Journal of Cleaner Production 184 (2018) 788–797

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Production weighted water use impact characterisation factors for the global mining industry

Stephen A. Northey [a, b, *], Cristina Madrid López [c, d], Nawshad Haque [b], Gavin M. Mudd [e], Mohan Yellishetty [a]

[a] Faculty of Engineering, Monash University, Clayton, VIC, Australia
[b] CSIRO Mineral Resources, Clayton, VIC, Australia
[c] Centre for Industrial Ecology, School of Forestry and Environmental Sciences, Yale University, Connecticut, USA
[d] Institute for Environmental Science and Technology, Universitat Autonoma de Barcelona, Spain
[e] Environmental Engineering, RMIT University, Melbourne, VIC, Australia

A R T I C L E I N F O

Article history:
Received 11 August 2017
Received in revised form
26 February 2018
Accepted 28 February 2018
Available online 1 March 2018

Keywords:
Impact characterisation
Mining industry
Mineral and metal production
Water stress index (WSI)
Available water remaining
Life cycle assessment (LCA)

A B S T R A C T

Methods for quantifying the impacts of water use within life cycle assessment have developed significantly over the past decade. These methods account for local differences in hydrology and water use contexts through the use of regionally specific impact characterisation factors. However, few studies have applied these methods to the mining industry and so there is limited understanding regarding how spatial boundaries may affect assessments of the mining industry's consumptive water use impacts. To address this, we developed production weighted characterisation factors for 25 mineral and metal commodities based upon the spatial distribution of global mine production across watersheds and nations. Our results indicate that impact characterisation using the national average ‘Water Stress Index’ (WSI) would overestimate the water use impacts for 67% of mining operations when compared to assessments using watershed WSI values. Comparatively, national average ‘Available Water Remaining’ (AWaRe) factors would overestimate impacts for 60% of mining operations compared to assessments using watershed factors. In the absence of watershed scale inventory data, assessments may benefit from developing alternative characterisation factors reflecting the spatial distribution of commodity production across watersheds. The results also provide an indication of the commodities being mined in highly water stressed or scarce regions.

1. Introduction

The global mining industry is situated across a wide range of regional hydrological contexts that can result in complex water related risks that must be managed by mining and mineral processing operations (CDP, 2013; Northey et al., 2017). In order to mitigate or manage these risks, mining operations will tailor their management practices and process design to address the specific hydrological conditions affecting the site (Kunz and Moran, 2016). As a result of this, it has been observed that there is significant variability in rates of water consumption and efficiency between mining operations (Mudd, 2008; Gunson, 2013; Northey et al., 2013). Given the myriad of drivers that influence water consumption throughout the mining industry, methodological approaches are required that enable the fair comparison of water consumption and efficiency of mine sites located across geographic regions, which may have significantly different climate, hydrological and water use contexts. To address this, recent studies that evaluate water consumption in the mining industry are increasingly utilising spatially explicit life cycle impact characterisation factors to account for differences in the local water scarcity or stress of mines located in different regions (Northey et al., 2016).

Life cycle impact assessment aims to quantify the environmental burdens associated with the provision of products or services. A variety of methods have been proposed over the last decade for characterising the relative water use impacts of production systems as part of life cycle assessment studies (Boulay et al., 2015a; Kounina et al., 2013). These methods differ based upon the

* Corresponding author. Faculty of Engineering, Monash University, Clayton, VIC, Australia.
E-mail addresses: stephen.northey@monash.edu, stephen.northey@csiro.au (S.A. Northey).

https://doi.org/10.1016/j.jclepro.2018.02.307

underlying conceptualisation of what constitutes a water use impact, their data underpinnings and the approach taken to calculating and normalising impact characterisation factors. These impact characterisation factors are typically modelled for (sub-)watersheds based on the outputs of global hydrological and water use models. Characterisation factors for different spatial scales (e.g. regional, national, continental) may be determined via weighting watershed factors based on the distribution of withdrawals or consumption across the region. Consequently, these national average factors are largely representative of the conditions where major water users, such as the agricultural industry, are situated. Although mining can occasionally be a large local consumer of water within an individual watershed, at national scales other industries – such as agriculture – typically consume at least an order of magnitude more water (Gunson, 2013; Hejazi et al., 2014). As the spatial distribution of mineral resources may not be correlated with the spatial distribution of overall water use or availability within a region, we hypothesise that assessments of the mining industry's water consumption may produce substantially different results depending on whether watershed or national average impact characterisation factors are used.

This paper tests the above hypothesis by developing production weighted average characterisation factors based on the spatial distribution of mine site production across watersheds and countries. Region specific weighted average factors are developed for twenty five mined commodities and compared with national average factors to understand the influence that spatial scale and watershed aggregation procedures would have on the accuracy of impact assessment of mined products. The results of the study also provide an indication of the relative exposure of global mining industry sub-sectors to water stress and scarcity related risks.

2. Background and methods

2.1. Water use impact characterisation factors

A variety of methods have been proposed over the last decade for characterising the relative water use impacts of production systems as part of life cycle assessment studies (Boulay et al., 2015a; Kounina et al., 2013). Our assessment focuses upon the widely used 'Water Stress Index'(WSI)(Pfister et al., 2009) and the recently developed 'Available Water Remaining' (AWaRe) methods (Boulay et al., 2016, 2017; WULCA, 2017). The potential influence that characterisation factors produced at different spatial scales would have on water use impact estimates for the mining industry is assessed by considering the spatial distribution of mine site production.

2.1.1. Water Stress Index (WSI)

The WSI was developed by Pfister et al. (2009) as a mid-point indicator to measure the potential for water use to lead to user deprivation. The basic data underpinning the WSI is the ratio of water withdrawals to long-term water availability (WTA) within a watershed. These WTA ratios are modified by a variation factor to account for the degree of precipitation variability and the regulation of flows within the watershed (defined by Nilsson et al., 2005), according to Equation (1) and Equation (2). The modified WTA is then scaled between 0.01 and 1 using a logistic function shown in Equation (3) to produce the WSI. This logistic function is calibrated so that a WSI of 0.5 corresponds to a WTA of 0.4 (assuming the median watershed variation factor), which is commonly considered the threshold between moderate and severe water scarcity. Pfister et al. (2009) provided annual WSI data on a watershed basis, using data from the WaterGAP 2 global hydrological and water use model (Alcamo et al., 2003), as well as national averages developed by weighting watershed data according to the spatial distribution of withdrawals. Although there has been criticism and debate over the conceptualisation of the WSI (Hoekstra, 2016; Pfister et al., 2017), it is perhaps the most widely used approach to assessing consumptive water use impacts within life cycle assessment studies to date. Other conceptualisations of the WSI with alternative normalisation methods have been proposed to account for differences when assessing marginal and consequential water use impacts in life cycle assessment (Pfister and Bayer, 2014). However, in this assessment we focus on the original WSI presented by Pfister et al. (2009) because it is the most extensively used water use impact characterisation factor.

$$WTA^{*} = \begin{cases} \sqrt{VF} \times WTA & \textit{for non}-\textit{strongly regulated flows} \\ VF \times WTA & \textit{for strongly regulated flows} \end{cases} \tag{1}$$

$$VF = \frac{1}{\sum P_i}\sum_{i=1}^{n} e^{\sqrt{\ln(S_{month})^2 + \ln(S_{year})^2}} \tag{2}$$

Where: P_i is the mean annual precipitation in each grid cell i within a watershed, and S_{month} and S_{year} represent the standard deviation of monthly and annual precipitation respectively.

$$WSI = \frac{1}{1 + e^{-6.4\cdot WTA^{*}}\left(\frac{1}{0.01} - 1\right)} \tag{3}$$

2.1.2. Available Water Remaining (AWaRe)

The international working group for Water Use in Life Cycle Assessment (WULCA) developed the Available Water Remaining (AWaRe) method as a consensus based approach for assessing the potential for water use to deprive other users of water (Boulay et al., 2015b, 2016, 2017; WULCA, 2017). The basic underpinning of the AWaRe method is the inverse of water availability minus demand (AMD) from environmental water requirements (EWR) and human water consumption (HWC) per unit area (equation (4)), which can be interpreted as the surface-time equivalent (STE) required to produce the excess water availability in a region (m^2. month.m^{-3}). The AWaRe characterisation factors are determined from sub-watershed AMD values that have been normalised according to Equation (5), so that a value of 1 is equivalent to the global consumption weighted average AMD (0.0136 m^3 m^{-2} $month^{-1}$). Therefore an AWaRe value of 20 represents a region where there is 20 times less excess water available per unit area than the global average.

$$\frac{1}{AMD_i} = \frac{Area}{A - D} = \frac{Area}{A - HWC - EWR} = STE_i \tag{4}$$

$$AWaRe_{ws,month} = \begin{cases} AMD_{world\ ave.}/AMD_i & \textit{for } D_i < A_i \\ 0.1 & \textit{for } AMD_i > 10\cdot AMD_{world\ average} \\ 100 & \textit{for } D_i \geq A_i \textit{ or } AMD_i < AMD_{world\ average}\big/100 \end{cases} \tag{5}$$

Table 1
Summary of 2014 production data and key results for the 25 mined commodities considered by this study.

	National Production [e]		Operation Production [f]				Global Production Weighted Average						% of Operation Production	
	Countries	Production	Operations	Countries	Production	Coverage	National Average (NA) [e]		Watershed (W) [f]		Ratio (W/NA)		Overestimated (W > NA)	
Commodity	No.	kg	No.	No.	kg	% of national	AWaRe	WSI	AWaRe	WSI	AWaRe	WSI	AWaRe	WSI
Antimony [a]	17	1.57×10^{8}	2	2	6.02×10^{6}	4	26.5	0.49	61.7	0.71	2.33	1.44	0	40
Bauxite [b]	31	2.60×10^{11}	47	15	1.91×10^{11}	74	19.9	0.37	6.2	0.11	0.31	0.31	88	90
Chromite [b]	18	3.00×10^{10}	31	7	1.45×10^{10}	48	20.6	0.67	18.7	0.48	0.90	0.72	47	92
Coal [b]	66	8.09×10^{12}	1138	30	4.93×10^{12}	61	20.2	0.46	25.2	0.45	1.25	0.98	53	60
Cobalt [a]	18	1.29×10^{8}	29	15	6.40×10^{7}	50	10.1	0.11	4.5	0.07	0.44	0.67	92	90
Copper [a]	56	1.84×10^{10}	270	44	1.60×10^{10}	87	23.1	0.49	40.9	0.55	1.77	1.13	36	44
Diamonds [b]	23	2.51×10^{4}	39	11	1.96×10^{4}	78	14.3	0.27	17.4	0.07	1.21	0.27	47	96
Gold [a]	88	3.02×10^{6}	661	75	2.30×10^{6}	76	18.9	0.38	21.7	0.31	1.15	0.83	56	64
Iron Ore [b]	48	3.38×10^{12}	280	35	1.77×10^{12}	52	21.8	0.42	22.5	0.15	1.03	0.36	38	88
Lead [a]	43	5.37×10^{9}	103	23	1.96×10^{9}	36	22.3	0.48	15.0	0.27	0.67	0.56	77	74
Lithium [b]	9	6.54×10^{8}	2	2	9.90×10^{7}	15	25.0	0.43	35.1	0.31	1.41	0.73	70	70
Manganese [b]	25	5.47×10^{10}	26	11	3.37×10^{10}	68	20.5	0.48	23.4	0.11	1.14	0.23	67	84
Molybdenum [a]	14	2.95×10^{8}	42	13	2.00×10^{8}	68	23.7	0.55	46.5	0.70	1.96	1.28	32	35
Nickel [a]	31	2.06×10^{9}	77	21	1.50×10^{9}	73	9.4	0.24	8.6	0.12	0.91	0.52	85	89
Palladium [a]	11	1.84×10^{5}	31	6	1.84×10^{5}	100	9.8	0.33	8.3	0.18	0.84	0.53	63	100
Phosphate [b]	40	2.45×10^{11}	22	8	4.71×10^{10}	19	29.7	0.56	9.3	0.51	0.31	0.91	87	52
Platinum [a]	10	1.45×10^{5}	40	7	1.61×10^{5}	111	14.9	0.51	15.8	0.39	1.06	0.77	29	99
Potash [c]	12	3.91×10^{10}	22	6	6.86×10^{10}	[c]	11.1	0.26	11.3	0.15	1.02	0.60	71	86
Rutile [b]	12	7.40×10^{8}	9	5	4.46×10^{8}	60	17.8	0.38	37.6	0.29	2.11	0.74	60	66
Silver [a]	65	2.74×10^{7}	257	40	1.77×10^{7}	64	17.9	0.51	21.5	0.46	1.21	0.90	63	60
Tin [a]	23	3.55×10^{8}	7	5	7.02×10^{7}	20	18.1	0.34	1.6	0.35	0.09	1.03	100	65
Tungsten [a]	20	8.53×10^{7}	4	4	1.28×10^{7}	15	25.1	0.42	2.6	0.07	0.11	0.16	100	100
Uranium [d]	18	6.59×10^{7}	55	15	6.40×10^{7}	97	21.8	0.42	27.7	0.44	1.27	1.04	56	58
Zinc [a]	49	1.37×10^{10}	140	33	8.08×10^{9}	59	21.2	0.50	15.4	0.35	0.73	0.70	73	68
Zircon [b]	17	1.57×10^{8}	11	7	8.48×10^{8}	72	19.3	0.47	31.0	0.14	1.60	0.29	71	85

Reporting Basis.
[a] Produced or contained metal., [b] Gross mineral., [c] National scale data is expressed on a K2O equivalent basis. Operation data expressed on a gross potash mineral basis., [d] U3O8 equivalent.
Production Data Basis.
[e] National production in 2014 (British Geological Survey, 2016)., [f] Operation production in 2014 (SNL, 2017).

WULCA (2017) has provided AWaRe factors for a variety of temporal and spatial scales based upon monthly sub-watershed data from WaterGAP 2.2, which is underpinned by a global hydrological model (Müller Schmied et al., 2014) and water use data (Flörke et al., 2013). Annual AWaRe factors at the watershed scale are produced via weighting monthly watershed factors by monthly water consumption in the watershed, according to Equation (6). National AWaRe factors are produced by first spatially averaging monthly watershed factors by the monthly water consumption occurring in each watershed in the country according to equation (7). The resulting monthly, national AWaRe factors are then weighted according to the total water consumption occurring in the country in each month, according to Equation (8), to produce the annual factor. In order to more accurately assess the impacts of different industries, AWaRe factors are available that have been weighted based upon the temporal and spatial distribution of agricultural, non-agricultural and total water consumption (for assessing unknown water use). The annual watershed and national average AWaRe factors weighted by the spatial and temporal distribution of non-agricultural water consumption are used in this study.

$$AWaRe_{ws,\,annual} = \frac{1}{C_{ws,annual}} \sum_{month=1}^{12} AWaRe_{ws,month} \cdot C_{ws,\,month} \tag{6}$$

$$AWaRe_{national,month} = \frac{1}{C_{national,month}} \sum_{ws=1}^{n} AWaRe_{ws,month} \cdot C_{ws,\,month} \tag{7}$$

$$AWaRe_{national,\,annual} = \frac{1}{C_{national,\,annual}} \sum_{month=1}^{12} AWaRe_{national,month} \cdot C_{national,\,month} \tag{8}$$

2.2. Mine production weighted averages and boundaries of assessment

To determine the potential influence of spatial aggregation of life cycle inventories and impact characterisation factors on assessments of mining industry water use, the deviation between watershed and national average factors was assessed at several different spatial boundaries - global, national and individual mining operations. Ideally this assessment would be based upon the spatial distribution of mining industry water consumption between watersheds and nations within these boundaries. However, there is currently no global inventory of the water use requirements of individual mining operations at a level of detail that would facilitate this. Fortunately, commodity production from individual mining operations is available for a large proportion of the mining industry (Table 1) and this has been used as a proxy for mine-site water use. Therefore weighted average WSI and AWaRe factors were estimated based upon the spatial distribution of annual commodity production amongst watersheds and nations (equation (9)).

$$Production\ Weighted\ Average = \frac{\sum_i CF_i \times Production_i}{\sum_i Production_i} \quad (9)$$

where: CF_i and $Production_i$ represent the AWaRe or WSI value and annual commodity production respectively of each watershed or nation "i" within the boundary of assessment.

Production data for the year 2014 was obtained for 25 mined commodities: antimony, bauxite, chromite, coal, cobalt, copper, diamonds, gold, iron ore, lead, lithium, manganese, molybdenum, nickel, palladium, phosphate, platinum, potash, rutile, silver, tin, tungsten, uranium, zinc and zircon (Table 1). National mine production data was sourced from the British Geological Survey (2016), whereas production and location data for individual mining operations was sourced from the SNL Mining & Metals database (SNL, 2017). Operations that did not intersect with both the spatial WSI and AWaRe datasets were excluded from the analysis. The operation production data covers approximately 50–90% of the national production for most commodities considered. The spatial distribution of the mining operations in relation to the WSI and AWaRe factors is shown in Fig. 1 and a summary of the production data is provided in Table 1 for individual commodities. Data for individual countries is provided in the electronic supplementary Tables S2 to S3. For several commodities there was inconsistency in the reporting basis (i.e. contained metal and gross mineral) used for the available national and operation production data. For uranium production, the national data was converted from a U to a U_3O_8 basis to ensure consistency with the operation data. For potash it was not possible to express the national and operational scale production data in consistent units. The national data represents production on a K_2O equivalent basis, whereas the operation data represents gross potash minerals (it was not possible to determine the mineralogy of each operation's products). However, our judgement is that the overall production coverage of potash is likely high, hence in the figures presented in subsequent sections, potash has been labelled as having greater than 75% production coverage.

3. Results and discussion

Production weighted WSI and AWaRe factors were developed according to equation (9) for all 25 mined commodities at global, national and operational boundaries of assessment. The results provide a basis for evaluating the influence that the use of watershed or national average factors would have upon impact assessments of the mining industry, as well as improving understanding of the relative exposure of mining supply chains to water stress and scarcity related risks. Key results for all commodities are provided in Table 1, with more detailed results for commodities production from individual countries being presented in the electronic supplementary information Tables S1 to S3 and Figures S1 to S7.

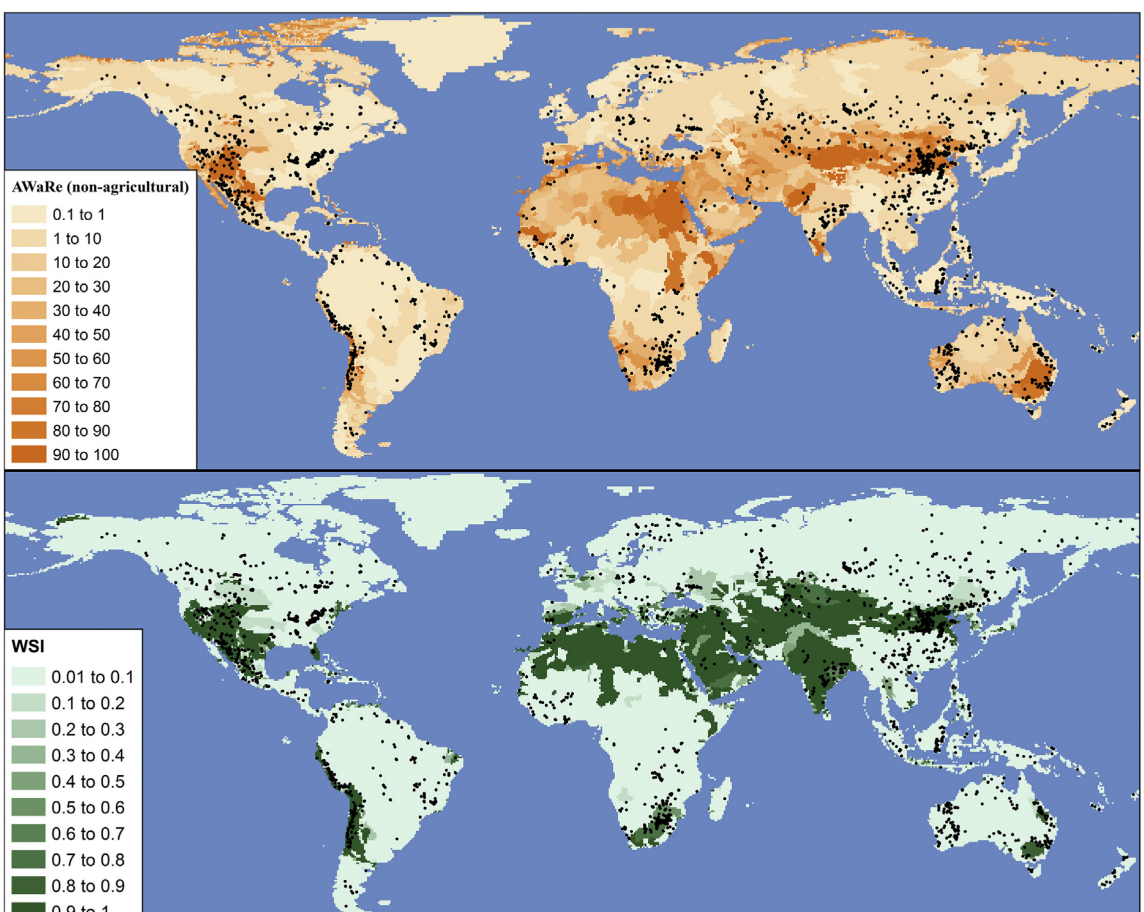

Fig. 1. Location of mining operations (SNL, 2017) considered in this study in relation to annual AWaRe factors for non-agricultural water use (Boulay et al., 2016, 2017; WULCA, 2017) and the WSI (Pfister et al., 2009).

3.1. Deviation between watershed and national average factors

The deviation between watershed and national average factors for estimating the water use impacts of mined commodities was assessed at several different spatial aggregation boundaries, shown in Fig. 2 for all commodities. For the boundary of individual mining operations, the local watershed factor is compared with the national average factor. At a national boundary, production weighted watershed values are compared with the national average factors. At the global boundary, watershed factors weighted according to operation production are compared with national average factors weighted production according to national production for each commodity assessed.

The ratio of watershed based factors to the national average based factors provides a measure of the potential error that may be introduced when assessing the impacts of the mining industry's water use. The ratio between factors can range up to several orders of magnitude for individual operations or countries (Fig. 3). Deviations are slightly reduced at higher levels of spatial aggregation (i.e. global). Figs. 2 and 3 support our hypothesis that the use of national average water use characterisation factors would be likely to overestimate impacts for the mining industry, when compared to results generated from watershed based assessments. Fig. 3 shows the magnitude of deviation and the proportion of mining operations whose water use impacts would be over or underestimated by the use of national average characterisation factors, when compared to the use of watershed specific factors.

Across the 25 mined commodities, the use of national average WSI is likely to overestimate impacts for 67% of mining operations and 72% of impact estimates at the national boundary. The use of non-agricultural AWaRe factors also leads to a similar tendency to overestimate water use impacts, albeit for only 60% operations and 60% of national estimates. It is clear that the use of national average factors will lead to a systemic bias to overestimate water use impacts of the mining industry, compared to if watershed scale data was used. This bias is observable at all scales of spatial aggregation, although the average deviation is reduced at higher levels of spatial aggregation.

The spatial distribution of mine-site production varies between commodities due to differences in the underlying geological formation processes required to produce a mineral deposit from which each specific commodity can be profitably extracted. Due to this there are differences in the results obtained for individual mineral or metal commodities. Assuming water use is uniform across production, global assessments based on national average factors would overestimate impacts for 20 (out of 25) commodities using the WSI and for 10 commodities using AWaRe factors for non-agricultural water use (see Fig. 4, Table 1 and electronic supplementary Fig S7). However, even when the overall results for a given commodity are under- or overestimated, it is important to recognise that the individual regions where this commodity is produced may display significant divergence between watershed and national average factors. The cumulative production distribution of individual commodities in relation to the national average and watershed AWaRe and WSI is shown in Table 1 and the electronic supplementary Fig. S1 to S4. These distributions highlight that while there is a tendency for the national average factors to overestimate the impacts across the mining industry, this can be highly variable between individual mined commodities — with a large proportion of individual commodity production being over-

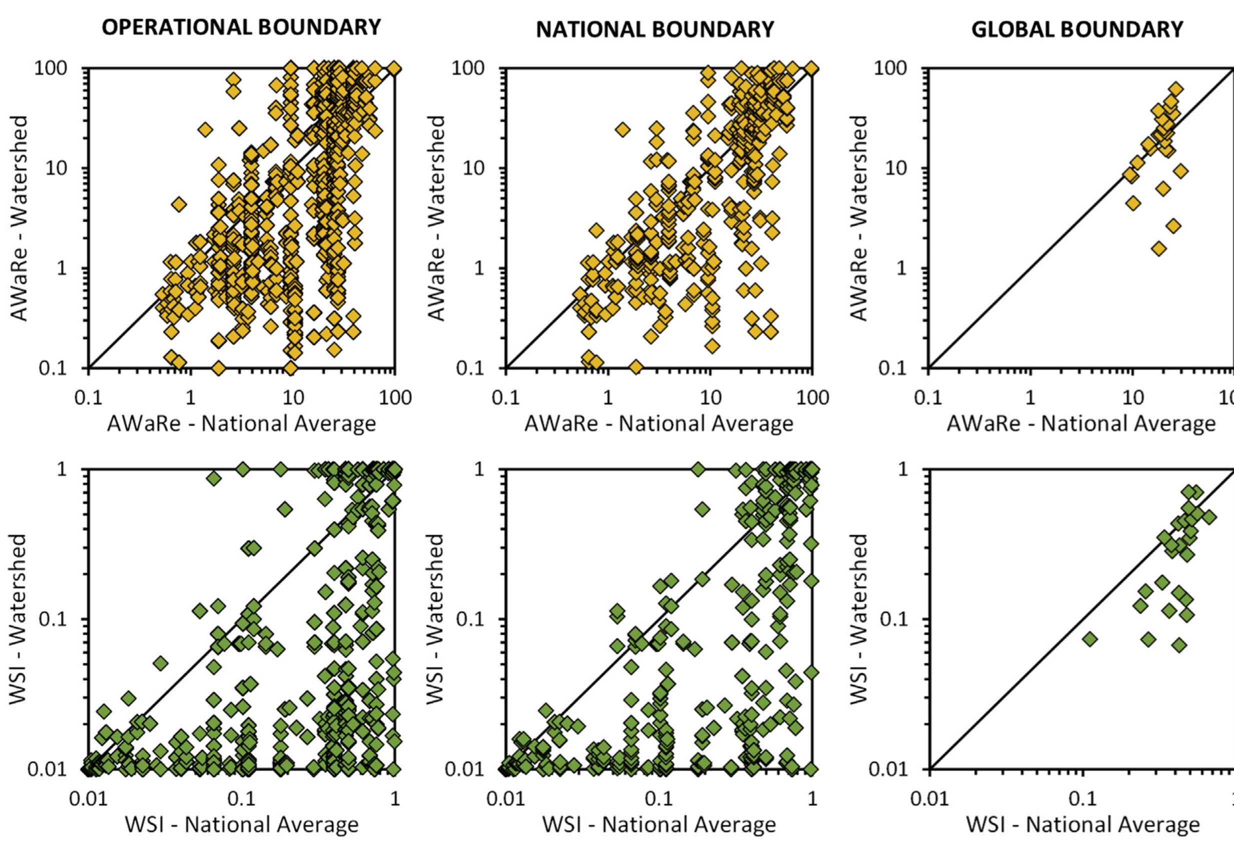

Fig. 2. A comparison of production weighted average AWaRe and WSI factors for 25 mined commodities determined at operational, national and global system boundaries. Watershed characterisation factors were weighted based on production from individual mining operations in 2014 (SNL, 2017), whereas national average characterisation factors were weighted based upon national production in 2014 (British Geological Survey, 2016).

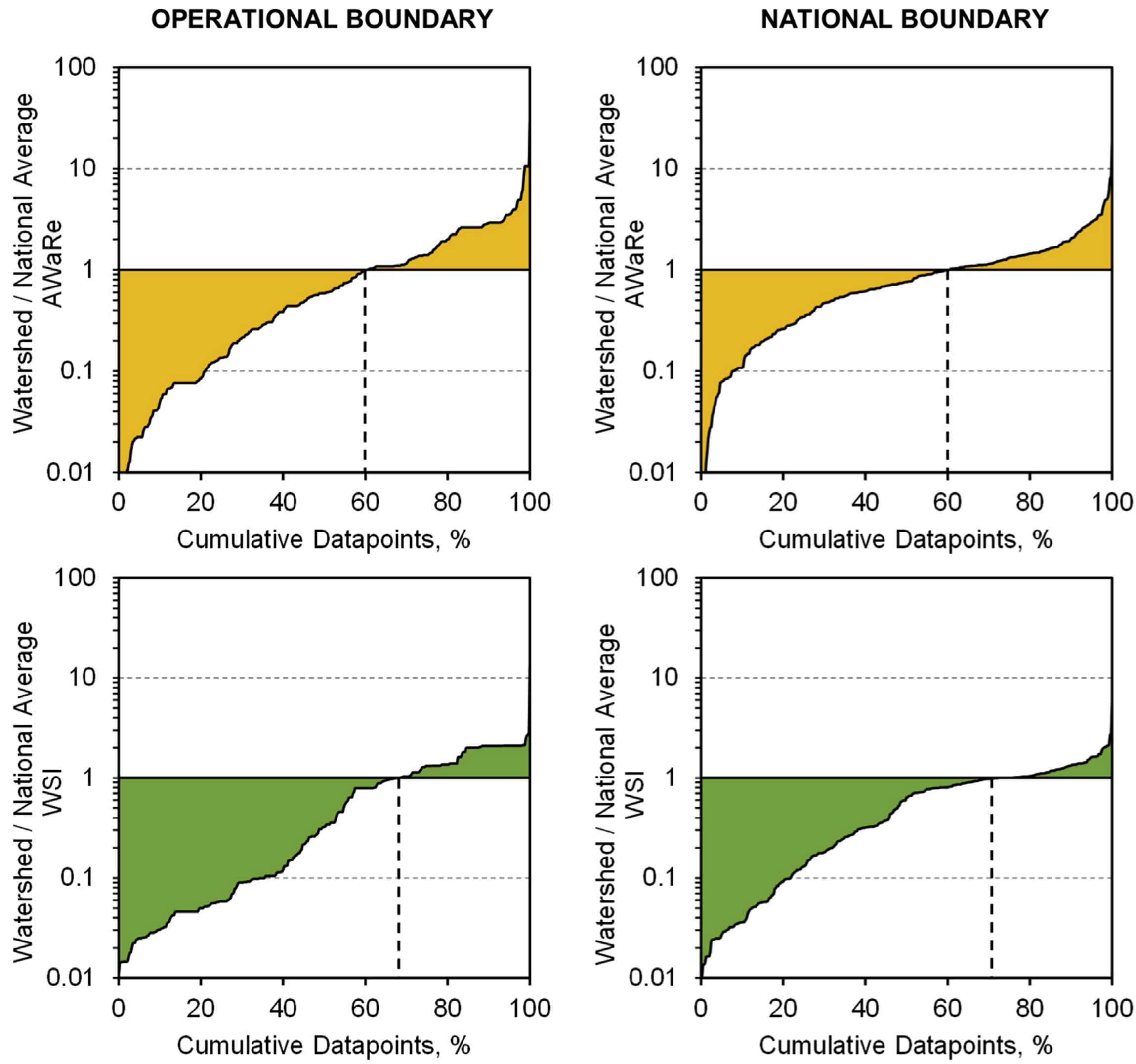

Fig. 3. Ratio between watershed and national average AWaRe and WSI factors for all commodities at the operational and national boundary. The proportion of datapoints overestimated by national average factors when compared to watershed factors is indicated by the vertical dotted lines.

or underestimated. Therefore, the reliability of life cycle assessment studies that seek to redistribute mined commodity production away from water stressed or scarce regions may be severely limited by the use of national average characterisation factors.

Given that non-agricultural products are less likely to be spatially correlated with overall water use, it is reasonable to expect that the results of this study for the WSI may be similar when assessing other minor water consuming industries (e.g. manufacturing). During the development of the AWaRe factors, the provision of factors specific to agricultural, non-agricultural and unknown water use partially addresses this issue. However our results (Figs. 2 and 3) show that the non-agricultural factors still show a bias to overestimate impacts of the mining industry. Therefore assessments of the consumptive water use impacts of mining should be conducted at watershed scales whenever possible.

To provide further evidence of this judgement, supporting information Fig. S7 shows that the use of national average factors will result in commodity production weighted factors that display a strong reversion to the global average WSI of 0.602 (Ridoutt and Pfister, 2013) and the global consumption weighted average AWaRe factor for non-agricultural water use of 20 (Boulay et al., 2016), when compared to the watershed based assessment. Therefore finer levels of spatial resolution provide improved discriminatory power when assessing water use impacts, particularly for assessments of production systems that are less likely to be spatially correlated with the distribution of water use across watersheds.

3.2. Relative exposure of commodities to water stress and scarcity

The WSI and AWaRe characterisation factors can also be interpreted as indicators of contextual water risk for the mining industry (Northey et al., 2014, 2017). Local scarcity or overexploitation of water resources in a region can impact mining operations in a range of ways, from making water sourcing more difficult to increasing tension with competing water users such as agriculture and/or other consumptive uses.

The relative exposure of commodity production to these issues may be ranked using the global production weighted average factors as shown in Fig. 4. Commodities being mined in highly water stressed or scarce regions include phosphate, molybdenum and copper. Other commodities such as nickel, cobalt and potash are predominantly mined in less water stressed regions. There are

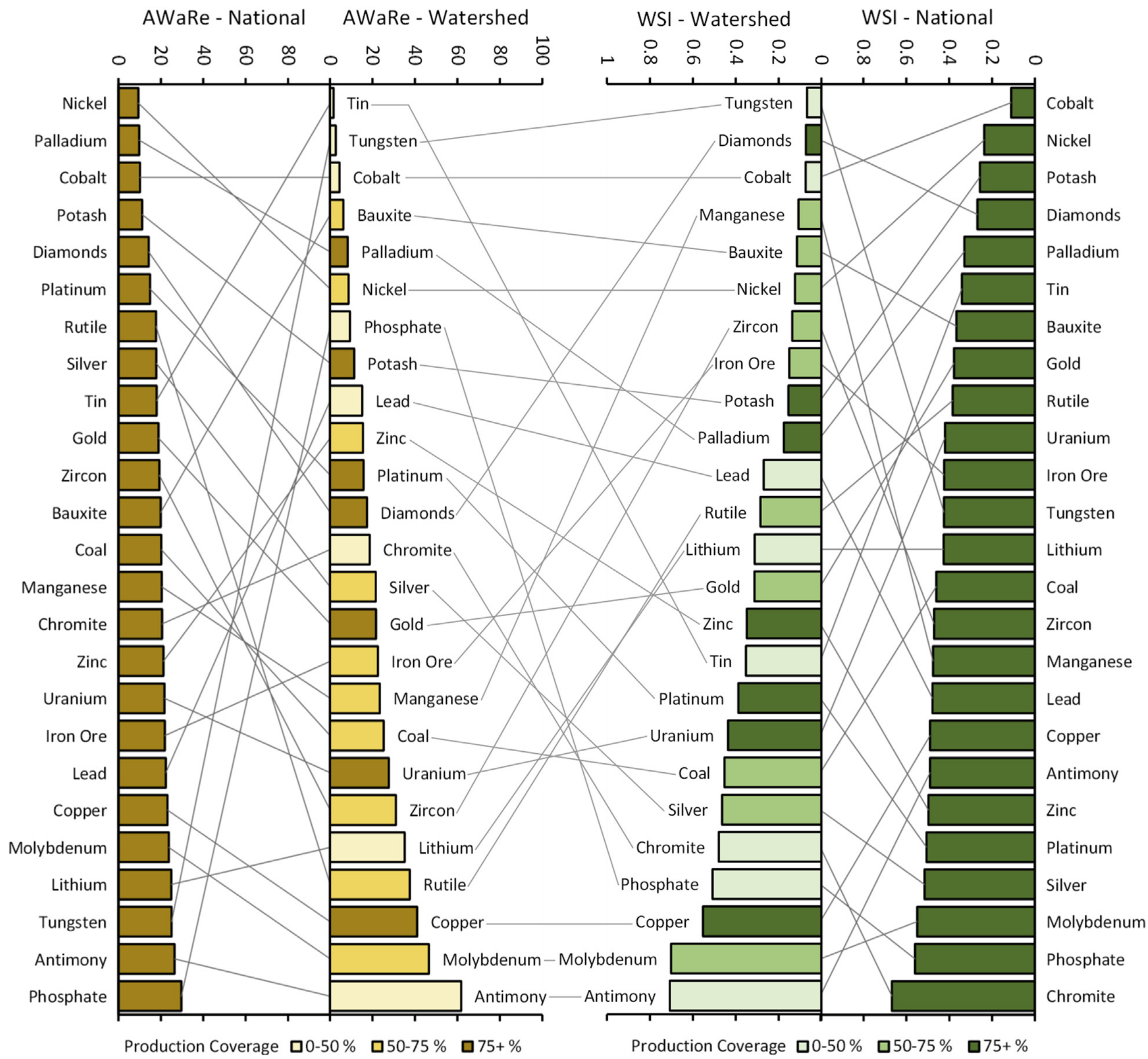

Fig. 4. Global production weighted average WSI and non-agricultural AWaRe factors for each commodity based upon watershed and national average water indices. Grey lines show the change in relative ranking of each commodity depending upon the scale and characterisation factor used. Watershed factors were weighted based upon production from individual mining operations in 2014 (SNL, 2017), whereas national average factors were weighted based upon national production in 2014 (British Geological Survey, 2016).

considerable differences in the relative 'ranking' of commodity risk depending on whether WSI or AWaRe factors are used. For instance, chromite is one of the most exposed commodities when using the WSI, however the AWaRe factors suggest that chromite production is only moderately exposed to these issues when compared with the other mined commodities. A major reason for these differences is that each of the indicators, WSI and AWaRe, are fundamentally measuring a different aspect of local hydrology due to the differences in their formulation. The WSI is a normalised measure of the ratio of withdrawals to long-term water availability modified by inter- and intra-annual hydrologic variability, which may be interpreted as a relative measure of the intensity of withdrawals or competition for water use between regions. Whereas the AWaRe index is an indicator based upon the absolute availability of water beyond current demands and so to a greater degree also reflects other hydrological factors – beyond the intensity of available water use – such as the general aridity of the region. Therefore, any comparison of the relative 'ranking' of the exposure to water risks of an individual commodity's production based upon these indicators should carefully consider the underlying formulation of each index, as well as the hydrological context of the countries producing each commodity (the distribution of commodity production amongst countries is provided in the electronic supplementary tables).

Differences in the relative ranking of commodities also occurs depending on if watershed or national average factors are used. Compared to the national average factors, watershed based assessment will result in the relative exposure ranking increasing for 11 and 15 commodities for the WSI and AWaRe factors respectively. However, it is important to emphasise that the uncertainty of the relative results based upon watershed assessment is closely related to the degree of operation production data available for each commodity (refer to Table 1 or the shading in Fig. 4). The operation production data covers less than 50% of global production for 8 of the 25 commodities (antimony, cobalt, chromite, lead, phosphate, lithium, tin, tungsten), and so the watershed based results are more uncertain for these commodities.

Previously, Northey et al. (2014) identified that different processing stages of mineral and metal supply chains (e.g. mining, mineral concentrating, smelting and refining) are not always co-located and may be located in regions experiencing substantially different water stress. Therefore, further assessment of the relative exposure of commodity production to water stress risks may benefit from considering the spatial distribution of the downstream production processes following mining – as this may alter the overall risk profile for an individual commodity.

The WSI and AWaRe factors were also used as part of an assessment of the global spatial distribution of copper, lead-zinc and nickel resources in relation to regional climate zones and water risks (Northey et al., 2017). The study used watershed scale data for AWaRe and the WSI, as well as several other indicators such as water criticality (Sonderegger et al., 2015), blue water scarcity (Hoekstra et al., 2012), and the water depletion index (Berger et al., 2014). Weighting of these indices was conducted based upon remaining resources rather than production levels, providing an indication of how future supply and life-of-mine production may be distributed in relation to water stress and scarcity. The key findings were that copper resources are located in regions with higher water stress, than either lead-zinc or nickel resources (Northey et al., 2017), which is broadly consistent with our assessment of the current production of these commodities.

3.3. Suitability of production weighted average characterisation factors

A valid question is whether the spatial distribution of mining production is a reasonable proxy for the spatial distribution of mining industry water consumption. Studies have shown that there is considerable variability in the water use requirements of mining operations when expressed on a cubic metre per tonne of product basis, even for operations producing the same commodity (Gunson, 2013; Mudd, 2008; Northey et al., 2013). There are a range of causal reasons for this, including differences in: mineral deposits (e.g. ore grades and grain sizes), processing methods, site infrastructure, local climate and site water management practices. The water balance of individual mining operations can be quite dynamic and an individual operation may face risks associated with both shortfalls and excesses of water at different periods of time (Gao et al., 2017; Kunz and Moran, 2016; Northey et al., 2016, 2017). Detailed water balance modelling exists for individual mining operations, however currently there is very limited statistical understanding of how mine site water consumption varies across regions in response to local climates and hydrological settings.

Conceptually, mining operations in dry climates will have lower surface runoff into on-site dams and greater evaporative losses, resulting in a greater dependence on surface and/or groundwater withdrawals. Conversely, mining operations in wet climates are likely to accumulate more water on-site and require active discharge through time. Given the role of local climates in governing regional water availability that underpins WSI and AWaRe factor estimates, there may be a correlation between mine water use intensity (i.e. cubic metre consumed per tonne of product) and the WSI or AWaRe factors. If this correlation was moderate, it would invalidate our assumption that mining production is a reasonable proxy for water use in this assessment. However, the absence of a comprehensive global mine water use dataset currently precludes our ability to test this assumption. Therefore, we must assume that mine production could be a reasonable proxy for estimation of mine water use across regions, whilst recognising that this assumption introduces uncertainty to the results of our assessment.

Although the input water requirements for mineral processing are relatively constant through the year, the overall water balance of a mining operation can vary substantially throughout the year and an individual operation will display seasonality in its water withdrawals from surrounding water sources or stores – as well as when water discharges will occur. All aspects including evaporation, flow into pits or mine workings, and runoff into water storage facilities may vary seasonally and in response to local catchment rainfall events (Northey et al., 2016). The temporal distribution of the mining industry's water use may differ from the temporal distribution considered during weighting of monthly factors when developing annualised characterisation factors.

Due to seasonal variations of water consumption, it has previously been determined that the annual WSI will, on average, underestimate impacts when assessing the agricultural industry – hence the use of sub-annual (e.g. monthly) characterisation factors is encouraged (Pfister and Bayer, 2014; Scherer et al., 2015; Scherer and Pfister, 2016). Another limitation of the WSI is that in some regions where water is physically scarce (e.g. central Australia), the region may not be considered water 'stressed' due to only limited water withdrawals occurring (possibly due to the regional water scarcity). Further compounding this is the tendency of the WaterGAP model to overestimate river discharge in arid regions (Scherer and Pfister, 2016). In contrast, the formulation of the AWaRe factors being based upon an *absolute* measure of excess water availability (Equation (4)) overcomes the inherent limitations associated with the WSI being based upon the *ratio* of water withdrawals to availability (Equation (1)). Therefore, we suggest that the use of AWaRe factors may be preferable to the WSI when assessing the water use impacts of mining operations located in arid regions, particularly when there are limited water withdrawals from other user groups.

Previous analysis of water use impact characterisation factors has found a substantial deviation when factors are developed at different spatial and temporal boundaries (Ansorge and Beránkova, 2017; Boulay et al., 2015a; Núñez et al., 2015; Scherer et al., 2015; Quinteiro et al., 2017). As the national average characterisation factors may not reflect the water use context of specific industries and commodities within a country, uncertainty data is available for the national average AWaRe factors reflecting the spatial and temporal differences in water use and availability across watersheds within a country (Boulay et al., 2017; WULCA, 2017). Fig. S5 in the supporting information shows that 81% of mining operations and 90% of national production weighted averages fall within 1 standard deviation of the spatial uncertainty associated with the national average.

3.4. Limitations in the impact assessment of groundwater use

Many mining operations consume water from confined and unconfined aquifer systems – to meet the requirements of ore processing, dust suppression, waste management practices, and aquifer depressurisation to prevent groundwater seepage into mine voids or to alleviate slope stability issues (Northey et al., 2016). The potential impacts of mining operations on groundwater systems are highly complex, uncertain and site specific (Currell et al., 2017). Existing life cycle assessment based water use impact methods are not tailored to assess the potential impacts of water use on groundwater systems. Current approaches typically utilise estimates of water availability derived from global hydrological models, such as WaterGAP, which has been calibrated to estimate discharge from major river systems (Alcamo et al., 2003; Müller Schmied et al., 2014). Water availability in the determination of characterisation factors therefore largely reflects what can be considered 'flow' water resources (Madrid et al., 2013), however many mining operations extract groundwater from what may be considered ‘fund’ (i.e. rechargeable aquifers) or ‘stock’ (i.e. fossil aquifers) groundwater resources – which may require assessment using different water use impact pathways (Kounina et al., 2013; Milà I Canals et al., 2009). Approaches for assessing the impacts of fund and stock groundwater depletion are still underdeveloped within life cycle assessment and require further conceptualisation. This topic has been a focus of discussion within the WULCA subcommittee that is developing a framework for considering water use impact characterisation pathways to the natural resources area-of-protection within life cycle assessment.

3.5. Implications for mine water use disclosures and reporting

Over the past two decades there has been increasing transparency and reporting of water use data as part of corporate sustainability and environmental management reporting in the mining industry (Leong et al., 2014; Mudd, 2008; Northey et al., 2013). There is growing recognition of the need for local water scarcity or stress information to be reported alongside mine-site water use to facilitate meaningful interpretation of data (Northey et al., 2014, 2016).

The International Council on Mining & Metals (ICMM) recently released reporting guidelines to improve the quality and consistency of the industry's water use and risk disclosures (ICMM, 2017). ICMM member companies are expected to implement these standards by November 2018. The standard was heavily based upon the previous Water Accounting Framework for the Minerals Industry that was developed for the Minerals Council of Australia (2014), which has been shown to be broadly applicable for mine sites regardless of the local hydrological context (Danoucaras et al., 2014). Beyond clearly outlining water accounting procedures, the ICMM's standard also recommends that companies report on the local water stress of regions that they operate within by using tools, such as: the WRI Aqueduct Water Risk Atlas (2013), the GEMI Local Water Tool (2016), the WBCSD Global Water Tool (2015), or the WWF Water Risk Filter (2012). Northey et al. (2017) demonstrated that a more meaningful understanding of the mining industry's water use contexts could be achieved by considering multiple water risk indices simultaneously. Therefore, alternative watershed risk indices such as Water Criticality (Sonderegger et al., 2015), the WSI (Pfister et al., 2009) or AWaRe factors (Boulay et al., 2016, 2017; WULCA, 2017) may add further insight to the industry's water use reporting, and also facilitate greater data interoperability with LCA and water footprint assessments.

Often mining companies will aggregate the water withdrawal or consumption estimates of multiple mining operations into divisional, national or corporate totals when reporting the companies water use (Mudd, 2008; Northey et al., 2016). In these cases we emphasise that any water scarcity or stress information provided alongside this data should be sourced from watershed scale data, rather than national data that may not be representative of the local water use context of the company's individual operations.

3.6. Implications for life cycle inventory development

The results of a recent life cycle assessment methodology harmonisation project for metal associations recommended that water scarcity impacts should not be reported as part of life cycle assessment studies of metal supply, due to limitations with existing inventory data (e.g. high levels of spatial aggregation) and the need for further methodological development (Santero and Hendry, 2016). Existing inventory data for mined commodities are highly spatially aggregated (i.e. global, continental or national boundaries – often with poor production coverage within the region). We recommend that future mine site water use inventory data be developed and reported at the scale of individual operations. If aggregation of site inventory data is required to protect commercially sensitive data, then aggregation to the scale of watersheds rather than national boundaries would facilitate more accurate assessment of water use impacts. Where this is not possible, then inventory developers could also develop weighted average impact factors that reflect the underlying spatial and temporal distribution of the inventory's water use data.

4. Conclusions

Life cycle assessment and water footprint studies of the mining industry are increasingly utilising spatially explicit characterisation factors when assessing consumptive water use impacts (Northey et al., 2016). This study has shown that the use of existing national average impact factors may lead to a bias to overestimate the consumptive water use impacts of the mining industry. Despite this observed biased at an industry wide scale, there is high variability in results for commodity production in specific countries and so for some regions national average factors may actually underestimate impacts for a particular commodity. Due to these disparities, it is encouraged that future assessments of the mining industries consumptive water use utilise watershed specific inventory data and impact factors. In the absence of watershed specific water use inventories for the mining industry, weighting watershed factors based upon the spatial distribution of commodity production may improve the estimation of the industry's relative water use impacts. Overall, there are significant opportunities for continued development of life cycle inventory datasets and impact characterisation procedures to improve the assessment of the mining industry's water use impacts.

Acknowledgements

The authors would like to thank Brad Ridoutt, Mark Cooksey and Daniel Jewell for providing valuable feedback on the article, as well as the anonymous peer reviewers. The financial support for this research project was provided by CSIRO Mineral Resources, Australia.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2018.02.307.

References

Alcamo, J., Döll, P., Henrichs, T., Kaspar, F., Lehner, B., Rösch, T., Siebert, S., 2003. Development and testing of the WaterGAP 2 global model of water use and availability. Hydrol. Sci. J. 48 (3), 317–337. https://doi.org/10.1623/hysj.48.3.317.45290.

Ansorge, L., Beránkova, T., 2017. LCA water footprint aware characterization factor based on local specific conditions. Eur. J. Sustain. Dev. 6 (4), 13–20. https://doi.org/10.14207/esjd.2017.v6n4p13.

Berger, M., van der Ent, R., Eisner, S., Bach, S., Finkbeiner, M., 2014. Water accounting and vulnerability evaluation (WAVE): considering atmospheric evaporation recycling and the risk of freshwater depletion in water footprinting. Environ. Sci. Technol. 48, 4521–45428. https://doi.org/10.1021/es404994t.

Boulay, A.-M., Motoshita, M., Pfister, S., Bulle, C., Muñoz, I., Franceschini, H., Margni, M., 2015a. Analysis of water use impact assessment methods (part A): evaluation of modelling choices based on a quantitative comparison of scarcity and human health indicators. Int. J. Life Cycle Assess. 20, 139–160. https://doi.org/10.1007/s11367-014-0814-2.

Boulay, A.-M., Bare, J., De Camillis, C., Döll, P., Gassert, F., Gerten, D., Humbert, S., Inaba, A., Itsubo, N., Lemoine, Y., Margni, M., Motoshita, M., Núñez, M., Pastor, A.V., Ridoutt, B., Schencker, U., Shirakawa, N., Vionnet, S., Worbe, S., Yoshikawa, S., Pfister, S., 2015b. Consensus building on the development of a stress-based indicator for LCA-based impact assessment of water consumption: outcome of the expert workshops. Int. J. Life Cycle Assess. 20 (5), 577–583.

https://doi.org/10.1007/s11367-015-0869-8.
Boulay, A.-M., Pfister, S., Motoshita, M., Schenker, U., Benini, L., Gheewala, S.H., de Figueirêdo, M.C.B., Harding, K., 2016. Chapter 5a: water scarcity. In: Global Guidance for Life Cycle Impact Assessment Indicators, vol. 2016. UNEP SETAC Life Cycle Initiative. http://www.lifecycleinitiative.org/applying-lca/lcia-cf/.
Boulay, A.-M., Bare, J., Benini, L., Berger, M., Lathuillière, M., Manzardo, A., Margni, M., Motoshita, M., Núñez, M., Pastor, A.V., Ridoutt, B., Oki, T., Worbe, S., Pfister, S., 2017. The WULCA consensus characterization model for water scarcity footprints: assessing impacts of water consumption based on available water remaining (AWARE). Int. J. Life Cycle Ass. 11 volume unassigned. https://doi.org/10.1007/s11367-017-1333-8.
British Geological Survey, 2016. World Mineral Production 2010-2014. British Geological Survey, Keyworth, Nottingham, United Kingdom. http://www.bgs.ac.uk/mineralsuk/statistics/wms.cfc?method=searchWMS. (Accessed 16 March 2017).
CDP, 2013. Metals & Mining: a Sector under Water Pressure. Analysis for institutional investors of critical issues facing the industry. Carbon Disclosure Project (CDP), United Kingdom, p. 20p. July 2013.
Currell, M.J., Werner, A.D., McGrath, C., Webb, J.A., Berkman, M., 2017. Problems with the application of hydrogeological science to regulation of Australian mining projects: Carmichael Mine and Doongmabulla Springs. J. Hydrol. 548, 674–682. https://doi.org/10.1016/j.jhydrol.2017.03.031.
Danoucaras, A.N., Woodley, A.P., Moran, C.J., 2014. The robustness of mine water accounting over a range of operating contexts and commodities. J. Clean. Prod. 84, 727–735. https://doi.org/10.1016/j.jclepro.2014.07.078.
Flörke, M., Kynast, E., Bärlund, I., Eisner, S., Wimmer, F., Alcamo, J., 2013. Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: a global simulation study. Global Environ. Change 23 (1), 144–156. https://doi.org/10.1016/j.gloenvcha.2012.10.018.
Gao, L., Bryan, B.A., Liu, J., Li, W., Chen, Y., Liu, R., Barrett, D., 2017. Managing too little and too much water: robust mine-water management strategies under variable climate and mine conditions. J. Clean. Prod. 22p volume unassigned. https://doi.org/10.1016/j.jclepro.2017.06.101.
GEMI Local Water Tool, 2016; http://gemi.org/localwatertool
Gunson, A.J., 2013. Quantifying, Reducing and Improving Mine Water Use. PhD Thesis. The University of British Columbia, Canada, p. 285.
Hejazi, M., Edmonds, J., Clarke, L., Kyle, P., Davies, E., Chaturvedi, V., Wise, M., Patel, P., Eom, J., Calvin, K., Moss, R., Kim, S., 2014. Long-term global water projections using six socioeconomic scenarios in an integrated assessment modelling framework. Technol. Forecast. Soc. Change 81, 205–226. https://doi.org/10.1016/j.techfore.2013.05.006.
Hoekstra, A.Y., 2016. A critique on the water-scarcity weighted water footprint in LCA. Ecol. Indicat. 66, 564–573. https://doi.org/10.1016/j.ecolind.2016.02.026.
Hoekstra, A.Y., Mekonnen, M.M., Chapagain, A.K., Mathews, R.E., Richter, B.D., 2012. Global monthly water scarcity: blue water footprints versus blue water availability. PLoS One 7 (2), e32688. https://doi.org/10.1371/journal.pone.0032688.
International Council on Mining & Metals (ICMM), 2017. A Practical Guide to Consistent Water Reporting, p. 72p. March 2017.
Kounina, A., Margni, M., Bayart, J.-B., Boulay, A.-M., Berger, M., Bulle, C., Frischknecht, R., Koehler, A., Milà I Canals, L., Motoshita, M., Núñez, M., Peters, G., Pfister, S., Ridoutt, B., van Zelm, R., Verones, F., Humbert, S., 2013. Review of methods addressing freshwater use in life cycle inventory and impact assessment. Int. J. Life Cycle Assess. 18, 707–721. https://doi.org/10.1007/s11367-012-0519-3.
Kunz, N.C., Moran, C.J., 2016. The utility of a systems approach for managing strategic water risks at a mine site level. Water Res. Ind. 13, 1–6. https://doi.org/10.1016/j.wri.2016.02.001.
Leong, S., Hazelton, J., Taplin, R., Timms, W., Laurence, D., 2014. Mine site-level water reporting in the Macquarie and Lachlan catchments: a study of voluntary and mandatory disclosures and their value for community decision-making. J. Clean. Prod. 84, 94–106. https://doi.org/10.1016/j.jclepro.2014.01.021.
Madrid, C., Cabello, V., Giampietro, M., 2013. Water-use sustainability in socioecological systems: a multiscale integrated approach. Bioscience 63, 14–24. https://doi.org/10.1525/bio.2013.63.1.6.
Milà I Canals, L., Chenoweth, J., Chapagain, A., Orr, S., Antón, A., Clift, R., 2009. Assessing freshwater use impacts in LCA: Part I—inventory modelling and characterisation factors for the main impact pathways. Int. J. Life Cycle Assess. 14, 28–42. https://doi.org/10.1007/s11367-008-0030-z.
Minerals Council of Australia, 2014. Water Accounting Framework for the Minerals Industry, User Guide, Version 1.3. January 2014.
Mudd, G.M., 2008. Sustainability reporting and water resources: a preliminary assessment of embodied water and sustainable mining. Mine Water Environ. 27, 136–144. https://doi.org/10.1007/s10230-008-0037-5.
Müller Schmied, H., Eisner, S., Franz, D., Wattenbach, M., Portmann, F.T., Flörke, M., Döll, P., 2014. Sensitivity of simulated global-scale freshwater fluxes and storages to input data, hydrological model structure, human water use and calibration. Hydrol. Earth Syst. Sci. 18, 3511–3538. https://doi.org/10.5194/hess-18-3511-2014.
Nilsson, C., Reidy, C.A., Dynesius, M., Revenga, C., 2005. Fragmentation and flow regulation of the World's large river systems. Science 308 (5720), 405–408. https://doi.org/10.1126/science.1107887.
Northey, S.A., Haque, N., Mudd, G.M., 2013. Using sustainability reporting to assess the environmental footprint of copper mining. J. Clean. Prod. 40, 118–128. https://doi.org/10.1016/j.jclepro.2012.09.027.
Northey, S.A., Haque, N., Lovel, R., Cooksey, M.A., 2014. Evaluating the application of water footprint methods to primary metal production systems. Miner. Eng. 69, 65–80. https://doi.org/10.1016/j.mineng.2014.07.006.
Northey, S.A., Mudd, G.M., Saarivuori, E., Wessman-Jääskeläinen, H., Haque, N., 2016. Water footprinting and mining: where are the limitations and opportunities? J. Clean. Prod. 135, 1098–1116. https://doi.org/10.1016/j.jclepro.2016.07.024.
Northey, S.A., Mudd, G.M., Werner, T.T., Jowitt, S.M., Haque, N., Yellishetty, M., Weng, Z., 2017. The exposure of global base metal resources to water criticality, scarcity and climate change. Global Environ. Change 44, 109–124. https://doi.org/10.1016/j.gloenvcha.2017.04.004.
Núñez, M., Pfister, S., Vargas, M., Antón, A., 2015. Spatial and temporal specific characterisation factors for water use impacts in Spain. Int. J. Life Cycle Assess. 20, 128–138. https://doi.org/10.1007/s11367-014-0803-5.
Pfister, S., Bayer, P., 2014. Monthly water stress: spatially and temporally explicit consumptive water footprint of global crop production. J. Clean. Prod. 73, 52–62. https://doi.org/10.1016/j.jclepro.2013.11.031.
Pfister, S., Koehler, A., Hellweg, S., 2009. Assessing the environmental impacts of freshwater consumption in LCA. Environ. Sci. Technol. 43, 4098–4104. https://doi.org/10.1021/es802423e.
Pfister, S., Boulay, A.-M., Berger, M., Hadjikakou, M., Motoshita, M., Hess, T., Ridoutt, B., Weinzettel, J., Scherer, L., Döll, P., Manzardo, A., Núñez, M., Verones, F., Humbert, S., Buxmann, K., Harding, K., Benini, L., Oki, T., Finkbeiner, M., Henderson, A., 2017. Understanding the LCA and ISO water footprint: a response to Hoekstra (2016) “A critique on the water-scarcity weighted water footprint in LCA”. Ecol. Indicat. 72, 352–359. https://doi.org/10.1016/j.ecolind.2016.07.051.
Quinteiro, P., Ridoutt, B.G., Arroja, L., Dias, A.C., 2017. Identification of methodological challenges remaining in the assessment of a water scarcity footprint. Int. J. Life Cycle Ass. 17 volume unassigned. https://doi.org/10.1007/s11367-017-1304-0.
Ridoutt, B.G., Pfister, S., 2013. A new water footprint calculation method integrating consumptive and degradative water use into a single stand-alone weighted indicator. Int. J. Life Cycle Assess. 18, 204–207. https://doi.org/10.1007/s11367-012-0458-z.
Santero, N., Hendry, J., 2016. Harmonization of LCA methodologies for the metal and mining industry. Int. J. Life Cycle Assess. 21 (11), 1543–1553. https://doi.org/10.1007/s11367-015-1022-4.
Scherer, L., Pfister, S., 2016. Dealing with uncertainty in water scarcity footprints. Environ. Res. Lett. 11, 054008. https://doi.org/10.1088/1748-9326/11/5/054008.
Scherer, L., Venkatesh, A., Karuppiah, R., Pfister, S., 2015. Large-scale modeling for calculating water stress indices: implications of improved spatiotemporal resolution, surface-groundwater differentiation, and uncertainty characterization. Environ. Sci. Technol. 49, 4971–4979. https://doi.org/10.1021/acs.est.5b00429.
SNL, 2017. SNL Metals & Mining Database. S&P Global Market Intelligence.
Sonderegger, T., Pfister, S., Hellweg, S., 2015. Criticality of water: aligning water and mineral resources assessment. Environ. Sci. Technol. 49, 12315–12323. https://doi.org/10.1021/acs.est.5b02982.
WBCSD Global Water Tool, 2015. http://www.wbcsd.org/work-program/sector-projects/water/globalwater-tool.aspx.
WRI Aqueduct Water Risk Atlas, 2013. World Resources Institute. http://www.wri.org/our-work/project/aqueduct.
WULCA, 2017. AWaRe version 1.2. Working Group for Water Use in Life Cycle Assessment (WULCA). http://www.wulca-waterlca.org. (Accessed 20 June 2017).
WWF-DEG Water Risk Filter, 2012. http://waterriskfilter.panda.org.