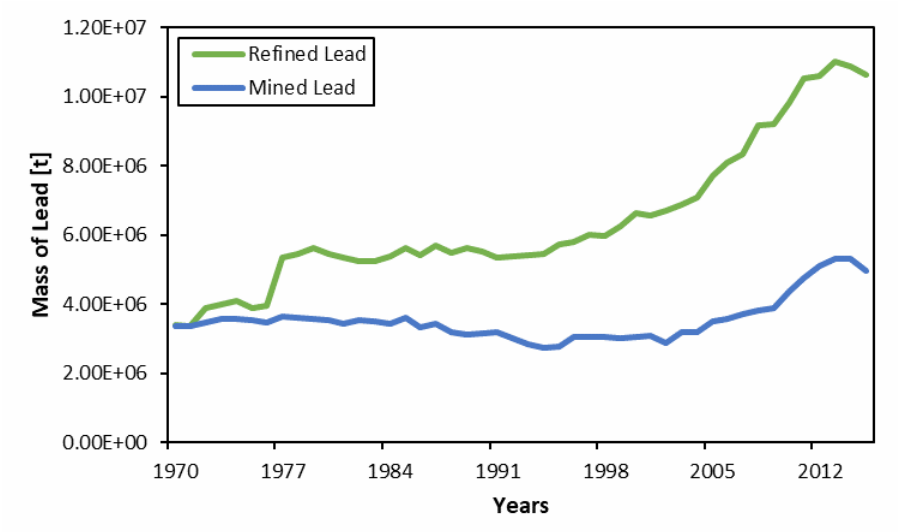

Figure A.12: Mined and refined lead production over time based on the global data from BGS

Lead production data is reported by both the BGS and USGS. The BGS lead dataset consists of “refined” and “mined” lead commodities. Similar to the copper datasets, refined lead consists of both primary and secondary lead, whereas mined lead just represents the lead contained in the extracted ore. As shown in Figure A.12, the mass of refined lead is much higher than the mined lead due to the reutilization of previously built up stocks, for example in lead-acid batteries of vehicles.

Table A.11: Lead production based on the USGS and BGS; recycled content for lead from (United Nations Environment Programme (UNEP) 2011).

Data Source	Parameter	2000	2005	2010	2015
British Geological Survey (BGS)	Global Total	6,632,617	7,718,125	9,847,832	10,637,135
	Total Mined	3,051,684	3,497,014	4,360,026	4,968,964
	Total Recycled	3,580,933	4,221,111	5,487,806	5,668,171
	Recycled Content (RC)	54.0%	54.7%	55.7%	53.3%
United States Geological Survey (USGS)	Global Total	6,580,000	7,640,000	9,530,000	10,400,000
	Total Mined	3,290,000	3,550,000	4,220,000	4,220,000
	Total Recycled	2,970,000	3,880,000	5,110,000	5,800,000
	Undifferentiated	320,000	210,000	200,000	380,000
	Recycled Content (RC)	45.1%	50.8%	53.6%	55.8%
United Nations Environment Program (UNEP)	Recycled Content (RC)	>50%			

The USGS dataset (Smith 2002; Guberman 2007, 2012, 2015) distinguishes between primary and secondary lead production. Secondary lead quantities from USGS along with the estimated recycled content values from BGS (subtracting mined from refined lead quantities) are listed in Table A.11.

The BGS and the USGS datasets report similar amounts of total lead globally produced. Additionally, the calculated recycled contents for both the datasets also align with the value reported by the reference literature (United Nations Environment Programme (UNEP) 2011). The impacts from lead production have been divided into three categories: mined, primary, and secondary. For primary and secondary lead production, the data from USGS was used, whereas for mining impacts calculation, data was taken from the BGS dataset.

Inventory Data

Regionalized lead mining impacts were calculated using the activity “primary lead concentrates”, which was created by removing the transportation and secondary lead sources from the base activity “market for lead concentrates”. The quantities from the primary sources were then normalized to obtain impacts for 1kg of lead.

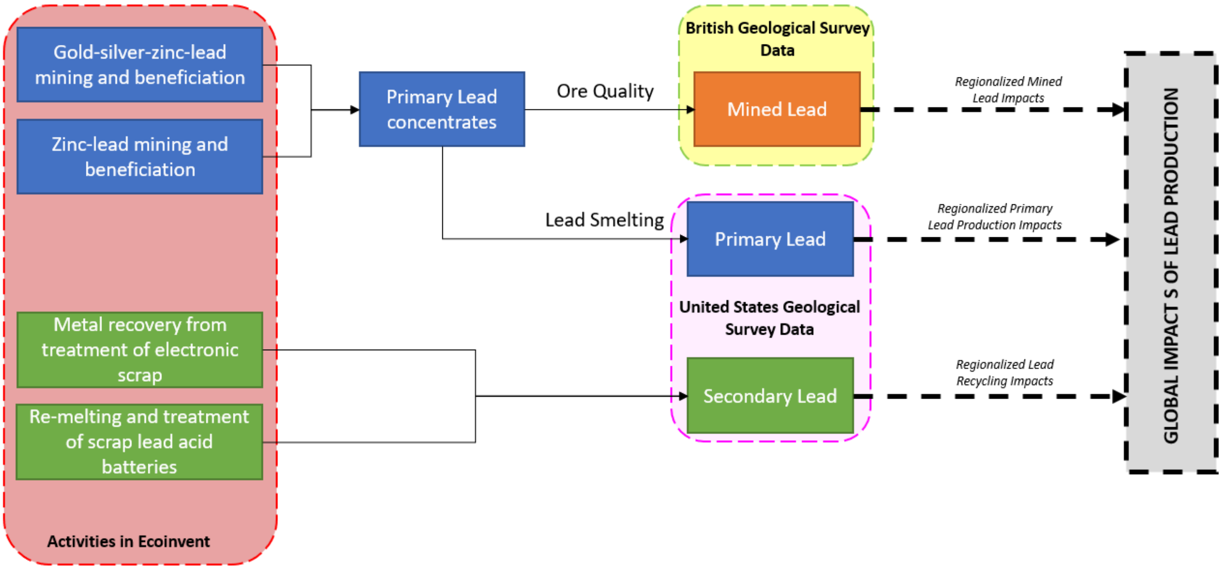

Figure A.13: Process overview linking the inventory datasets of ecoinvent 3.4 to lead extraction quantities in the BGS and USGS dataset

As illustrated in Figure A.13, primary lead concentrates need to be smelted and refined. These processes are modelled in the inventory activity “primary lead production (without mining)”. This new activity omits mining impacts by removal of primary lead concentrates intake from “Lead production from concentrate”. The impacts of lead mining are calculated separately with the existing ecoinvent v3.4 inventory “zinc-lead mine operation” that produces “lead concentrate”.

Table A.12: Modified and original inventory activities based on the ecoinvent v3.4 database along with the respective impact scores for the activities

Activity used	Product	Location	IPCC 2013 | climate change | GWP 100a [kg CO2eq./kg]	USEtox | ecotoxicity [CTU/kg]	USEtox | human toxicity | weighted carcinogenic and noncarcinogenic [DALY/kg]	UNEP air pollution | average approach, average estimate [DALY/kg]	Original Ecoinvent v3.4 Activity
Regionalized Lead Mining Impacts							
primary lead concentrate	Lead Concentrate (kg)	GLO	0.4100	45.0000	1.30E-05	7.90E-07	Market for lead concentrate
Regionalized Primary Lead Production Impacts							
primary lead production process (without mining)	Lead (kg)	GLO	1.431297	14.138388	0.000043	0.000003	Lead production from concentrate
Regionalized Secondary Lead Recycling Impacts							
secondary lead production from scrap	Lead (kg)	GLO	0.554243176	2.47637806	8.80529E-07	2.32026E-06	Market for lead

For lead recycling, the activity “secondary lead production from scrap” was created on the basis of “market for lead". All the primary sources as well as transportation activities were removed from the base activity and the remaining contributions from the secondary activities were normalized in order to create the new activity.

A.5.1.6 Zinc

Production data

Regionalized zinc extraction is documented by the BGS database as “Mined” and “Slab” zinc and it is based on registered trade of the respective commodities. As illustrated in Figure A.14, the productions of both these commodities have increased over time and show a strong correlation.

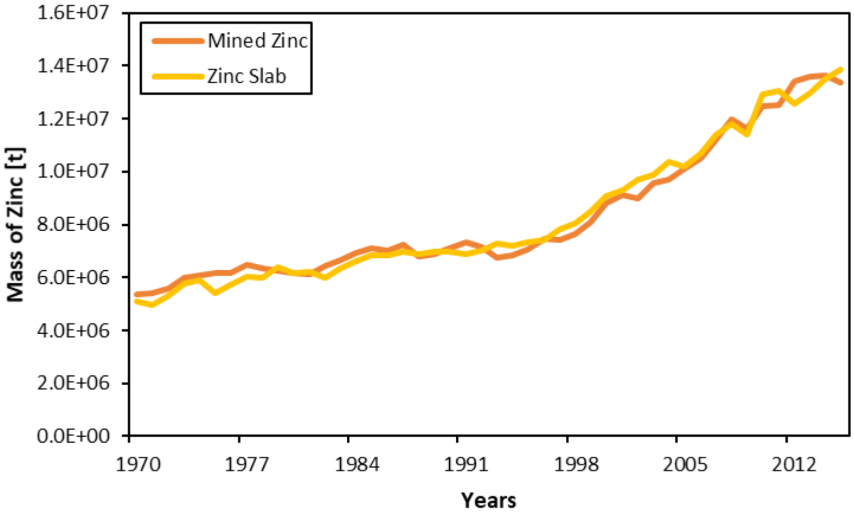

Figure A.14: Mined and Slab zinc production over the years based on BGS Data

In the BGS database, "slab" zinc refers to all the zinc metal traded after refining and the actual amount of zinc in the market. This not only accounts for primary metal, but also for the secondary material that is recycled and refined to the grade of the primary metal. The commodity of "mined" zinc, estimates the amount of zinc that should be in the market based on the amounts of ores extracted and their respective grades. Although the "mined" dataset represents the actual primary zinc metal produced, it does not account for the losses during the smelting and refining of the metal.

In contrast to the database from BGS, the USGS (Plachy 2002; Tolcin 2007, 2012, 2015) reports regionally distinguished primary and secondary zinc data. However, for some cases, this differentiation is not known (depending on how the data is reported for each country) and in such cases another category of "undifferentiated" zinc is listed as reported in Table A.13. For the BGS database, quantity of secondary zinc was estimated by subtracting the "mined" zinc from the "slab" zinc. This method does not account for smelting and refining inefficiencies, which is why some regional quantities of secondary zinc were found to be negative (implying more zinc is mined than produced). In Table A.13, the recycled content of zinc is much lower in USGS than the reported values from UNEP (United Nations Environment Programme (UNEP) 2011). The exemption of the tailings and process scrap recycling in the USGS and BGS databases, which results in lower amounts of accounted secondary zinc (BGS 2004), explains this result.

Table A.13: Data reported by the British and United States Geological Survey and the recycled zinc content from (United Nations Environment Programme (UNEP) 2011).

Data Source	Parameter	2000	2005	2010	2015
British Geological Survey (BGS)	Global Total Slab	9,070,084	10,185,357	12,909,859	13,856,552
	Total Mined	8,806,594	10,108,635	12,484,194	13,380,694
	Total Recycled	263,490	76,722	425,665	475,858
	Recycled Content	2.9%	0.8%	3.3%	3.4%
United States Geological Survey (USGS)	Global Total	9,190,000	10,400,000	12,800,000	13,900,000
	Total Primary	4,190,000	4,520,000	4,570,000	5,430,000
	Total Secondary	341,000	398,000	170,000	48,000
	Total Undifferentiated	4,660,000	5,510,000	8,100,000	8,370,000
	Known Recycled Content	3.7%	3.8%	1.3%	0.3%
United Nations Environment Program (UNEP)	Recycled Content	18-27%			

The BGS data was used to estimate the impacts of zinc mining, while the USGS data was used for calculating the impacts from primary production of zinc and recycling of zinc. This method ensures that the impacts are distributed to the correct regions, especially considering that the mining of ore and the smelting process may occur in different regions. In the case of "mined" zinc, the data from BGS was first converted into the corresponding mass of ore extracted based on respective ore grades.

Inventory Data

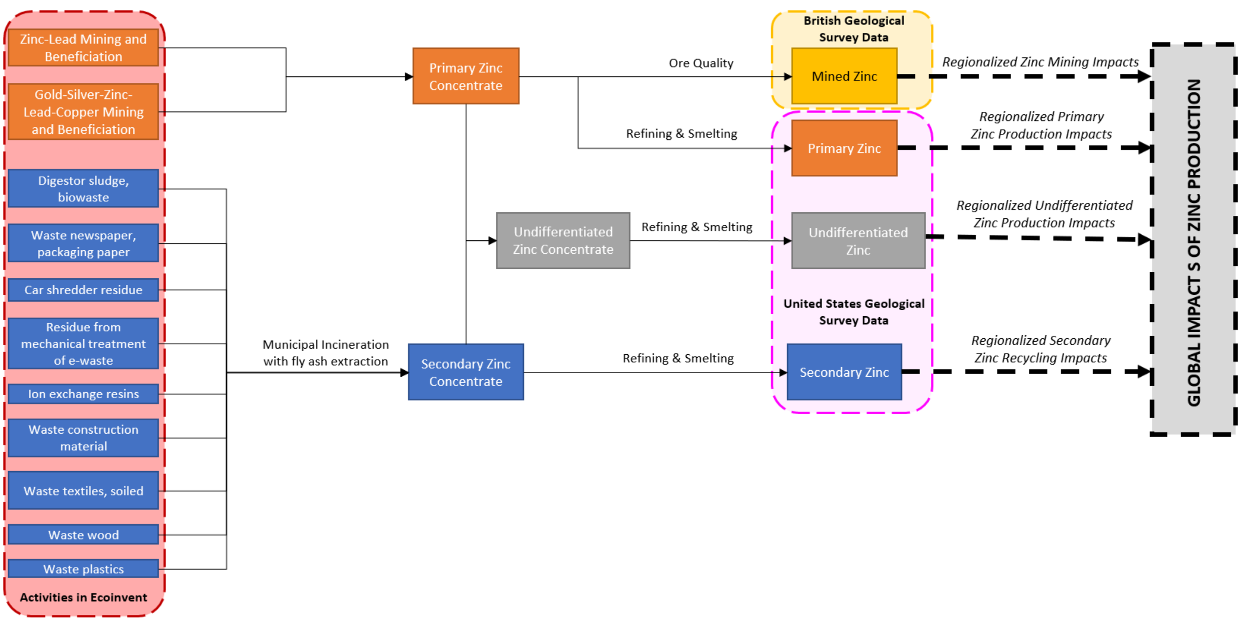

Figure A.15: Matching inventory datasets in ecoinvent v3.4 to the zinc mining and production data from BGS and USGS.

Impacts are calculated per processing step: mining of ores, refining of metal, and enrichment of zinc from primary, secondary, and undifferentiated sources (Figure A.15 and Table A.14). The first activity selected was the "market for zinc concentrate", which yields zinc concentrates from both primary and secondary sources and considers transportation as input activities. After removing the transportation component, two newer activities were created, namely "market for primary zinc concentrates" (all secondary sources removed) and "market for secondary zinc concentrates" (with all primary sources removed). The activity "market for primary zinc concentrates" was directly utilized to model zinc mining impacts.

Table A.14: Modified and original inventory datasets and impact scores from ecoinvent v3.4.

Activity used	Product	Location	IPCC 2013 | climate change | GWP 100a [kg CO2eq./kg]	USEtox | ecotoxicity [CTU/kg]	USEtox | human toxicity | weighted carcinogenic and noncarcinogenic [DALY/kg]	UNEP air pollution | average approach, average estimate [DALY/kg]	Original Ecoinvent v3.4 Activity
Regionalized Zinc Mining Impacts							
Market for Primary Zinc Concentrate	Zinc Concentrate (kg)	GLO	0.4952	45.7898	1.36E-05	8.69E-07	Market for Zinc concentrate
Regionalized Primary Zinc Production Impacts							
Primary Zinc Production Process (without mining)	Zinc (kg)	GLO	4.3074	49.4291	1.00E-04	6.85E-06	Primary Zinc Production from concentrate
Regionalized Secondary Zinc Recycling Impacts							
Secondary Zinc Production from secondary concentrate	Zinc (kg)	GLO	4.4477	49.7278	1.01E-04	6.98E-06	Primary Zinc Production from concentrate
Regionalized Undifferentiated Zinc Production Impacts							
Undifferentiated Zinc Production from undifferentiated concentrate	Zinc (kg)	GLO	4.3453	49.5098	1.00E-04	6.88E-06	Primary Zinc Production from concentrate

To assess the impacts of primary zinc production, the base activity "primary zinc production from concentrates" was modified into "primary zinc production process (without mining)". To do so, the activity that supplied the zinc concentrates (in this case "market for zinc concentrates") was removed from the original activity. In this way the new activity describes only the impacts from smelting and refining of zinc, while omitting the process of mining (which is separately analyzed).

In the case of secondary zinc recycling, as previously stated, "market for secondary zinc concentrates" was created by removing all primary concentrate activities and then further normalizing the remaining secondary concentrate contributions to obtain the impacts for a unit of mass. Since this activity yields secondary zinc concentrate, the original activity "primary zinc production from concentrate" was modified by changing the zinc concentrate source to "market for secondary zinc concentrates". This implies that beyond the sourcing process of zinc concentrates, the refining and smelting procedure follows, which is identical for primary and secondary zinc. This is important because the impact scores for the primary zinc production are comparable to the impacts from secondary zinc production.

For undifferentiated zinc production, a weighted average between the impact scores of primary (73%) and secondary (27%) production processes were taken based on the recycled content ratio from UNEP (United Nations Environment Programme (UNEP) 2011) in Table A.13. Considering that the impact scores of primary and secondary zinc production were found to be similar (due to the much larger impacts from the smelting and refining than mining) this simplification seemed reasonable.

A.5.1.7 Tin

Production data

Both BGS and USGS report global as well as country-specific tin production. The time series data from the BGS is shown in Figure A.15 and consistently indicates higher "smelter" tin amounts, due to the addition of secondary tin to the mined quantity.

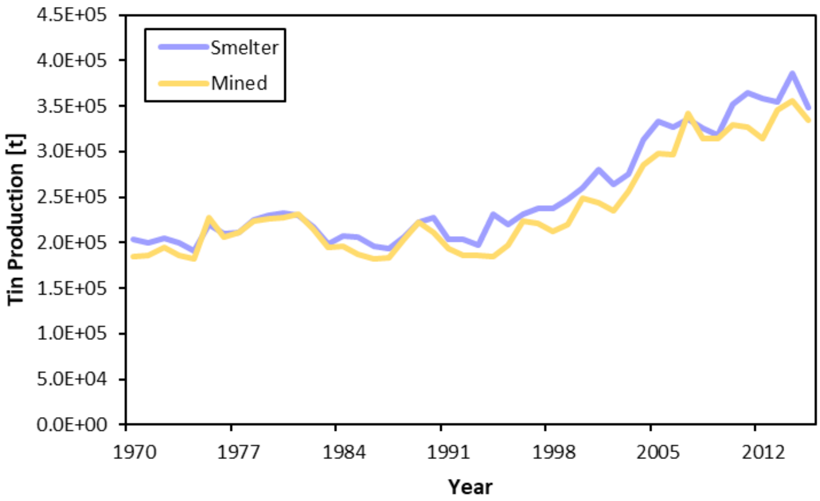

Figure A.16: Global smelter and mined tin production over the years based on the BGS database

Table A.15: Tin production data reported by the BGS and USGS and recycled content from UNEP (United Nations Environment Programme (UNEP) 2011)

Data Source	Parameter	2000	2005	2010	2015
British Geological Survey (BGS)	Global Total	260,669	333,600	351,848	347,928
	Total Mined	249,026	297,812	329,099	335,051
	Total Recycled	11,643	35,788	22,749	12,877
	Recycled Content	4.5%	10.7%	6.5%	3.7%
United States Geological Survey (USGS)	Global Total	288,000	344,000	335,000	349,000
	Total Mined	271,000	324,000	318,000	326,000
	Total Recycled	16,600	20,200	17,200	23,200
	Recycled Content	5.8%	5.9%	5.1%	6.6%
United Nations Environment Program (UNEP)	Recycled Content	22%			

The USGS database (Carlin 2002, 2007, 2012; Anderson 2015) also reports amounts of primary and secondary tin in the market and is found to be consistent with the BGS data with respect to the total global tin production (see Table A.15). For comparison purposes, the recycled tin amounts in the BGS dataset were estimated by subtracting “mine” from “smelter” tin.

The recycled contents based on the USGS and BGS databases are lower than the values reported by literature (United Nations Environment Programme (UNEP) 2011) (given in Table A.15). The reason for this is probably the exclusion of the tailing and process scrap quantity in the BGS and USGS databases, similar to the case of zinc (BGS 2004). Additionally, the values reported by IRP 2011 only consider a few industrial cases and may not be indicative for the entire industry.

Inventory data

The global tin production data used for impact assessment was based on the USGS database because it reports quantities of primary and secondary tin by country.

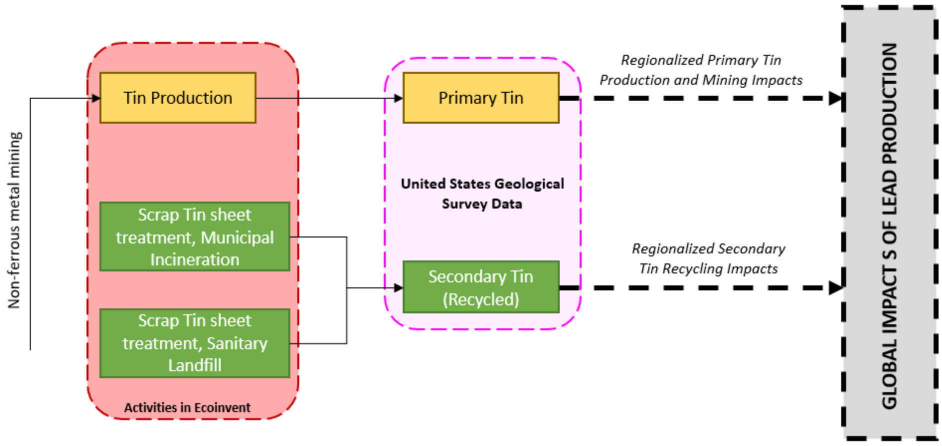

Figure A.17: Process description linking the activities in the ecoinvent 3.4 database with the tin extraction reported in the USGS database

Impacts from tin were calculated separately for primary tin production and tin recycling. Based on the ecoinvent 3.4 database, the original "tin production" activity was used to calculate the impacts of primary tin production. Mining could not be separated from this activity because it was implicitly modelled and no activity in the database yields "tin ore" or "tin concentrate" as a product. Hence, for this study, the impact scores of mined and refined tin have been calculated jointly as shown in Table A.16.

Table A.16: Original and modified inventory datasets and impact scores from ecoinvent v3.4.

Activity used	Product	Location	IPCC 2013 | climate change | GWP 100a [kg CO2eq./kg]	USEtox | ecotoxicity [CTU/kg]	USEtox | human toxicity | weighted carcinogenic and noncarcinogenic [DALY/kg]	UNEP air pollution | average approach, average estimate [DALY/kg]	Original Ecoinvent v3.4 Activity
Primary Tin Production							
Tin Production	Tin (kg)	RER	15.71415631	78.30413228	4.19477E-05	3.71133E-05	Tin Production
Tin Production	Tin (kg)	RoW	24.6615233	83.509643	4.49406E-05	6.16004E-05	Tin Production
Secondary Tin Production							
Recycling of Scrap Tin	Tin (kg)	GLO	0.013136376	16.60044816	9.86209E-07	4.72E-08	Market for Scrap Tin sheet

To derive the impact scores of the tin recycling process, the activity "market of scrap tin" was modified. The original activity had negative impacts because its reference product was "-1 kg of scrap tin sheet", implying that the activity takes 1 kg of scrap tin sheet for recycling. Therefore, the activity had to be modified so that, instead of accepting, it yielded 1 kg of tin; a conversion factor based on 90% efficiency of tin recovery (Meylan and Spoerri 2014) was applied to the activity. Additionally, all scrap tin sheet input activities within the market activity were altered to result in a total of 1 kg of tin. Finally, the product was changed to 1 kg of tin to create the activity "recycling of scrap tin"; this resulted in positive impact scores.

A.5.1.8 Gold

Production data

Data on primary gold production is available through the BGS World Mineral Statistics database, which reports official figures for the mass of gold recovered from gold ores and as a by-product of other metal primary processing. In addition to the values reported, a non-negligible portion of gold is extracted in the informal sector by small scale mining operations. The quantities extracted through these mining operations are not reported and the methods vary widely when compared to larger industrial scale mining. Therefore, the quantitative assessment of the environmental burdens associated to these activities requires an in-depth study to establish the life cycle inventories. This was outside of the scope and reach of this work, therefore artisanal informal mining activities were neglected here and only discussed in a qualitative manner in the main report.

Inventory data

Background inventory data from ecoinvent v3.4 is available on the mining and refining of gold. No sectorial subdivisions are present, but the whole value chain is modelled from mining of the ores to the final refined gold in one activity.
The datasets selected to assess the environmental impacts of gold are reported in Table A.17.

Table A.17: Inventory dataset for gold used in this study (from ecoinvent 3.4).

metal	**Ecoinvent v3.4 activity**	**Ecoinvent v3.4 product**	**Locations**
Gold	gold production	Gold	ZA, TZ, AU, US, CA, RoW

A.5.1.9 Silver

Production data

For calculating the impacts from primary silver production, “mined silver” data reported by BGS was considered; this data is based on the listings of stocks.
The World Silver Survey estimates the scrap or secondary silver production globally (O’Connell et al. 2018). This data was distributed regionally corresponding to the silver production of the respective region for assessing impacts of secondary silver recycling.

Inventory data

A new dataset “primary silver refining” was created from the existing ecoinvent 3.4 dataset “market for silver” by removing the transportation activities and the secondary silver sources; the contributions from the remaining primary sources were also normalized. The same principle was adopted for the creation of the “secondary silver extraction” activity; all the transportation activities and the primary silver sources were removed from “secondary silver extraction” prior to normalization of contribution from the secondary sources of silver.
Although literature (Graedel and Et.Al. 2011) suggests a significant contribution to silver recycling from municipal waste treatment (due to the traditional use of silver in mirrors), no relevant activity was available in the ecoinvent database. Therefore, the impacts from this activity were exempted during computation of secondary silver impacts.

A.5.1.10 Platinum

Production data

The BGS provided mining data for platinum group metals (PGM’s).

Inventory data

In ecoinvent 3.4, there are two inventory datasets regard the primary production of platinum. No sectorial subdivisions are present, but the whole value chain is modelled from mining of the ores to the final refined platinum. The original activities are listed in Table A.18.

Table A.18: Inventory datasets from ecoinvent v3.4 used in this study for platinum.

metal	Ecoinvent v3.4 activity	Ecoinvent v3.4 product	Locations
Platinum	platinum group metal mine operation, ore with high rhodium content	Platinum	ZA
Platinum	platinum group metal mine operation, ore with high palladium content	Platinum	RU

These two inventories differ as a consequence of the ore type (high rhodium or palladium content), but both have high impacts due to electricity consumption. To regionalize the inventories for the other platinum producing countries, both activities are used as prototypes, since the ore type specific to country is not known. The final impacts are calculated as the average between the two inventories with regionalized electricity mixes for each country.

A.5.1.11 Regionalisation of electricity mix

Some processes were characterised by a large share of environmental impacts being caused by electricity consumption. This is for instance the case for the production of aluminium from aluminium oxide and secondary steel via electric arc furnace (EAF). The electricity inputs of these inventories were regionalised on a country level, if national grid electricity mixes were available in ecoinvent v3.4.

The regionalization proceeds as follows:

1. One or more prototype activities are copied to the activity to serve as a model for regionalized activities
2. The technosphere exchange “market for electricity, medium voltage” is substituted with the activity of identical name, which corresponds to the location of the new regionalized activity, or with the corresponding market group activity “market group for electricity, medium voltage”, when available (for large countries, such as USA, CA, IN, CN).

The variation in the electricity mix across countries is responsible for a variation in the environmental impacts, due to different modes and shares of electricity generation. For example, in Figure A.18, the climate change impacts for the production of 1 kg of secondary steel and primary aluminium are shown to vary considerably after regionalization of the background electricity mix used. For other metals that do not use electricity as a main energy input (but fossil fuels), the influence of the electricity mix and the variation was much lower.

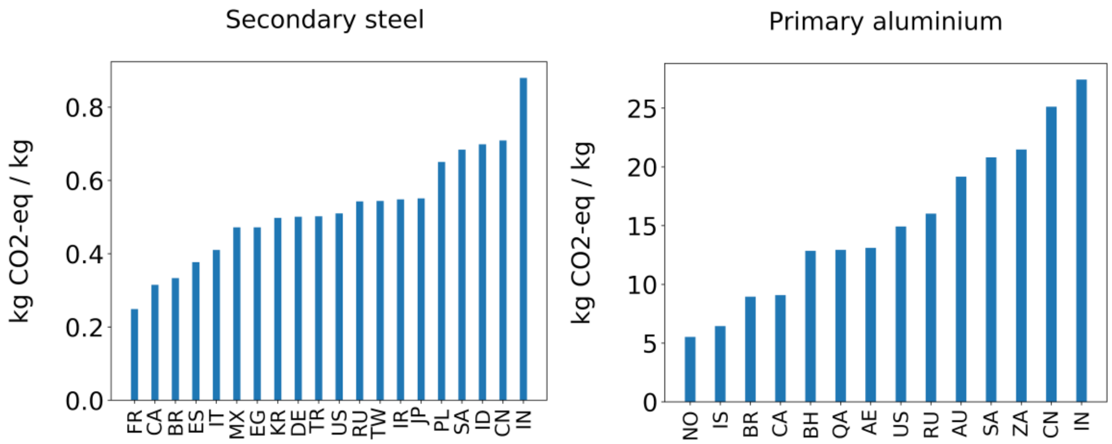

Figure A.18: Variation of climate change impacts of steel recycling (left) and aluminium primary production (right) for the top producing countries. Country-adapted cradle-to-gate impacts from ecoinvent v3.4. Note the difference in scales between the two graphs.

A.5.1.12 Impact assessment

The methods documented in Section A3 were used in the bottom-up analysis. Impacts of climate change and ecotoxicity were used as implemented in ecoinvent 3.4. For human-toxicity impacts, the results in terms of CTUh (Comparative Toxic Units) were taken from ecoinvent (for cancinogenic and non-cancinogenic effects) and then multiplied with the following damage factors to translate these effects into the unit of DALYs: 11.5 DALYs/CTUh for carcinogenic and 2.7 DALYs/CTUh for non-carcinogenic effects (Huijbregts et al. 2005).

For PM health impacts, characterization factors recommended in the “Global Guidance For Impact Assessment Indicators” (UNEP SETAC 2016) were applied to Ecoinvent emission flows. The characterization factors used correspond to those calculated taking an average slope between the theoretical minimum-risk level and the current level. The original characterization factors used are reported in Table A.19 and the matching to Ecoinvent emission flows in Table A.20:

Table A.19: UNEP-SETAC characterization factors for PM and precursor particle emissions

pollutant	location	height of release	kg intake/kg emitted	Average slope characterization factor [DALY/kg]	category
PM25	Outdoor urban	Ground level (RES)+	3.59E-05	4.87E-03	U1
PM25	Outdoor urban	Low stack	1.24E-05	1.68E-03	U2
PM25	Outdoor urban	High stack	9.53E-06	1.29E-03	U3
PM25	Outdoor urban	Very high stack	5.15E-06	6.97E-04	U4
PM25	Outdoor rural	Ground level	6.34E-06	2.32E-04	R1
PM25	Outdoor rural	Low stack	2.19E-06	8.00E-05	R2
PM25	Outdoor rural	High stack	1.68E-06	6.16E-05	R3
PM25	Outdoor rural	Very high stack	9.08E-07	3.32E-05	R4
NOx	Outdoor urban	–	2.00E-07	3.10E-05	U
NOx	Outdoor rural	–	1.70E-07	4.00E-06	R

SOx	Outdoor urban	–	9.90E-07	1.50E-04	U
SOx	Outdoor rural	–	7.90E-07	1.90E-05	R
NH3	Outdoor urban	–	1.70E-06	2.60E-04	U
NH3	Outdoor rural	–	1.70E-06	4.00E-05	R

Table A.20: Matching of Ecoinvent emissions and characterization factors for PM health impacts from (UNEP SETAC 2016)*. The notations in the second column refer to the categories shown in Table A.19.*

Ecoinvent emission flow	**average of UNEP-SETAC emission categories**	**Characterization factor [DALY/kg]**
'Particulates, < 2.5 um' (kilogram, None, ('air', 'low population density, long-term'))	R1,R2,R3,R4	1.02E-04
'Particulates, < 2.5 um' (kilogram, None, ('air',))	U1,U2,U3,U4,R1,R2,R3,R4	1.12E-03
'Particulates, < 2.5 um' (kilogram, None, ('air', 'urban air close to ground'))	U1	4.87E-03
'Particulates, < 2.5 um' (kilogram, None, ('air', 'non-urban air or from high stacks'))	R1,U3	7.61E-04
'Particulates, < 2.5 um' (kilogram, None, ('air', 'lower stratosphere + upper troposphere'))	R4	3.32E-05
'Sulfur dioxide' (kilogram, None, ('air', 'lower stratosphere + upper troposphere'))	R	1.90E-05
'Sulfur dioxide' (kilogram, None, ('air', 'low population density, long-term'))	R	1.90E-05
'Sulfur dioxide' (kilogram, None, ('air', 'non-urban air or from high stacks'))	R	1.90E-05
'Sulfur dioxide' (kilogram, None, ('air', 'urban air close to ground'))	U	1.50E-04
'Sulfur oxides' (kilogram, None, ('air',))	R,U	8.45E-05
'Sulfur dioxide' (kilogram, None, ('air',))	R,U	8.45E-05
'Nitrogen oxides' (kilogram, None, ('air', 'lower stratosphere + upper troposphere'))	R	4.00E-06
'Nitrogen oxides' (kilogram, None, ('air', 'non-urban air or from high stacks'))	R	4.00E-06
'Nitrogen oxides' (kilogram, None, ('air', 'low population density, long-term'))	R	4.00E-06
'Nitrogen oxides' (kilogram, None, ('air',))	U,R	1.75E-05
'Nitrogen oxides' (kilogram, None, ('air', 'urban air close to ground'))	U	3.10E-05
'Nitrogen oxides' (kilogram, None, ('air', 'lower stratosphere + upper troposphere'))	R	4.00E-06
'Nitrogen oxides' (kilogram, None, ('air', 'non-urban air or from high stacks'))	R	4.00E-06
'Nitrogen oxides' (kilogram, None, ('air', 'low population density, long-term'))	R	4.00E-06
'Nitrogen oxides' (kilogram, None, ('air',))	U,R	1.75E-05

'Nitrogen oxides' (kilogram, None, ('air', 'urban air close to ground'))	U	3.10E-05
'Ammonia' (kilogram, None, ('air', 'non-urban air or from high stacks'))	R	4.00E-05
'Ammonia' (kilogram, None, ('air', 'low population density, long-term'))	R	4.00E-05
'Ammonia' (kilogram, None, ('air', 'lower stratosphere + upper troposphere'))	R	4.00E-05
'Ammonia' (kilogram, None, ('air',))	U,R	1.50E-04
'Ammonia' (kilogram, None, ('air', 'urban air close to ground'))	U	2.60E-04

A.5.1.13 Bottom-up and top-down approach: results comparison

The climate change impacts of the main metal categories calculated with the bottom-up and top-down approaches were compared for the most relevant metal categories. The comparison is based on the data for the year 2010, as Exiobase 3 relies on historical data with the final reporting year of 2011.

Table A.21: Comparison of climate change impact scores for metals following the top-down and the bottom-up approach.

	Exiobase category	exiobase kg CO2eq	Ecoinvent category	ecoinvent kg CO2eq	Error % (ecoinvent – exiobase)/ecoinvent
Precious metals	Mining of precious metal ores and concentrates	5.77E+10	- (mining together with production)		
	Precious metals production	3.53E+10	production of gold	4.17E+10	
			production of platinum	5.43E+09	
			production of silver	8.83E+09	
	subtotal precious metals	**9.31E+10**		**5.60E+10**	**-66.20%**
Aluminium	Mining of aluminium ores and concentrates	5.80E+09	mining (up to alumina production)	1.09E+11	
	Aluminium production	4.17E+11	aluminium smelting	7.68E+11	
	Re-processing of secondary aluminium into new aluminium	8.58E+10	secondary aluminium	1.99E+10	
	subtotal aluminium	**5.08E+11**		**8.97E+11**	**43.34%**
Iron and Steel	Mining of iron ores	9.23E+09	iron mining	2.25E+11	
	Manufacture of basic iron and steel and of ferro-alloys and first products thereof	2.18E+12	pig iron production (without mining)	1.73E+12	
			steel production, converter, low-alloyed (cutoff)	8.19E+11	
	Re-processing of secondary steel into new steel	5.35E+11	steel production, electric, low-alloyed	2.12E+11	
	subtotal iron & steel	**2.73E+12**		**2.99E+12**	**8.69%**
Lead, Zinc, tin	Mining of lead, zinc and tin ores and concentrates	1.25E+10	mining of lead	3.29E+09	
	Lead, zinc and tin production	2.16E+10	lead production (excl. mining)	1.21E+10	
			zinc production (incl. Mining)	5.49E+10	
			tin production (incl. Mining)	7.85E+09	
	Re-processing of secondary lead into new lead	4.20E+09	lead secondary production	5.76E+09	
	subtotal lead, zinc, tin	**3.83E+10**		**8.39E+10**	**54.34%**
Copper	Mining of copper ores and concentrates	1.45E+11	copper mining	6.47E+10	
	Copper production	9.70E+10	primary copper	3.39E+10	
	Re-processing of secondary copper into new copper	5.40E+09	secondary copper	5.08E+09	
	subtotal copper	**2.48E+11**		**1.04E+11**	**-138.80%**
	TOTAL	**3.62E+12**		**4.13E+12**	**12.43%**

For the iron and steel sector, the difference between the global CO_2-equivalent impacts calculated is small, with Exiobase underestimating impacts by 8.7% compared to ecoinvent. The ecoinvent value (adapted with efficiency gains over time, as documented in Table A.5) of around 3 million tonnes of CO_2-eq is consistent with data from the World Steel Association and the International Energy Agency (Worldsteel Association 2018).

For other metals, such as aluminium and zinc-lead-tin, the impacts calculated with ecoinvent are higher (~50% higher) than those calculated with Exiobase, while for copper the reverse is the case. Also, precious metal results are higher for Exiobase, which may be explained by the fact that the list of precious metals considered in ecoinvent is not complete. Concerning system boundaries, the data from Exiobase shown above does not include metals that were used in the production of other resource types (e.g. fossil fuels), due to the correction of double counting (see Section A.3.3). This is part of the reason why the total climate score tends to be smaller for metals in Exiobase than in ecoinvent. Another reason may be that the ecoinvent data is partially outdated and may have missed industrial efficiency improvements. Exiobase, on the other hand, lacks the level of detail that ecoinvent provides, and may lack accuracy. The overall difference of 12% between the total metals impacts calculated with the top-down and bottom-up approaches are reasonable, considering the notable differences in modelling of both approaches (in particular the correction of double counting that we performed for the Exiobase analysis, but not the ecoinvent analysis) and the differences in system boundaries.

A.5.2 Non-metallic minerals

A.5.2.1 Method for the overall analysis of non-metallic minerals

The data of amounts of non-metallic mineral extraction was taken from the global IRP MFA database and then coupled with the mass-specific ecoinvent data. For the processing, cement, fertilizer production from minerals, clay brick and clay plaster production were considered. Since mass data of these materials were not available from the IRP MFA database and could not be extrapolated from the extraction data, additional data sources were used. For cement production, time series production data (amounts) and efficiency increases in cement production data were taken from (WBSC 2018) and then coupled with the adapted ecoinvent dataset “cement production, Portland, RoW”. Data for production amounts of various types of fertilizers were taken from FAOSTAT and for the year 2015 from (FAO 2017). Global production amounts for (clay) bricks were taken from ecoinvent v3.4. Processing of minerals to glass and ceramics was neglected, as production amounts were not available.

Table A.22: Matching of data between the IRP MFA database and ecoinvent v3.4 environmental background data

Name in MFA database	Dataset name ecoinvent v3.4 for extraction process
Chalk	calcium carbonate production, precipitated
Chemical minerals nec	market for kaolin, GLO
Dolomite	market for dolomite, GLO
Fertilizer minerals nec	market for phosphate rock, as P2O5, beneficiated, dry, GLO
Gypsum	market for gypsum, mineral, GLO
Industrial minerals nec	market for kaolin, GLO
Industrial sand and gravel	gravel and sand quarry operation, RoW
Limestone	market for limestone, crushed, washed, RoW
Ornamental or building stone	market for limestone, crushed, washed, RoW

Other non-metallic minerals nec	market for kaolin, GLO
Salt	sodium chloride production, powder, RoW
Sand gravel and crushed rock for construction	market for rock crushing, GLO
Specialty clays	clay pit operation, RoW
Structural clays	clay pit operation, RoW

The impact assessment followed the same procedure as documented in Section A 5.1.12.

A.5.2.2 Additional results for cement

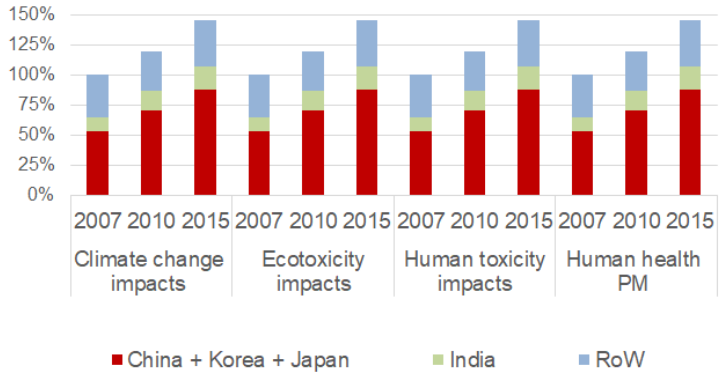

Figure A.19: Regional split of impacts for global cement production (values from 2007 indexed to 1). The graph shows the Top cement-producing regions in terms of impacts along with the temporal evolution. Data from WBSCD and ecoinvent 3.4.

A.5.2.3 Method and additional results for phosphorus fertilizer (box)

Phosphorus fertilizer mix

The section about fertilizer minerals is based on ecoinvent v3.3 database (Ecoinvent center 2017). Figure A.20 shows the system boundaries of the analysis. All direct emissions regarding fertilizer application are considered (short- and long-term), however, indirect emissions and impacts (e.g. through machinery) are not accounted for. In the course of an in-depth analysis, the processes of phosphate rock mining and beneficiation as well as phosphoric acid production as major components of any phosphorus fertilizer were extensively adapted and improved. The most important changes are listed in the Table A.23 below.

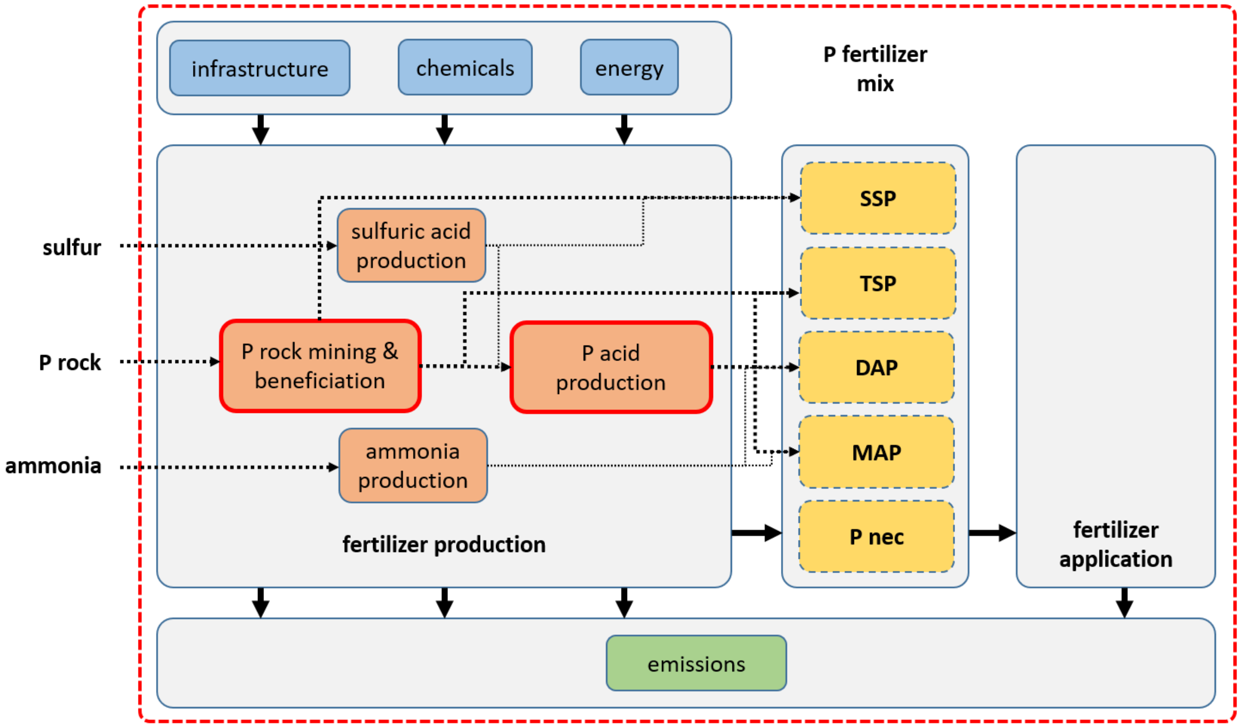

Figure A.20: System boundaries of the cradle-to-grave analysis of phosphorus fertilizer. The red framed processes "P rock mining & beneficiation" as well as "P acid production" were extensively revised in an in-depth analysis (see also Table A.23). Infrastructure includes both mining and processing infrastructure, chemicals include all chemicals needed apart from the displayed chemicals "sulfuric acid" and "ammonia", energy includes fossil fuels and electricity for mining, processing and transport. Emissions include emissions to all environmental compartments during mining, processing and fertilizer application.

Table A.23: Major changes to "P rock" and "P acid" ecoinvent v3.3 datasets.

Original v3.3 dataset		**Revised dataset**
location	MA, US	MA, US, IL
P rock beneficiation	MA: dry, US: flotation	MA, US: flotation; IL: dry
Long-term emissions	Not considered	considered
Phosphogypsum	-	Corrected transfer coefficients
Main data sources for -chemical composition P rock	Becker 1989	Gilmour 2013, EC 2007
-transfer coefficients	Becker 1989	Gilmour 2013, EC 2007
-chemicals use	Becker 1989	Gilmour 2013

The phosphorus (P) fertilizer mix consists of the five fertilizer types diammonium phosphate (DAP), monoammonium phosphate (MAP), triple superphosphate (TSP), single superphosphate (SSP) as well as P fertilizer not else covered (P nec). Corresponding ecoinvent v3.3 processes are listed in Table A.24.

Table A.24: Original ecoinvent v3.3 datasets used for fertilizer production.

DAP	Diammonium phosphate production	Phosphate fertiliser, as P2O5	RER
MAP	Monoammonium phosphate production	Phosphate fertiliser, as P2O5	RER
TSP	Triple superphosphate production	Phosphate fertiliser, as P2O5	RER
SSP	Single superphosphate production	Phosphate fertiliser, as P2O5	RER
P nec	P nec (*P fertilizer not else covered*) is not based on an ecoinvent process, but was assumed as mean of all four other P fertilizer types		

Impact assessment methods

As presented in section A.2, the best-practice guidelines of the UNEP-SETAC Life Cycle Initiative for use in Life Cycle Assessment were followed (UNEP SETAC 2016). The analysis includes climate change, eco- and human toxicity, as well as particulate matter formation. Additionally, eutrophication is assessed with the method from LC-impact (Azevedo et al. 2014).

Global impact analysis

Figure A.21 shows the amounts of the different phosphorus fertilizer types globally applied for the years 2000, 2005, 2010 and 2015. Data are based on FAO and World Bank (FAO 2015; FAO and World Bank 2018). Data gaps were overcome by taking values from neighboring years. By combining data of globally applied fertilizer amounts and environmental impact of fertilizer production, the global impact of phosphorus fertilizer production and application was calculated (see Figure A.22).

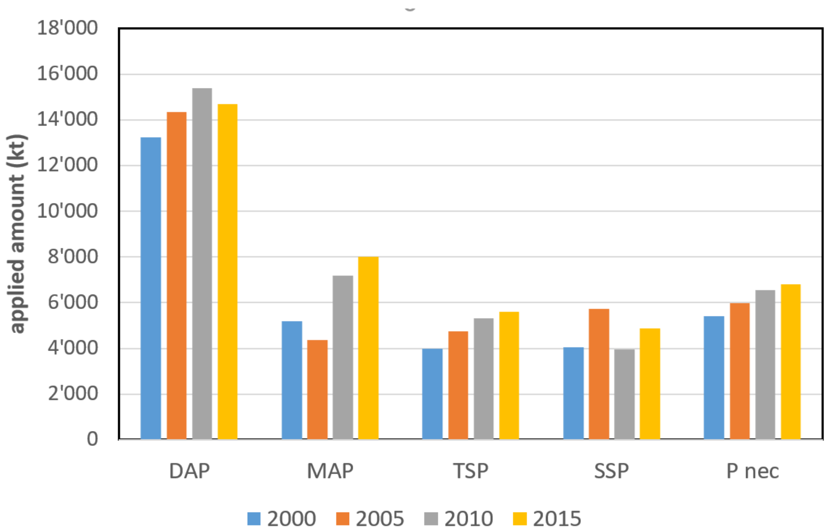

Figure A.21: Globally applied fertilizer amounts in kilo tons, divided by fertilizer type. Based on data from FAO and World Bank (FAO 2015; FAO and World Bank 2018).

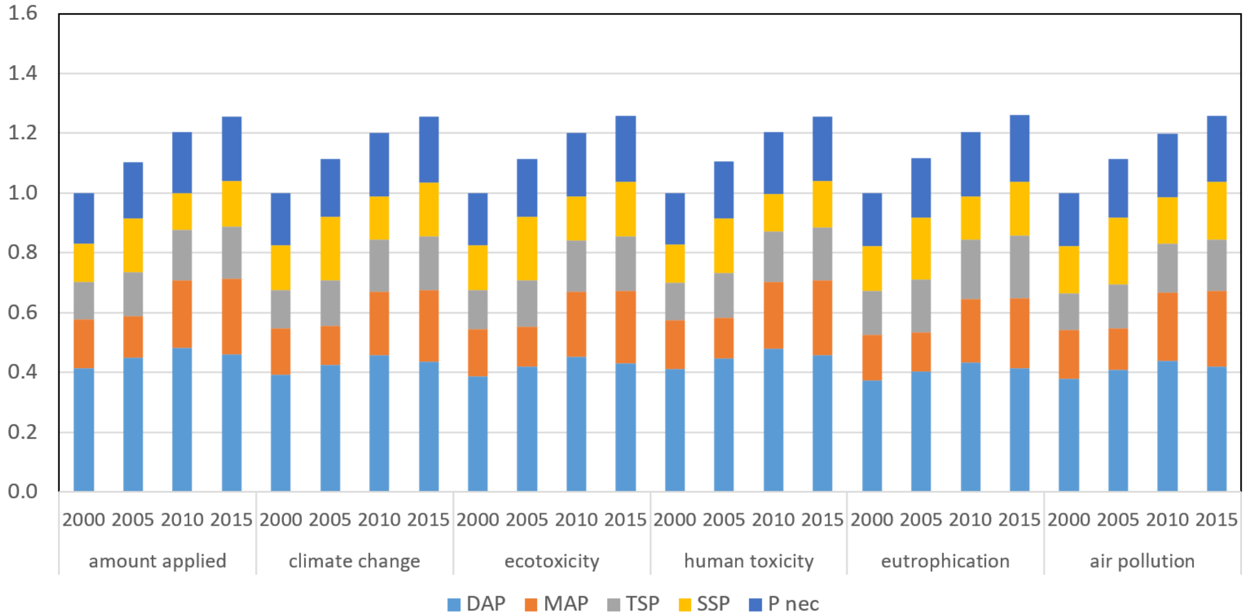

Figure A.22: Environmental impact of phosphate fertilizer, divided by fertilizer type and impact assessment method. Based on data from FAO and World Bank (FAO 2015; FAO and World Bank 2018)*. Indexed to value of the year 2000.*

Phosphorus fertilizer use - regionalized assessment

In the country-scale assessment of species loss due to fertilizer application, the global endpoint characterization factors for phosphorus emissions to soil (as CF_{soil} in Eq. 8) according to LC-impact (Azevedo et al. 2014) were used and multiplied with country-based data on applied fertilizer amounts (FAO and World Bank 2018) (see Figure A.23). The potentially disappeared fraction of species (PDF) for each country was calculated with the following formula:

$$A * r_A * CF_{soil} \quad \text{(eq. 8)}$$

Where:
A = area of arable land in [ha] (FAO and World Bank 2018)

r_A = average fertilizer application rate in [kg P2O5/ha*yr] (FAO and World Bank 2018)
CF_{soil} = global endpoint characterization factor for P emissions to soil in [PDF*yr/kg P]
The conversion factor from P2O5 to P is 2.29. The first part of the formula ($A*r_A$) can be considered as the amount of P fertilizer applied per year for each country.

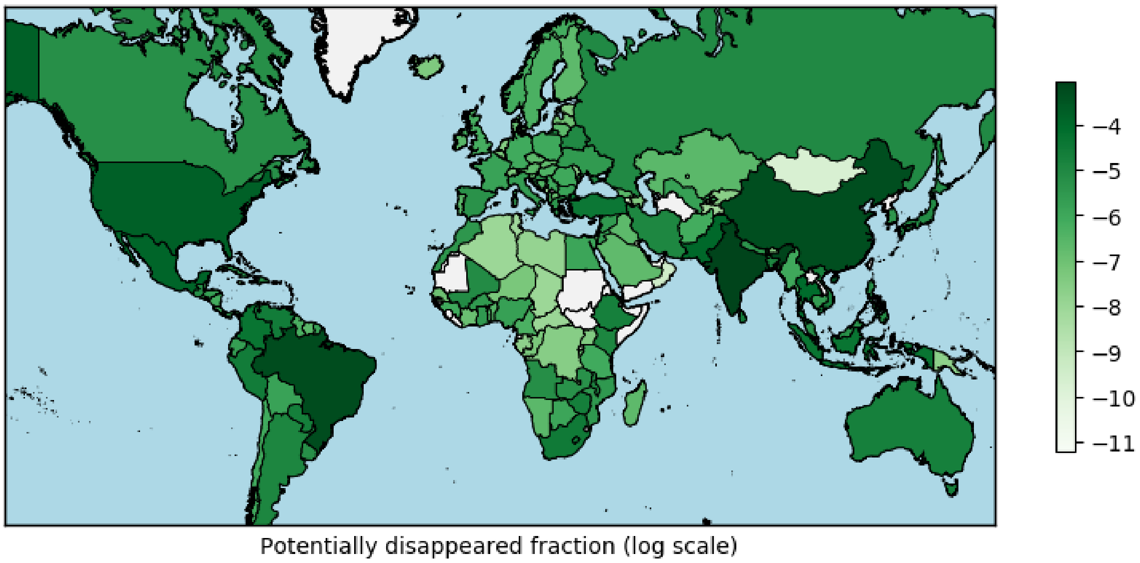

Figure A.23: Eutrophication impacts on aquatic freshwater ecosystems due to phosphate fertilizer application. The potentially disappeared fraction of aquatic species is calculated per country in total. The values are in log-scale.

A.5.3 Fossil resources

A.5.3.1 Life cycle inventory analysis of coal (box)

The life cycle inventory of airborne $PM_{2.5}$, SO_2 and NO_x emissions per coal power plant was taken from Oberschelp et al. (Oberschelp et al. 2019) for the year 2012. This included mining emissions, transport emissions and emissions from coal combustion at the plants.

Impacts of co-generation power plants were allocated to coal electricity and useful heat output based on the exergy content of these two outputs (as described in Heck (Heck 2007)) and total reported electricity-to-heat-ratios of the coal co-generation power plants per country in 2012 (IEA 2018). In case of data gaps, the global average electricity-to-heat-ratio was used (with the exception of China, where, due to its relevance for total impacts, the plant-level data used in Oberschelp at al. (Oberschelp et al. 2019) was extrapolated to all Chinese coal power plants). The calculated exergy factor for heat was 0.17 (based on an assumed ambient temperature of 20°C and a useful heat temperature of 80°C) and it was 1 for electricity. Resulting national allocation factors for coal power generation other than 1 are shown in Table A.25.

Table A.25. Electricity health impact allocation factors for coal power generation per country in 2012 (where deviating from 1).

Country	Allocation factor
Austria	0.787
Bosnia and Herzegovina	0.909
Bulgaria	0.909
China	0.994
Czech Republic	0.876
Denmark	0.897
Finland	0.861
Germany	0.888
Greece	0.999
Hungary	0.984
Indonesia	0.995
India	0.998
Italy	0.998
Japan	0.990
Kyrgyzstan	0.573
Kazakhstan	0.825
Moldova	0.868
Mongolia	0.998
Mauritius	0.939
Norway	0.875
Philippines	0.997
Poland	0.967
Réunion	0.955
Romania	0.950
Russia	0.906
Sweden	0.654
Slovenia	0.994

Slovakia	0.967
South Africa	0.999
Thailand	0.983
Turkey	0.999
Ukraine	0.931
United States	0.999
Vietnam	0.999

Statements on coal trade via ship were based on the time series coal trade data obtained from (United Nations 2018). Trade data for the years 2000, 2005, 2010 and 2015 are presented in Figure A.24. Out of these amounts, China imports at least 53.9% via ship while the US exports at least 72.9% via ship. That can be inferred from the country-level trade data since the bulk transport to and from some trading partner countries (e.g. Australia, Indonesia, Japan) is only possible in an economic way via ship.

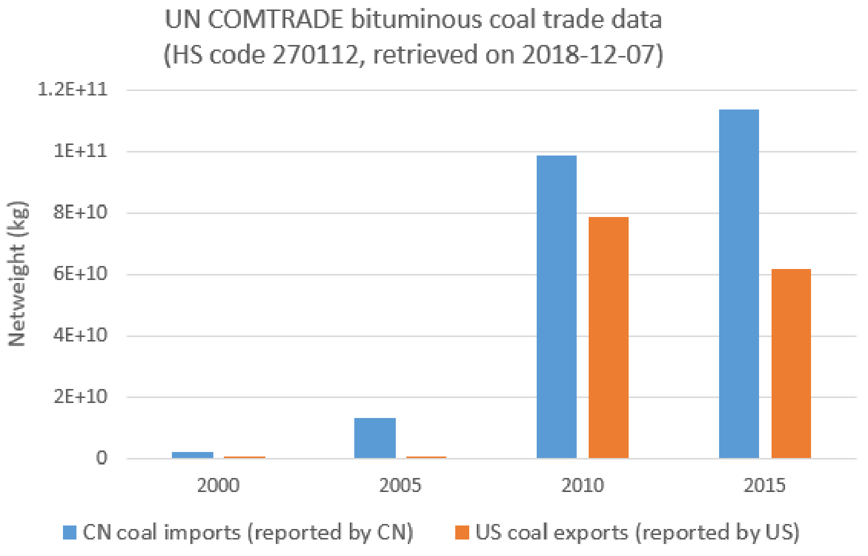

Figure A.24. Coal trade data for different years from (United Nations 2018).

A.5.3.2 Life Cycle Impact Assessment of coal (box)

Life cycle impact assessment is based on the LC-Impact v0.5 methodology (Verones et al. 2016). This methodology is used because (1) high-resolution spatial emission inventory data is available, (2) LC-Impact offers spatially resolved PM impact assessment, and (3) lack of spatial differentiation has been identified as the key weakness in the recommended interim PM impact assessment methodology of UNEP (UNEP SETAC 2016).

Country-level characterization factors have been applied to all emissions within national boundaries, while for emissions in international waters, the global average characterization factors have been applied. The nationality of power plants and mines is obtained from the raw data used in Oberschelp at al. (Oberschelp et al. 2019). Starting coordinates of transport pathway segments have been matched to the country boundaries from Natural Earth (Natural Earth 2018), which have then been matched to the national LC-Impact characterization factors.

In case of missing matches with specific countries, end coordinates of transport pathway segments have been matched instead, and any remaining missing matches used the global average characterization factors.

A.5.4 Biomass

The direct GHG impact of biomass extraction have been calculated based on the satellite matrix from Exiobase 3.4 and the characterization factors from IPCC (IPCC 2013). These emissions do not include land use change related effects.

A.5.5 Water resources

Water resources are principally non-tradeable and thus need to be assessed with a spatially and temporally explicit impact assessment model in order to derive meaningful results (ISO 14046 2014; Pfister et al. 2017). In order to assess a water scarcity footprint based on ISO 14046, water consumption needs to be weighted using a scarcity measure that relates water use to availability (similar to the Sustainable Development Goal 6.4.2 indicator).
We use crop water consumption data modeled on watershed and monthly level (Pfister and Bayer 2014)(Stoessel et al. 2012) to quantify water consumption amounts and locations in agriculture, which is the dominating sector for water consumption. Then we apply the UNEP recommended AWARE characterization factors to derive water scarcity impacts on watershed level with monthly resolution. In a next step, we aggregate the results on sector and region level as done in previous research for Exiobase v2 (Lutter et al. 2016; Pfister and Lutter 2016). For other water uses, we apply the country average annual characterization factors of the AWARE method (Pfister et al. 2017) for non-agricultural water use. This allows to perform also a top down analysis as described above (section A.4).

A.5.6 Land resources

A.5.6.1 Method

Land resources are mainly used through land occupation and corresponding activities. We use the land use data provided in Chapter 2 of the main report and classify the land use / land cover classes into the classes needed for the biodiversity impact assessment of the UNEP recommended characterization factors, as specified in Table A.26. The factors are available on an ecoregion level (~800 units globally) and used in this resolution to quantify global potential species loss due to land occupation.
For the trade analysis we apply the same method as for water resources (section A.5.5): For agriculture, crop production data for 160 crops (land use and location) from Pfister et al. (Pfister et al. 2011) (approximately 10 km x 10 km spatial resolution), representing the year 2000 are multiplied with respective characterization factors for land use (on ecoregion level, (Chaudhary et al. 2015), as above). Classification into permanent and annual cropland for each crop is based on the following FAO classification (FAO 2010).
In a second step, the total species loss per crop and location are aggregated on the sector and regions combination of Exiobase, based on Lutter et al. (Lutter et al. 2016). The resulting total species loss was divided by the respective Exiobase land use extensions to derive production weighted characterization factors for each sector and region combination (which accounts for

the spatial distribution and production volume of different crops in each sector-region). This is required to analyze the time series. For the remaining land use types, characterization factors as presented in Table A.26 are used.

Table A.26: Match of land use type of characterization factors (characterization factors) and land use classes from Chapter 2.

LU Type (CF)	Classes land use (chapter 2)
Urban	190
Intensive forestry	420
Extensive Forestry	440
Permanent crop	1000, 1014, 1018
Annual crop	1002, 1003, 1007, 1009, 1011, 1012, 1013, 1016, 1020
Pasture	2001

Table A.27: Match of land use extensions of Exiobase 3.4 and of characterization factors (CF)

Exiobase land use	CF (Chaudhary et al 2016)
Cropland - Cereal grains nec	calculated based on crop model
Cropland - Crops nec	calculated based on crop model
Cropland - Fodder crops-Cattle	calculated based on crop model
Cropland - Fodder crops-Meat animals nec	calculated based on crop model
Cropland - Fodder crops-Pigs	calculated based on crop model
Cropland - Fodder crops-Poultry	calculated based on crop model
Cropland - Fodder crops-Raw milk	calculated based on crop model
Cropland - Oil seeds	calculated based on crop model
Cropland - Paddy rice	calculated based on crop model
Cropland - Plant-based fibers	calculated based on crop model
Cropland - Sugar cane, sugar beet	calculated based on crop model
Cropland - Vegetables, fruit, nuts	calculated based on crop model
Cropland - Wheat	calculated based on crop model
Forest area - Forestry	Intensive forests
Forest area - Marginal use	Extensive forests
Infrastructure land	Urban
Other land Use: Total	Average of all CFs
Permanent pastures - Grazing-Cattle	Pasture
Permanent pastures - Grazing-Meat animals nec	Pasture
Permanent pastures - Grazing-Raw milk	Pasture

A.5.6.3 Additional results

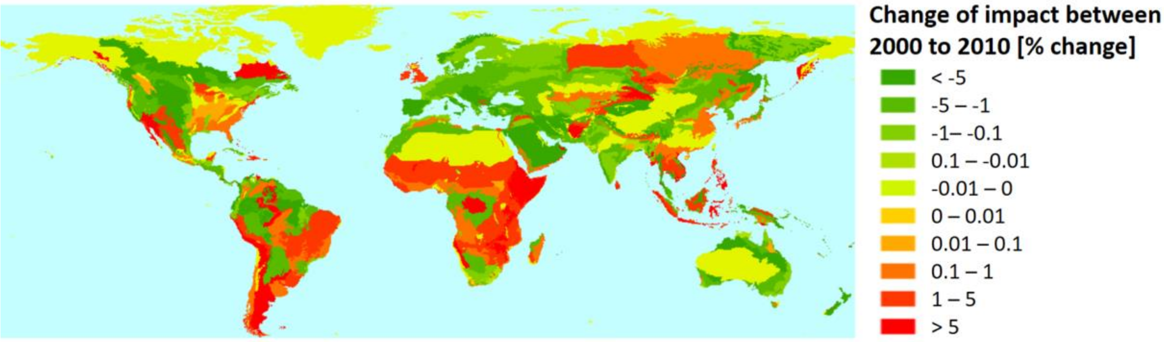

Figure A.25: Change in land use biodiversity impacts between 2000 and 2010 per ecoregion. Negative numbers correspond to potential biodiversity recovery, positive numbers to biodiversity loss. The loss is measured as % global species loss and not as % change between 2000 and 2010. Land use data from Chapter 2 combined with biodiversity assessment (UNEP SETAC 2016).

A.6 Socio-economic assessment

A.6.1 HDI and GDP assessment (method and additional results)

The goal of a sustainable economy is to achieve long-term human wellbeing. One purely economic indicator to measure wellbeing is gross domestic product (GDP), however other indicators, such as the human development indicator (HDI), combine several aspects like GDP, health and education. In order to relate resource use and wellbeing, we analyzed the environmental impacts of water consumption and land use with HDI and GDP on a regionalized level to test whether regions with high impacts also experience levels of high wellbeing.

We use the data from the environmental assessment (described in section A.5.5 and A.5.6) aggregated on state-level regions (Admin 1 level covering 2885 units based on natural earth data (Natural Earth 2018)) and compare it with spatially explicit data for GDP/HDI representing 2011 prices from Kummu et al. (Kummu, Taka, and Guillaume 2018).

We analyzed each region and grouped it by HDI. Table A.28 shows the biodiversity loss, GDP, GDP share and species loss (PDF) per GDP for each HDI class. The analysis shows that in high spatial resolution (i.e. taking into account variabilities and inequalities within countries), the population in areas with HDI>0.8 has more than 50% of global GDP but only ~10% of biodiversity loss. The biodiversity loss per GDP generated generally increases with decreasing HDI, mainly due to low GDP in low HDI regions.

Table A.28: Regional analysis of HDI, GDP and biodiversity loss due to land use (BD Loss land use). PDF indicates potentially disappeared fractions, or species loss.

HDI	BD Loss Land use		HDI	GDP			PDF/GDP
>0.9	0.70%		>0.9	2.03E+13	26%		0.35
0.8-0.9	0.59%		0.8-0.9	1.95E+13	25%		0.30
0.7-0.8	3.74%		0.7-0.8	2.13E+13	27%		1.76
0.6-0.7	3.44%		0.6-0.7	1.21E+13	15%		2.83
0.5-0.6	1.36%		0.5-0.6	2.88E+12	4%		4.73
0.4-0.5	1.16%		0.4-0.5	2.72E+12	3%		4.28
<0.4	0.38%		<0.4	1.42E+11	0%		26.60

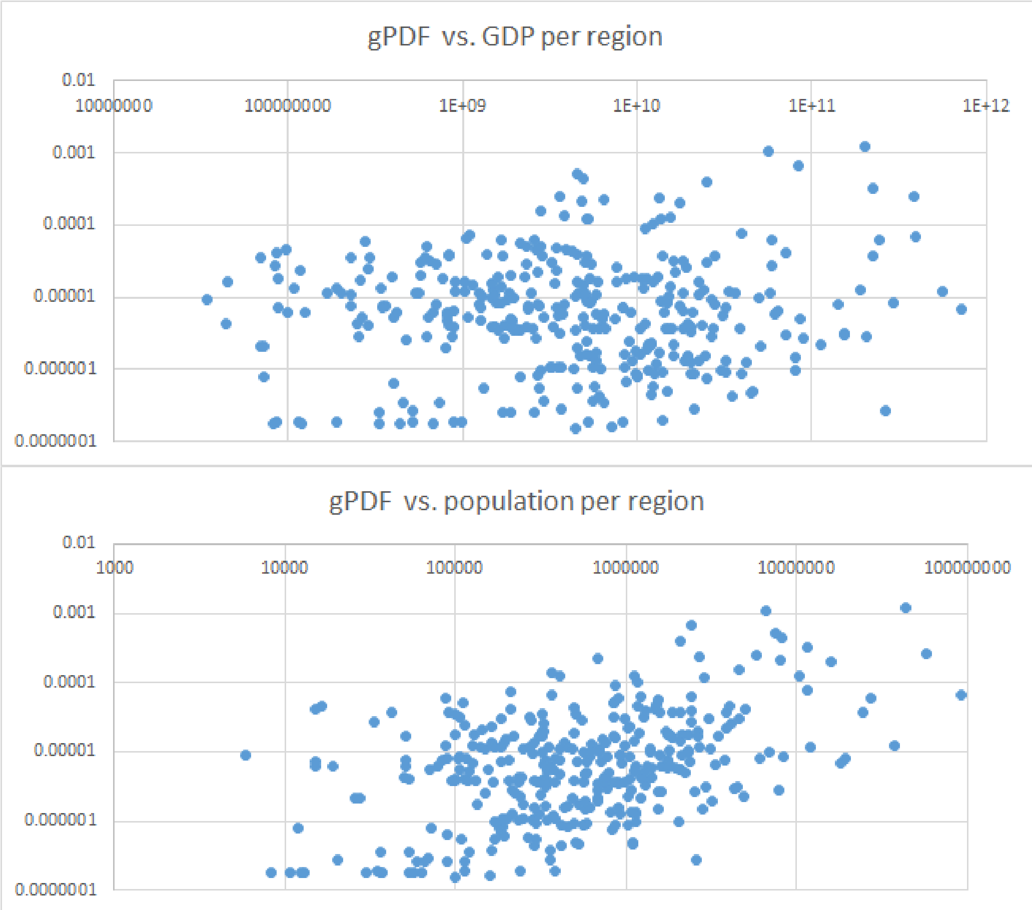

Figure A.26: Log-scale scatter plots of biodiversity loss due to land use (y axis, gPDF) and GDP (top graph, x axis)/ population (bottom graph, x axis).

A.6.2 Social LCA and assessment of employment and added value (method and additional results)

In order to account for socio-economic aspects related to resource production, we apply the methodology by Zimdars et al. (Zimdars, Haas, and Pfister 2018), which relates work-related and other social risks per sector and country as specified in the social hotspot database (Benoit-Norris, Cavan, and Norris 2012) into quantitative numbers. This provides a social risk weight to employment. While employment is per se a positive aspect as it provides income, work conditions differ largely among regions and sectors. Zimdars et al. (Zimdars, Haas, and Pfister 2018) provide the risks for Exiobase v2.2. For the analysis based on Exiobase v3, we needed to include Croatia as a new region, for which we use the values of the “Rest of Europe” region from Zimdars et al. (Zimdars, Haas, and Pfister 2018). We apply an average scale to quantify the qualitative risks important for work conditions into numbers using a factor of 1, 2, 4, 8 or 16 for low to high risk, respectively. We use these numbers in the same way as characterization factors for environmental aspects as further described in Zimdars et al. (Zimdars, Haas, and Pfister 2018). By applying these characterization factors to the employment extensions in the trade analysis, we can calculate the average employment risk factor over the supply chain or production system. In Figure 3.31 of the main report, we normalize the risks in each region by the global average employment risks in order to indicate overall work conditions compared to global average conditions.

In addition to these work risks, it is also important to relate added value (i.e. the economic benefit of work) to the employment (i.e. investment in work). Figure A.27 presents the results for the classes of employment and added value. It is obvious that employment share is much higher than the added value share, which indicates the low economic remuneration of the large workforce, especially of vulnerable, low and medium skilled labors. Especially agriculture is highlighted with high shares of employment but low shares of added value generated. The summary of these two graphs per economic sector is provided in Figure A.28.

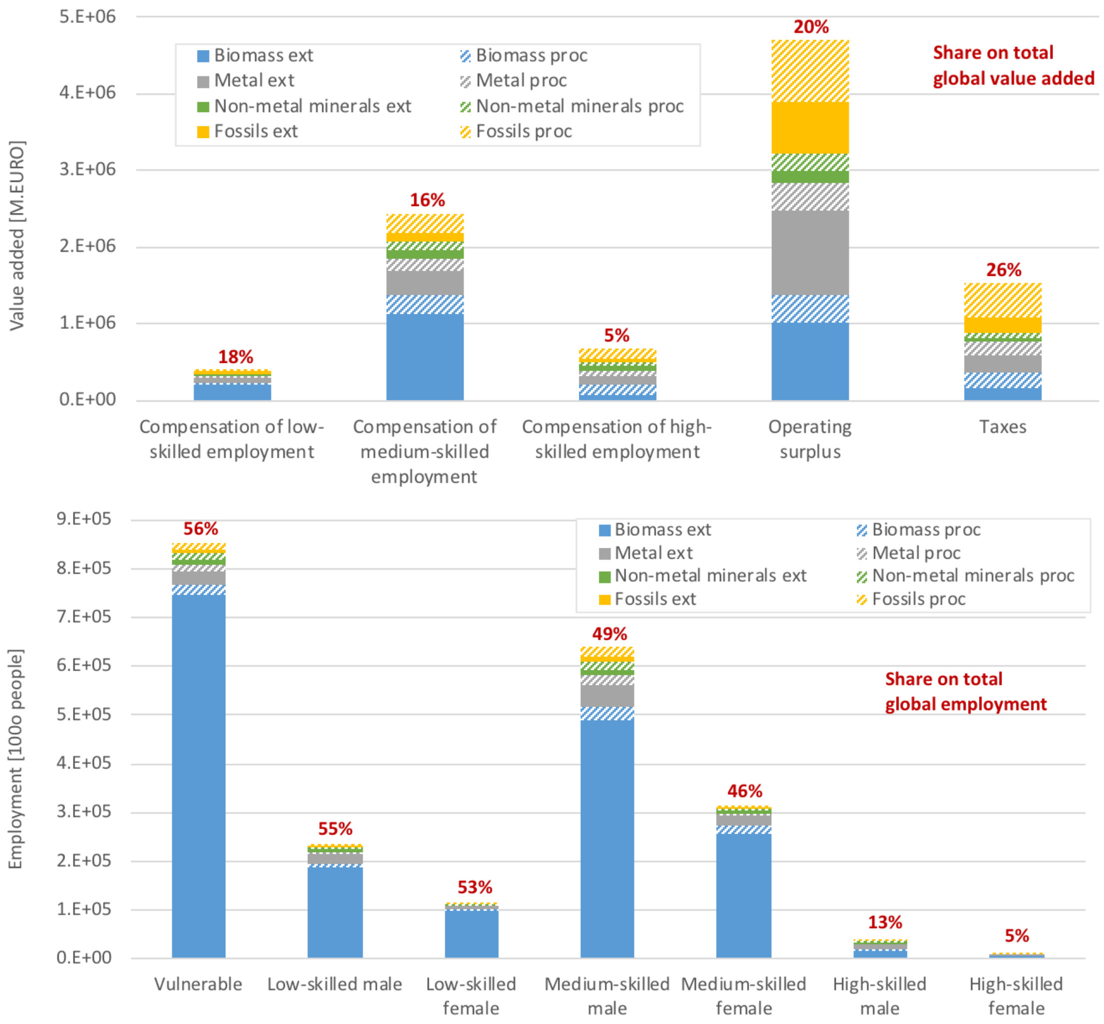

Figure A.27: Split of the added values (top) employment (bottom) classes by resource category (colors) and phase (extraction is marked with solid filled colors, processing with stripes), Total share is indicated by the red numbers above the bar (i.e. the rest is remaining economy). Data sources: Exiobase 3.4, combined with land-use data from Chapter 2 and impact assessment methods (Section 3.1). Reference year: 2015.

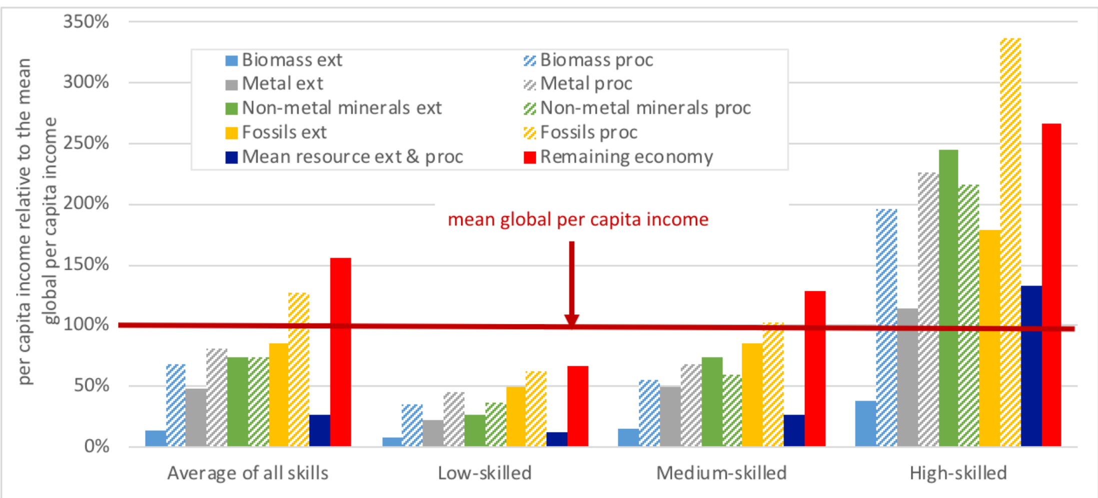

Figure A.28: per capita worker income in each aggregated resource sector and remaining economy per skill type.

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