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Original Articles Scarcity-weighted global land and metal footprints

David Font Vivanco^{a,b,*}, Benjamin Sprecher^{b,c}, Edgar Hertwich^b

^a UCL Institute for Sustainable Resources, University College London, 14 Upper Woburn Place, WC1H ONN London, United Kingdom

^b Center for Industrial Ecology, School of Forestry and Environmental Studies, Yale University, 06511 New Haven, CT, United States

^c Leiden University, Institute of Environmental Sciences (CML), Einsteinweg 2 (Bio-Science Park), 2333 CC Leiden, The Netherlands

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ABSTRACT

Resource scarcity poses an increasing threat to the supply security of modern economies. Some grand challenges ahead are the limits to agricultural expansion and the geologic scarcity of metals. To better understand the drivers behind land and metal depletion, footprint-type indicators are gaining importance. Such indicators, however, fail to differentiate between vastly different degrees of resource availability across regions. Using crop suitability areas and metal reserve base data, we calculate scarcity-weighted land and metal footprints for the major economies with the EXIOBASE global multi-regional input-output model. Scarcity-weighting causes a significant reordering of the global rankings of countries for both land and metal footprints. Land scarcity focuses mostly on cereals (~54% from the total agricultural land used) and oil crops (~15%), the former being notably affected by water scarcity issues in Asia and the Middle East. Metal scarcity focuses on copper ores (\sim 69%) and iron (~11%), the former being a globally scarce metal impacting multiple economies. The large impact of scarcity-weighting suggests that, while non-weighted resource footprints are a valid proxy of resource use, these are not always aligned with further implications of resource depletion and supply security. In this sense, scarcityweighting can offer an initial overview of those countries where analyses at finer scales may be more valuable. Our results also show that international trade is a major driver of land and metal depletion in some developing regions. This highlights the intersection of environmental justice and globalization, as the burden of resource depletion often falls into poorer regions which critically rely on exports.

1. Introduction

Modern economies depend on the reliable and sustainable access to a variety of natural resources. Key resources include freshwater, primary energy carriers, arable land, minerals, and metals (EC, 2011; Steffen et al., 2015). The supply security of these resources is affected by systemic constraints at multiple levels (Andrews-Speed et al., 2012). A key constraint is the physical availability of resources, the repercussions of which are expected to increase if current economic growth rates are sustained. Grand challenges include deficits in freshwater availability (WRG, 2009), limits to agricultural land expansion (Popp et al., 2017; van Vuuren and Faber, 2009), and geologic scarcity of some base and minor metals (Henckens et al., 2014). In response to such challenges, resource management policies are increasingly favoring footprint-type indicators in order to better understand the economic drivers behind resource depletion (Tukker et al., 2016).

Resource footprints (RFs) describe the resource requirements associated with or 'embodied' in any given final demand, such as the domestic consumption of any given country (Kitzes, 2013; Rees, 1992; Steen-Olsen et al., 2012). The emerging importance of RFs is due to the fact that many developed countries have stabilized or even decreased resource use within their territorial boundaries, while simultaneously increasing imports from other countries, mostly developing and emerging (Giljum et al., 2016; Tukker et al., 2016). Due to the increasing importance of trade and economic specialization, global models, especially multi-regional input-output (MRIO) models, are seen as a sound and consistent way to calculate RFs (Tukker et al., 2016; Tukker and Dietzenbacher, 2013; Wiedmann et al., 2006). However, RFs generally fail to differentiate between vastly different degrees of resource availability across regions (Lenzen et al., 2013). In other words, by merely keeping track of how much and where resources are being used, they ignore whether, and to which degree, these resources are actually scarce.

The inclusion of scarcity issues in footprint calculations is mostly unexplored, with only a handful of studies that have focused on freshwater scarcity. These studies include those from Lenzen et al. (2013) on scarcity-weighted global water footprints, Feng et al. (2014) on inter-regional scarce water footprints in China, and Zhang et al.

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^{*} Corresponding author at: UCL Institute for Sustainable Resources, University College London, 14 Upper Woburn Place, WC1H 0NN, London, United Kingdom. *E-mail addresses:* d.vivanco@ucl.ac.uk, dfontv@gmail.com (D. Font Vivanco).

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(2017) on scarce water footprints from inter-provincial electricity transmission in China. All of these studies find notable variations in the structure of embodied water flows when scarcity is considered, often disfavoring water-stressed regions that rely on trade. Because considerations of scarcity implicitly factors trade-imbalance and resource exploitation issues into RFs, it can have profound implications for improving local and global resource management practices, as well as provide the clarity necessary for increased social development and environmental justice (Hossay, 2006). Due to the lack of similar exercises for land and metal, however, a similar hypothesis for these resources cannot be resolved.

Although not considering scarcity, the literature provides various examples of land and metal footprints. Land footprints have been calculated for the EU27 member states (Steen-Olsen et al., 2012), world regions (Tukker et al., 2014; Weinzettel et al., 2013) and global household consumption (Ivanova et al., 2016). Metal footprints have been calculated globally for iron and bauxite (Wiedmann et al., 2015), and for metals in general (Bulavskayaa et al., 2016; Giljum et al., 2016). Some of these studies include a form of weighting; the land footprints in Steen-Olsen et al. and Weinzettel et al. are weighted by the bioproductivity of the land, and the metal footprint actually measures the total amount of ore mined and hence represents metal use normalized by the richness of the ore. Not surprisingly, these studies find the biggest economies, such as the United States and China, to lead both land and metal footprints in absolute terms.

The main research objectives of this paper are (1) to develop a method to calculate global land and metal scarcity-weighted footprints by country/region, (2) to compare the results of this method with their non-weighted equivalents in order to improve the understanding on the economic drivers behind land and metal depletion worldwide, and (3) to assess potential implications for resource management and sustainable development policies.

2. Methods

This section presents the methods and data sources to calculate scarcity-weighted land and metal footprints. A summary of all data sources and related variables is presented in Table 1. To calculate land and metal footprints, we use the MRIO database EXIOBASE 3.3 for the year 2007, which has a resolution of 163 industries and 49 regions (44 of the largest world economies and 5 rest-of-continent regions) (Wood et al., 2014). Further details can be found in a number of technical reports (Exiobase, 2017; Koning et al., 2011), and a comparative discussion with other MRIO databases can be found in Moran and Wood (2014), Tukker et al. (2016) and Giljum et al. (2016). According to EXIOBASE 3.3, land is represented by nine different croplands: rice, wheat, 'other cereals', vegetables, fruits and nuts, oil crops, sugar crops, fibers, fodder crops, and 'other crops'. The cropland categories are based on FAOSTAT and the 'other' categories aggregate other FAO crops that are not individually represented. Also according to EX-IOBASE 3.3, metal requirements correspond to used extraction of twelve different metal ore types: bauxite and aluminum, copper, gold, iron, lead, nickel, other non-ferrous metals, platinum-group metals,

Variable(a) (within breakets, the symbol of the associated variable)

silver, tin, uranium and thorium, and zinc.

Footprints associated with any given final demand were calculated using the standard demand-pull Leontief model (Miller and Blair, 2009):

$$footprint_r = s_r Ly = s_r (I - A)^{-1} y$$
(1)

Where subscript *r* indicates a given resource (land or metal type), *s* is an $n \times 1$ vector of direct resource requirements (*s*) per unit of economic output, being *n* the number of industries, *A* is an $n \times n$ matrix of technical coefficients indicating the inter-industry inputs required to supply one unit of output, *I* is an $n \times n$ identity matrix, *y* is a given $1 \times n$ final demand vector, and *L* is the Leontief inverse containing the multipliers for the direct plus indirect inter-industry inputs required to satisfy one unit of *y*.

In order to incorporate scarcity into our footprint calculations, we apply the approach developed by Lenzen et al. (2013) for virtual water. First, we calculate resource exploitation indices (REIs) for each country i by dividing actual resources required (RR) by total resources available (RA):

$$REI_i = \frac{RR_i}{RA_i} \tag{2}$$

Actual resource requirement by country/region in physical units (km² and kt for each land and metal use type, respectively) is calculated using direct resource requirement (s) data from EXIOBASE 3.3 in order to keep consistency. Resource availability by country/region has been compiled using various data sources as described following. For land, crop suitability areas (CSA) indicating the area in km² suitable to produce a certain crop specie per country have been obtained from the Global Agro-ecological Zones (GAEZ) 3.0 model (Fischer et al., 2012). Concretely, CSA have been calculated under the following assumptions: all suitability levels, rain-fed water supply, intermediate input level (improved management assumption), without CO₂ fertilization, and under current climate conditions. Country-level CSA data have been aggregated to EXIOBASE countries and rest-of-continent regions following the concordances provided in Supplementary data A. Because the GAEZ model is represented by specific crop species, proxies have been assigned when necessary to each cropland type according to the highest global production volume (FAO, 2017) to minimise uncertainty: rice (proxy: wetland rice [Oryza sativa]), wheat, other cereals and other crops (wheat [Triticum spp.]), vegetables, fruits and nuts (tomato [Lycopersicon lycopersicum]), oil crops (sunflower [Helianthus annuus]), sugar crops (sugarcane [Saccharum spp.]), fibers (cotton [Gossypium hirsutum]), and fodder crops (alfalfa [Medicago sativa]). For metals, we use reserve base values by country in kt for the year 2007 reported by the US Geological Service (USGS, 2008), except uranium, which is based on OECD and IAEA data (OECD/IAEA, 2008). From the USGS data, we use reserve base rather than reserves, because reserves are generally defined in economic terms (extractable metal at current prices) rather than total technically extractable reserves, the latter being more relevant to a scarcity index. The OECD data reports recoverable uranium resources at different cost ranges. Following the same logic, we use the data for the highest reported cost range,

Data courac(a)

variable(s) (within blackets, the symbol of the associated variable)	Data source(s)
Direct resource requirements (s and RR) for land use and metal ore use extraction, technical coefficient matrix (A), and final demand vector (y) by industry sector.	EXIOBASE 3.3 (Wood et al., 2014)
Crop suitability areas (RA _{land}) by country.	Global Agro-ecological Zones (GAEZ) 3.0 model (Fischer et al., 2012)
Crop production volumes by country (RA _{land}).	Food and Agriculture Organization crop production data (FAO, 2017)
Metal reserve base by country (RA _{metal})	US Geological Service (USGS, 2008)
Uranium reserve base by country (RA _{metal})	OECD and IAEA (OECD/IAEA, 2008)

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