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Overview and recommendations for regionalized life cycle impact assessment

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1 Abstract

Purpose Regionalized life cycle impact assessment (LCIA) has rapidly developed in the past decade, though its widespread application, robustness, and validity still faces multiple challenges. Under the umbrella of UNEP/SETAC Life Cycle Initiative, a dedicated cross-cutting working group on regionalized LCIA aims to provides an overview of the status of regionalization in LCIA methods. We give guidance and recommendations to harmonize and support regionalization in LCIA for developers of LCIA methods, LCI databases, and LCA software.

Method A survey of current practice among regionalized LCIA method developers was conducted. The survey included questions on chosen method spatial resolution and scale, the spatial resolution of input parameters, choice of native spatial resolution and limitations, operationalization and alignment with life cycle inventory data, methods for spatial aggregation, the assessment of uncertainty from input parameters and model structure, and variability due to spatial aggregation. Recommendations are formulated based on the survey results and extensive discussion by the authors.

Results and discussion Survey results indicate that majority of regionalized LCIA models have global coverage. Native spatial resolutions are generally chosen based on the availability of global input data. Annual modelled or measured elementary flow quantities are mostly used for aggregating characterization factors (CFs) to larger spatial scales, although some use proxies, such as population counts. Aggregated CFs are mostly available at the country level. Although uncertainty due to input parameter, model structure, and spatial aggregation are available for some LCIA methods, they are rarely implemented for LCA studies. So far, there is no agreement if a finer native spatial resolution is the best way to reduce overall uncertainty. When spatially differentiated models CFs are not easily available, archetype models are sometimes developed.

Conclusions Regionalized LCIA methods should be provided as a transparent and consistent set of data and metadata using standardized data formats. Regionalized CFs should include both uncertainty and variability. In addition to the native-scale CFs, aggregated CFs should always be provided, and should be calculated as the weighted averages of constituent CFs using annual flow quantities as weights whenever available. This paper is an important step forward for increasing transparency, consistency and robustness in the development and application of regionalized LCIA methods.

Keywords: regionalization, impact assessment, standardization, archetypes, uncertainty, variability, spatial differentiation

2 Introduction

Life Cycle Assessment (LCA) is frequently used to quantify the environmental impacts of a product or a service throughout its entire life cycle (ISO 2006a, b). Life cycle impact assessment (LCIA) method developers have long recognized that, for many impact categories, the impact of a given elementary flow depends on the where that flow occurs, and have therefore provided site-dependent characterization factors (CFs) (Potting and Hauschild 2006). In the last decade, regionalized methods have included impact categories such as air pollution (Roy et al. 2012; van Zelm et al. 2016), freshwater and terrestrial acidification (Roy et al. 2014; Azevedo et al. 2015), eutrophication (Azevedo et al. 2013; Scherer and Pfister 2015), respiratory effects from particulate matter (Humbert et al. 2009), water scarcity and related impact on human health and ecosystem (Pfister et al. 2009; Verones et al. 2010, 2013, 2017b; van Zelm et al. 2011; Hanafiah et al. 2011; Helmes et al. 2012; Pfister and Bayer 2014; Motoshita et al. 2014; Scherer et al. 2015; Pfister and Suh 2015; Sonderegger et al. 2015; Boulay et al. 2018), land use, biodiversity, and soil quality (Núñez et al. 2010, 2012, de Baan et al. 2012, 2013; Chaudhary et al. 2015; Chaudhary and Brooks 2018), toxicity and exposure effect (Wegener Sleeswijk and Heijungs 2010; Owsianiak et al. 2013; Kounina et al. 2014; Wannaz et al. 2018a, b), as well as overarching methods such as EDIP 2003 (Hauschild and Potting 2005), TRACI (Bare 2011), IMPACT World + (Bulle et al. 2012), eco-scarcity 2013 (Frischknecht and Knöpfel 2013), and LC-IMPACT (Verones et al. 2016). Such regionalized LCIA models and methods include spatial inputs from fields such as climatology, geology, hydrology, ecology, human geography, and environmental engineering. In theory, maps of regionalized LCIA characterization factors can be combined with site-dependent life cycle inventories to produce more accurate and less uncertain LCA results. In practice, such regionalized LCA can be limited by a lack of standardization in regionalized LCIA data formats, poor site-dependent inventory data availability, and a lack of widespread software support. Regionalized normalization and weighting also present a separate set of challenges, primarily due to data quality and availability. This paper is the consensus output of a UNEP-SETAC Life Cycle Initiative working group on the harmonization of LCIA regionalization (Frischknecht and Jolliet 2016; Verones et al. 2017a), and provides an overview of the status of regionalization in LCIA methods and recommendations for LCIA method, LCI database, and software developers to harmonize and support regionalization in LCIA. We do not discuss the development of regionalized inventory databases, which is the focus of a separate working group, or the development of the impact assessment models themselves.

3 Methodology

3.1 Recommended nomenclature

We recommend and use the following specific terms for concepts that have been used inconsistently in previous literature:

- *Spatial unit*: The geometrical definition and metadata of a spatial feature, such as the coordinates of a raster cell or a polygon and all associated spatial and non-spatial metadata.
- *Spatial resolution*: The set of spatial units used in an inventory database or LCIA method. We note that this differs slightly from the traditional definition of spatial resolution being the smallest distinguishable parts (Lam and Quattrochi 1992), as the spatial units used in LCIA, such as watersheds, can have dramatically different sizes.
- *Native spatial resolution*: The spatial resolution of LCIA method CF maps which the method developers best feel represents the spatial variability of CF values.
- *Aggregated spatial resolution*: A transformation of the native spatial resolution to a new spatial resolution, usually at the country, continental, or global scale.

We use the terms *site-specific*, *site-dependent*, and *site-generic* as defined and used by Potting and Hauschild (2006).

3.2 Survey of current practice

A survey of developers from every recent regionalized LCIA method known to the working group were conducted by phone or email. A summary of the questions asked are shown in Table 1, and the full list of questions and answers are given in the supporting information.

3.3 Formulation of recommendations

The recommendations in this paper and technical appendix were developed over online meetings from 2015 to 2018 and during a Pellston Workshop in Valencia, Spain in January 2016.

4 Results

4.1 Summary of survey results

In this survey, methods for twenty seven regionalized impact indicators were reviewed. Both widely used LCIA methods, such as TRACI (3 impact categories, hereafter IC), Ecological scarcity 2013 (2 IC), and EDIP 2003 (3 IC) , as well as more recent LCIA methodologies like LC Impact (5 IC), IMPACT World+ (13 IC), and AWARE (1 IC) were included (Hauschild and Potting 2005; Bare 2011; Bulle et al. 2012; Frischknecht and Knöpfel 2013; Verones et al. 2016; Boulay et al. 2018). They cover the following environmental issues: water use, land use, acidification, eutrophication, human toxicity, respiratory inorganics, smog formation, and photochemical ozone formation. Most methods had global spatial coverage, except for TRACI (USA) and EDIP (Europe).

The survey results are summarized in Figure 1 and discussed in detail in the following sections.

4.1.1 Choice of native spatial resolution

In theory, the native spatial resolution should reflect the observed spatial variability of a given environmental issue and elementary flow. Surveyed method developers were aware of how the choice of native spatial resolution could influence the produced characterization factors. However, in our survey, the native spatial resolution choice was driven in most cases by the following factors: input data availability, especially when global coverage was desired; optimizing model robustness and consistency instead of finer spatial resolution; and the limited availability of models for specific impact categories. Few developers used tools like spatial interpolation or minimization of spatial autocorrelation (Mutel et al. 2012) to actively choose a spatial resolution not already found in their input data. Instead, several method developers tested multiple possible native spatial resolutions, and the chosen native spatial resolution was then a compromise between scientific fidelity and practical considerations, such as data size and calculation times.

The surveyed native spatial resolutions ranged from very small to very large regions (i.e. from tens to millions of square kilometers); from tens to thousands of spatial units; and from spatial units based on biophysical or political boundaries to grid cells. In some cases, such as acidifying emissions to air, consumption of surface and ground water, and toxicity assessment, individual substances, such as ammonia or SO_x, or classes of substances, such as water from surface sources or water from aquifers, will each have their own spatial resolution within one impact category.

4.1.2 Desirability of finer native spatial resolutions

Most impact assessment (IA) method developers mentioned they would prefer a finer native spatial resolution to better represent their CF spatial variability. However, most of them cited data availability and time effort as the limiting factors to do so. Some developers mentioned they would prefer to focus on improving underlying LCIA model details, such as assumptions and input parameter data quality, rather than the spatial resolution, as this was a more efficient path to reduce CF uncertainty. In our survey, the IA method developers were split about whether a finer native spatial resolution was the best way to reduce overall uncertainties. Those who answered “yes” considered their native spatial resolutions too coarse and felt that a finer resolution would better reflect spatial impact variability. Those who answered “no” presented several arguments against a finer spatial resolution: 1) inventory data is not ready, or has very poor spatial resolution; 2) result uncertainty is driven by inventory or impact assessment model uncertainty, not IA spatial uncertainty; 3) results on a finer spatial resolution would actually have higher uncertainty, due either to the use of either spatial interpolation, more detailed but less accurate models or uncertainty on the exact location of withdrawal or emission (e.g. for water supply or effluents); 4) the amount of work and new tools needed to deal with big data can be overwhelming or infeasible.

4.2 Aggregation of characterization factors

Method developers aggregate native resolution CF to larger spatial resolutions (e.g. regional, continental, and global levels) to meet specific study or software requirements. During this aggregation, method developers face challenges in 1) the selection of appropriate techniques used to aggregate native CFs; 2) the definition of aggregation-scale regions; and 3) the handling of native-scale regions for which no CFs are provided.

4.2.1 Selection of appropriate aggregation techniques

As shown in Table 2, method developers have handled aggregation in an ad hoc and uncoordinated fashion. When aggregating, most developers used a weighted average of the native-scale CFs, but significant differences were observed in the choice and source of data used as weights. The most widely used weighting data were annual elementary flow quantities in each native-scale region. This approach assumes that the specific activities in each given study, and their corresponding elementary flows, are more likely to happen in areas where they are generally already occurring. This approach is practical, as such flow data is often gathered during method development. One can even differentiate such flow quantities by industrial sector, for example differentiating consumption of water for agricultural and non-agricultural purposes (Boulay et al. 2016), and thus generate sector-specific aggregated CFs.

Proxy weighting data has been used when data on the actual distribution of the elementary flow quantities were unavailable. Population counts have been used as weighting proxy, with the assumption that the spatial patterns of stressors are well correlated with population distributions (Humbert et al. 2011). Given no other suitable proxy data, the surface area of each native-scale region could be used as a last resort (Mutel et al. 2012).

4.2.2 Definition of aggregation regions

Aggregation to country and continent scales can be another source of discrepancies across methods. Country borders can change over time, as can the number of countries. Country boundaries can also vary based on the chosen data source and that source's spatial resolution. Not all country borders are recognized by other countries, and different data sources treat disputed areas differently. The situation is even less clear when it comes to continental boundaries; while the United Nations has a country-based list of regions and sub-regions (United Nations Statistics Division 2018), few method developers follow this standard. In particular, the boundary between Asia and Europe can differ by more than one thousand kilometers, depending on the data source. Method developers doing aggregation need to check whether their country definitions span multiple continents, which could lead to unexpected results. Discrepancies on the spatial definitions of countries and continents can lead to mismatches with life cycle inventory datasets, even if the formal name of the spatial unit is identical.

4.2.3 Handling of no data values

Regionalized LCIA methods with global coverage will still have some areas where no CFs are provided. Such “no data” CFs can arise due to a lack of data, such as isolated islands, or in regions where it would not make physical sense to provide a CF, such as land use in the ocean. The way these "no data" values are handled in the aggregation process can significantly affect the aggregated CF values, but is seldom described. Four approaches to handle "no data" values in weighted, average aggregation techniques are present in the literature: 1) treat no data values as zeros; 2) assign a default value such as the global average; 3) interpolate from neighboring areas where real-value native CFs are present; 4) exclude “no data” spatial units from the weighted average.

The choice among these four techniques should reflect the reason that such "no data" values occur. In areas where it is reasonable not to have a CF, such Antarctica, the last option (4) is preferable. Equating no data regions with zero CFs (1) is the most widely used but can introduce significant and systematic downward bias in aggregated CFs. The use of default values (2) is a good compromise for spatial units where a CF is expected to be non-zero but not available. Interpolation from near neighbors (3) has been used to fill in no data values for coastal areas (Pfister et al 2011), but should only be used as a last resort; it would be far preferable to fill the missing input data in the LCIA model.

5 Discussion

5.1 Spatial Archetypes

Archetypes are classes of similar scenarios or situations that can explain some of the variability in CFs. Archetypes can incorporate geographical information ("low population density," "agricultural"), though spatial differentiation is not always the primary consideration ("from high stacks," "indoor"). Archetypes can impart information more efficiently than spatial units when such spatial units would need to be defined on a very fine spatial resolution, or when spatial differentiation is not the main driver for variability. For example, some intake fractions are driven by population density around emission sources (Apte et al. 2012; Hodas et al. 2016). In this case, it is more important to know whether a particulate matter emission happens in a city or a rural area than to know whether it takes place in France or Italy. Even a regionalized IA method with a native spatial resolution of 50 km by 50 km (van Zelm et al. 2016) will be less accurate than urban versus rural archetypes, as most of the grid cells will be composed of a mix of high and low population density and will therefore not be able to reflect the actual variability in intake fractions.

Archetypes may further represent an efficient way to link inventory and impact assessment. It may be difficult to know the exact location where an emission takes place, but we can easily differentiate whether it takes place indoors or outdoors, or the fraction occurring in an urban versus rural area.

Several challenges need to be addressed to ensure the consistent and efficient use of archetypes. To be practical, archetypes must be general enough that they can be used across different impact categories and LCIA methods. Proliferation of category-specific archetypes is not practical since this would mean that different inventory flows would be reported in different ways depending on the considered category. The definition of archetypes therefore requires coordination between LCI databases and LCIA methods, as well as across LCIA methods, to ensure consistent archetype use and definitions.

Archetypes should be relatively easy to use (Helmes et al. 2012). Kounina et al. (2018) defined archetypes for the fate of eutrophying or toxic substances in freshwater based on the residence time of water to the sea and the water depth. In this case, it is easier to provide a map, as the input data needed to choose the archetype would require site-specific (Kounina et al. 2018).

Finally, archetypes may not be able to reflect the entire range of variability. For example, the archetype label "urban" may include large variations in population densities between a small and a large city, or between a North American low density and an Asian high-density city. A hybrid approach that combines archetypes with location-specific inputs can be one way forward (Fantke et al. 2017). Parameterizing archetypes for different regions, like different parameters for a default urban area in each continent of the world (Fantke et al. 2017), could also be tried, though such an approach could lead to inconsistencies without community consensus.

5.2 Uncertainty and variability

Current LCA practice merges input parameter and model uncertainty, commonly understood as reducible through model refinement or data acquisition, and inherent variability, which is not. Both input parameter and model uncertainty and inherent variability have a spatial and non-spatial component. The merging of those uncertainties into a single probability distribution presents challenges for regionalized IA method developers, as it is difficult to give practitioners guidance on how much of the total uncertainty is spatially correlated, and how much is due to inherent variability and should therefore be independently sampled from spatial unit to spatial unit.

5.3 Value choices in aggregation

The choice of the proxy can have considerable influence on the resulting aggregated CFs. For example, the use of population counts to upscale CFs for freshwater eutrophication at local resolution may lead to different aggregated CFs compared to the use of phosphorus emissions as proxy. A large fraction of phosphorus emissions stem from agricultural sources, which are not highly-populated areas, thus generating important bias in the aggregation. In addition, for a country with important exports from a strong agricultural sector, the population densities will be decoupled from the emission intensities in that country, and their use will thus contribute to a bias in the obtained CF compared to other countries. Illustrations of such biases have been shown in previous studies, e.g. land use impact assessment.

Using current annual flow quantities or proxy data such as population counts in the aggregation calculation introduces uncertainty due to practitioner choice: the implicit assumption of such techniques is that current patterns are good predictors of the spatial pattern of stressors caused by a specific functional unit. There is a parallel here with current debates on “attributional” versus “consequential” LCA; using current spatial patterns of stressors is analogous to the attributional approach, whereas a consequential perspective might, for example, prefer to use a model of where agricultural land could be transformed or intensified due to increased demand when calculating land use impacts.

6 Recommendations

6.1 Overall recommendations

Our first overall recommendation is that method developers should provide more complete set of information than is currently provided. This recommendation is specified in detail in the following sections and includes 1) a transparent and consistent set of metadata; 2) LCIA CFs with separate characterization of uncertainty and variability; 3) aggregated CFs with include variability due to spatial aggregation.

We recommend that methods be provided in, and LCA software support, a standardized regionalized LCIA data format. Existing LCIA formats do not support regionalized CFs and do not enjoy broad community support. A draft standard is provided in the supporting information. The proposed data format is not a new creation, but rather a standardized way of using existing data and metadata formats such as GeoTIFFs, GeoJSON, and the Open Knowledge Foundation's Data Package, and will be tested and applied to both IMPACT World+ (Bulle et al. 2012) and LC-IMPACT (Verones et al. 2016). Feedback from the broader LCA community as well as LCA software developers will be solicited.

Specific recommendations are given below to IA developers (Section 6.2), LCI database providers (Section 6.3), and LCA software developers (Section 6.4).

6.2 Recommendations for IA method developers

Transparent and comprehensive documentation. Regionalized methods developers should clearly and transparently state 1) which parameters are regionalized, and at what spatial resolution, in their LCIA model and input data sets; 2) aggregation method, if any; 3) value choices. All IA method developers should indicate the basis for their choice of native spatial resolution, even if they have chosen site-generic modeling. Regionalized methods should indicate whether they would have preferred a different native spatial resolution.

Standard data formats. Regionalized IA method metadata and CFs should be provided in a standardized data format. We have proposed and will test one such format, described in the supporting information.

Common and comprehensive elementary flow nomenclature. CFs should be provided using a common and comprehensive nomenclature such as found in the ELCD or ecoinvent databases or produced through community reconciliation efforts such as the Global LCA Data Network (GLAD).

Native spatial resolution. Spatial input datasets for regionalized impact assessment models should be aggregated as little as possible, as such aggregation causes loss of information. In cases where IA model input datasets have different resolutions, it is preferable to downscale the input data to the finest spatial resolution instead of aggregating all input data to the coarsest resolution.

Archetype development. When similar scenarios or situations can explain a large fraction of CF variability, we recommend defining archetypes that reflect this similarity. This development should be done under the condition that related LCI information could easily be adapted to match such archetypes. In cases where the use of archetypes could lead to additional complexity in their implementation, we recommend calculating sector- or industry-specific average CFs.

Spatial aggregation. Regionalized IA method developers should provide aggregated characterization factors, and document how such aggregated factors were calculated.

- Global factors should always be provided; continental and region- or country-specific factors should be provided when these spatial units are larger than the native resolution. Continental region and sub-region definitions are encouraged to follow the United Nations geoscheme (United Nations Statistics Division 2018), and any other continental- resolution regions should be labelled as such and be given names not overlapping those found in the United Nations geoscheme. Data sources for continent and country borders should be documented and publicly accessible, including their URLs, version numbers, and access dates.
- The approach used to handle no data CF values in aggregation should be explained. We recommend that no data values should be skipped in the aggregation algorithm (the fourth approach in section 4.2.3), though care should be taken when a large fraction of an aggregated spatial unit has no data CF values.
- Aggregation techniques across impact categories within an LCIA method should be as consistent as possible. We recommend the use of annual flow quantities in the weighted average aggregation calculation whenever available. Alternative aggregation approaches, such as using proxies based on population counts, can be used if necessary. LCIA method developers should document the rationale for using those alternative proxies.
- The data used for the aggregation should be as consistent as possible with the data used in the IA model, including having the same reference year and spatial resolution. Any discrepancies between these data sources should be documented.

Should there be high variability in regionalized CFs within large and diverse countries, sub-national or regional CFs may be developed.

Report uncertainty factors separately. IA method developers should include quantitative estimates of uncertainty and variability in their published CFs at both the native and aggregated spatial resolutions. For aggregated spatial units, CFs should include a separate estimate of variability due to spatial aggregation. In all cases, a total probability distribution function for the CF should be given.

Changing the spatial resolution of model inputs. Many fields of scientific inquiry contribute datasets and models that could be useful for impact assessment applications, each with their own spatial and temporal resolution and level of detail. Adapting and transforming these inputs is the first step for most impact assessment method development, but such modifications can change statistical or other data properties due to the modifiable areal unit problem (Fotheringham and Wong 1991). Method developers should check, understand, and document changes introduced by the adaptation and transformation of model inputs.

Global coverage. Global coverage of regionalized IA methods is recommended, but is not a requirement - in some cases, region-specific models may have higher accuracy. Some parameterized models can be adapted to many regions provided region-specific input data is available, like the InVEST model (Sharp et al. 2014). This is a promising approach, though we caution that model developers should thoroughly and critically evaluate the global application of such models.

Develop regionalized archetypes. Combining archetypes, such as population density classes, with spatial information, such as a city name and location, could be an efficient way to provide high fidelity CFs. If global spatially differentiated CFs cannot be easily developed for certain impact categories, such as particulate matter formation, using detailed location-specific archetypes can capture important CF variabilities (Fantke et al. 2017). More research is needed on the implementation and trade-offs of such an approach.

Validity check with case study. Regionalized LCIA developers should use their methods in LCA case studies or method comparison studies to show the practicality and usefulness of their CFs.

6.3 Recommendations for inventory databases

Prioritize the development of regionalized inventories. Regionalized inventories are necessary to unlock the value of the data that already exists in regionalized LCIA methods. Therefore, database developers should prioritize the development of regionalized inventories when high spatial variability is observed or expected.

Document the spatial resolution of the inventory. Inventory databases should document and make available the geographical definition of each spatial unit used in the database, as well as how these definitions were derived. A good example is the ecoinvent geography definitions report, which includes all spatial units in four different spatial data formats, built using open data and software (Mutel 2017). We encourage inventory databases to use existing and widely available data and definitions, such as Natural Earth data and the United Nations geoscheme (United Nations Statistics Division 2018) whenever possible.

Three-dimensional spatial information. In addition to the geographic location, some impacts are impacted by the altitude of the stressor. The most prominent example are the varying climate change impacts of air emissions at low and high altitudes (Fuglestvedt et al. 2010). The existing archetype approach is, however, adequate to capture this variability.

Support archetype developments. Inventory database developers should support the development of regionalized archetypes where appropriate, including conducting trial applications on existing datasets, providing their experience implementing archetypes in a consistent fashion, and integrating archetypes with proven value in a timely manner.

6.4 Recommendations for software developers

Support for native resolution CFs. LCA software should support regionalized LCA calculations and the data formats for regionalized LCIA methods. Such support can include integrating GIS directly into the LCA software or using external services for on-demand or pre-calculated GIS operations.

Clear and tested calculation algorithms. The algorithms used in regionalized LCA calculations should be documented and publicly available. Transparency is vital to build trust in the results and understanding of such advanced and novel calculations.

Support the standard data format. LCA software should support the standard data format proposed in the supporting information for documenting CFs, as this will simplify the use of and ensure consistency in the implementation of regionalized LCIA methods.

7 Conclusions

Based on our survey of all major recent regionalized LCIA methods, developers face the following challenges when developing robust and usable methods: 1) data availability for LCIA characterization factors with global coverage; 2) lack of standardization and harmonization of when calculating weighted spatially-aggregated CFs; 3) insufficient quantification and differentiation of uncertainty factors; 4) inconsistent metadata and data formats. There are also practical challenges posed by poor spatial resolution and understanding of spatial dynamics in LCI databases and software support for regionalized LCA calculations.

The recommendations for regionalized method, inventory database, and software developers in this manuscript can help improve transparency, consistency, and data quality of both regionalized LCIA methods and their use in LCA software and inventory databases. With spatially differentiated LCI data and advanced LCA calculation routines becoming increasingly available, regionalized LCA can contribute to improving the robustness of LCA results by reducing uncertainties due to spatial variability.

8 Disclaimer

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***Table 1** – Survey questions*

Meta information	LCIA method name
	Contact person
	Midpoint or endpoint (damage) modelling
	Impact category (water scarcity, land occupation, etc.)
Spatial resolution and scale	Spatial coverage (global, country level, etc.)
	Description of the chosen native spatial resolution: use of spatial differentiation or archetype?
Spatial resolution for input parameters in the LCIA model	Fate factor
	Effect factor
Improvements/Limitations - Short term (interim approach) - overall (directional)	How was the native spatial resolution chosen?
	Was the chosen native spatial resolution compared with alternatives?
	Would a finer native spatial resolution be preferred?
	Is a finer native spatial resolution the best way to reduce overall uncertainties?
	Would a finer native spatial resolution be operational?
Operationalization	Did you try to align the LCIA spatial resolution with the spatial resolution of available inventory data?
	To which spatial resolutions was the aggregation performed?
	What method used for spatial aggregation, if any?
	Which aggregation scale would you recommend?
Uncertainty assessment	Was basic uncertainty from input parameters assessed?
	Was basic uncertainty from the model structure assessed?
	Was spatial variability due to spatial aggregation assessed?

Table 2 *Weighting proxies to upscale the native CF to country, continental and global CF for regional and local impact categories (non-exhaustive list)*

Impact categories	Elementary flow type	LC-Impact	IMPACT World +	ReCiPe 2016
Photochemical ozone formation	Emission (kg)	Annual flow quantity	NR [a]	Annual flow quantity
Particulate matter formation	Emission (kg)	Annual flow quantity	Population count	Annual flow quantity
Terrestrial acidification	Emission (kg)	Annual flow quantity	Annual flow quantity	Annual flow quantity
Aquatic acidification	Emission (kg)	NA [a]	Annual flow quantity	NA [a]
	Emission (kg)	- Emissions from fertilizer and manure applications - Crop area (for erosion)	Population count	Population count
Marine eutrophication	Emission (kg)	NA [a]	Airborne Annual flow quantity	NA [a]
Terrestrial eutrophication	Emission (kg)	NA [a]	NA [a]	NA [a]
Land stress	Land occupation (area occupied over time, m^2/yr.), land transformation (area transformed, m^2)	Total ecoregion area (biodiversity indicator)	- Ecoregion area used for each land use type - Area of climate zones or of Holridge life zones used for each land use type	NR [a]
Water stress / water use	Water consumption (m^3)	Water consumption	Water consumption	Water consumption
Ionizing radiation	Emission (Bq)	NR [a]	NR [a]	NR [a]

[a] NR = not regionalized; NA = not available yet

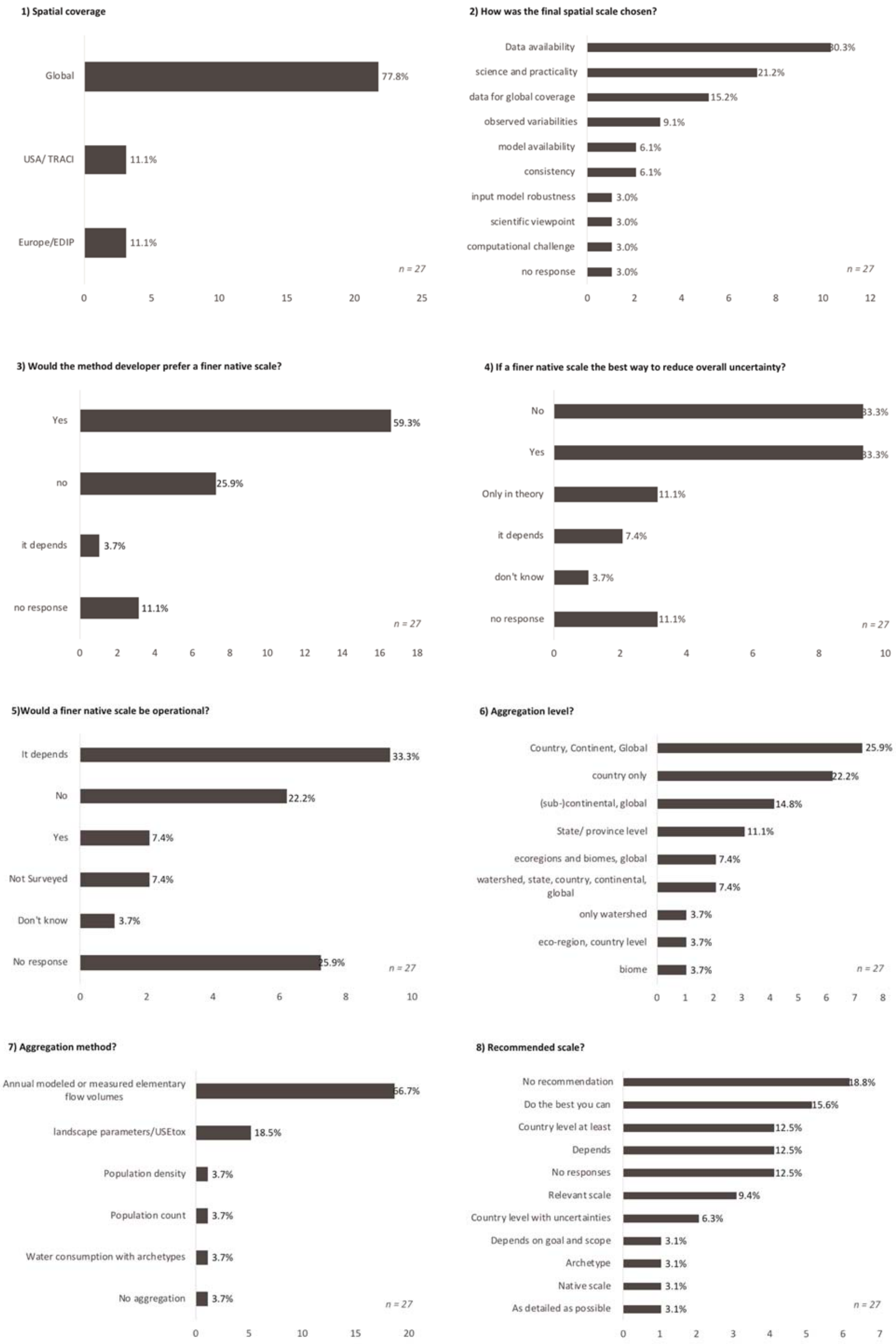

Figure 1 Summary of quantitative survey results