



Universiteit  
Leiden  
The Netherlands

## Assessing the use of land system archetypes to increase regional variability representation in characterisation factors: a soil erosion case study

Migoni Alejandre, E.; Guinee, J.B.; Bodegom, P.M. van

### Citation

Migoni Alejandre, E., Guinee, J. B., & Bodegom, P. M. van. (2022). Assessing the use of land system archetypes to increase regional variability representation in characterisation factors: a soil erosion case study. *International Journal Of Life Cycle Assessment*, 27(3), 409-418. doi:10.1007/s11367-022-02037-w

Version: Publisher's Version

License: [Creative Commons CC BY 4.0 license](https://creativecommons.org/licenses/by/4.0/)

Downloaded from: <https://hdl.handle.net/1887/3453365>

**Note:** To cite this publication please use the final published version (if applicable).



# Assessing the use of land system archetypes to increase regional variability representation in country-specific characterization factors: a soil erosion case study

Elizabeth M. Alejandre<sup>1</sup> · Jeroen B. Guinée<sup>1</sup> · Peter M. van Bodegom<sup>1</sup>

Received: 30 April 2021 / Accepted: 2 March 2022 / Published online: 13 April 2022  
© The Author(s) 2022

## Abstract

**Purpose** The characterization of land use impacts in life cycle assessment (LCA) requires a constant compromise between highly specific impacts models and coarse geographical scales available in life cycle inventory, where most information is provided at country level as the highest degree of geographical specificity. The derivation of country-specific characterization factors is usually done estimating impacts with the use of land cover and potential natural vegetation maps, assuming the most predominant biome per country as representative. This study explores the use of land system archetypes to derive country-specific characterization factors for land use-related soil erosion impacts that can better represent intra-national variations, while accounting for several biogeographical and socioeconomic differences.

**Methods** Land use-specific characterization factors were derived as the potentially enhanced soil erosion rate, using the soil erosion rates of each archetype as a reference state, and correction factors to reflect the relative increase or decrease in soil erosion rates associated with each of the eight land use types assessed: forest, permanent crops, grassland, farmland, fallow ground, moorland, urban/industrial, and mining/landfill. Country-specific characterization factors for land use erosion impacts of occupation (in ton/(m<sup>2</sup>·year)) were calculated by taking into account the land system archetypes present in each country, the land use-specific characterization factors, and the likelihood of each land use type occurring across archetypes (based on rule of thumb expert estimates). The country-specific characterization factors were produced specifically for occupation impacts for each of the eight land use types, and covering 263 countries and territories/dependencies.

**Results and discussion** The resulting 2,104 country-specific characterization factors displayed in average a considerably greater variation in comparison with characterization factors produced when only the most predominant archetype per country is assumed as representative per country. The results indicate that world generic values might underestimate up to 10 times the degree of impacts associated with land use types such as permanent crops, fallow ground, mining, and landfill. The use of land system archetypes presents a viable approach to derive country-specific characterization factors while taking into account key intra-national variations, as well as biogeographical and socioeconomic factors.

**Keywords** Life cycle assessment · Regionalization · Land use · Characterization

## 1 Introduction

The level of regionalization in life cycle assessment (LCA) for the estimation of land use impacts is commonly determined by the available geographical scales found in life

cycle inventory (LCI) databases, and the resolution of the characterization factors used to translate the inventory of a product system into potential impacts (Nordborg et al. 2017). Most LCI databases present information aggregated as either country-specific or world generic values (Wernet et al. 2016; Othoniel et al. 2016). Given the current structure and operationalization of LCA through its large-scale background databases, compatibility with available LCI scales is essential to reflect the potential impact of background processes (those obtained from LCI databases, such as ecoinvent), since the application of high resolution characterization factors is usually limited to foreground processes (those created

---

Communicated by Thomas Koellner.

✉ Elizabeth M. Alejandre  
e.migoni@cml.leidenuniv.nl

<sup>1</sup> Institute of Environmental Sciences (CML), Leiden University, P.O. Box 9518, 2300 Leiden, RA, Netherlands

by LCA practitioners) (Bos et al. 2020; Othoniel et al. 2019). LCA results are strongly influenced by background processes, as Heijungs (2012) showed by describing how the use of a single process from the ecoinvent database can be linked with ~2000 other processes. Background processes are commonly aggregated at country level as maximum degree of specificity (Yang 2016; Mutel et al. 2019; Pavan and Ometto 2016). Therefore, most regionalized impact methods that have been developed for LCA, such as LC-Impact (Verones et al. 2020), IMPACT world+ (Bulle et al. 2019), and TRACI (Bare 2011), provide country-specific characterization factors. These country-specific estimates are usually obtained by utilizing land cover and potential natural vegetation (PNV) maps to characterize potential impacts, assuming the most predominant biome per country as a representative estimate for country-specific factors (Verones et al. 2020; Bulle et al. 2019; Saad et al. 2013; Bos et al. 2020). However, the estimation of country-specific values based on most predominant biomes per country might not accurately represent intra-national variation. Furthermore, land use impacts are influenced by a variety of factors that go beyond biogeographical characteristics, and that relate to socio-economic and environmental dynamics. In contrast with the general practices where the degree of land use impact is based on PNV land cover maps and biogeographical parameters, we hypothesize that land system archetypes can be used to increase representativeness of regional variations in the calculation of country-specific characterization factors.

The use of spatial archetypes has been proposed in the literature as a potential way towards regionalization of impact categories (Mutel et al. 2019). Archetypes, defined as groups or categories that share similar characteristics and patterns, can help incorporating information beyond spatial units. Moreover, land system archetypes can account for multiple factors, both socio-economical and biogeographical, that influence the degree of potential environmental impacts. An example of archetypes application in LCA is the case of the toxicity impact model, USEtox, which utilizes freshwater archetypes to assess the variability of impacts related to exposure to toxic substances and particulate matter (Gandhi et al. 2011; Rosenbaum et al. 2008; Kounina et al. 2014). Archetypes present potential advantages for application on several other impact categories, with land use as the clearest example of an impact driver that is highly dependent on multidimensional conditions varying across the globe (IPBES 2019).

The objective of this study was to assess if the use of land system archetypes help to better represent intra-national variations when deriving country-specific characterization factors for soil erosion impacts as a representative example of land use-related impacts. Our focus was on illustrating the potential benefits of adopting land system archetypes for the derivation of characterization factors, rather than assessing

or further developing a specific method for soil erosion impacts. By presenting the application and comparison of characterization factors based on land system archetypes, we provide further evidence of their potential benefits for a wider application in LCA studies and a better representation of socio-economical and biogeographical differences across the globe.

## 2 Methods

### 2.1 Land system archetypes

In this study, 12 land system archetypes (LSAs) produced by Václavík et al. (2013) were used for the characterization of land use impacts. These archetypes are based on clustered patterns of land systems data, covering approximately 30 indicators related to land use intensity (e.g. soil erosion, irrigation, temporal trends of cropland), socioeconomic factors (e.g. population density, GDP), and environmental factors (e.g. temperature, precipitation) (Václavík et al. 2013). Each of the 12 LSAs presents a specific combination of land use and human–environment interactions. We used the soil erosion rates that are associated with each of the 12 land system archetypes as the reference state ( $Q_{ref,a}$ ) to assess land use-related soil erosion impacts (further explained in Sect. 2.2). These soil erosion rates (see Table 1) have been derived from spatially explicit models of soil erosion based on the universal soil loss equation, and used in conjunction with global databases of land use, soil, climate, accounting for parameters such as slope steepness and soil organic carbon (Van Oost et al. 2007).

For further clarification, throughout this study, we refer to the terms “land system archetypes” and “land use types.” The first one refers to the 12 archetypes produced by Václavík et al. (2013), while land use types refer to the specific use of land that can have an erosion impact on the studied land (e.g. agricultural crops, natural landscape, roads). Therefore, one or multiple land use types can take place in a land system archetype (e.g. a road through a forest system in the tropics).

### 2.2 Determination of land use-specific characterization factors

Before deriving country-specific characterization factors, we first calculated land use-specific characterization factors. Land use-specific characterization factors were calculated as the potentially enhanced land use-specific soil erosion rate ( $CF_{a,b}$ ) expressed in  $\text{ton}/(\text{m}^2\cdot\text{year})$ , which describes the potential soil erosion impact of land use  $b$  on archetype  $a$ , calculated as the difference in soil erosion rates between the

**Table 1** Soil erosion rates associated with each of the land system archetypes by Václavík et al. (2013)

Land system archetype		Soil erosion rate (in ton/(ha·year))
LSA 1	Forest systems in the tropics	2.6
LSA 2	Degraded forest/cropland systems in the tropics	120.3
LSA 3	Boreal systems of the western world	0.2
LSA 4	Boreal systems of the eastern world	0.1
LSA 5	High density urban agglomeration	3.1
LSA 6	Irrigated cropping systems with rice yield gap	6.2
LSA 7	Extensive cropping systems	5.9
LSA 8	Pastoral systems	1.8
LSA 9	Irrigated cropping systems	2.4
LSA 10	Intensive cropping systems	2.8
LSA 11	Marginal lands in the developed world	0.7
LSA 12	Barren lands in the developing world	0.3

reference state ( $Q_{ref,a}$ ) and the state under the given land use  $b$  ( $Q_{LU,a,b}$ ).

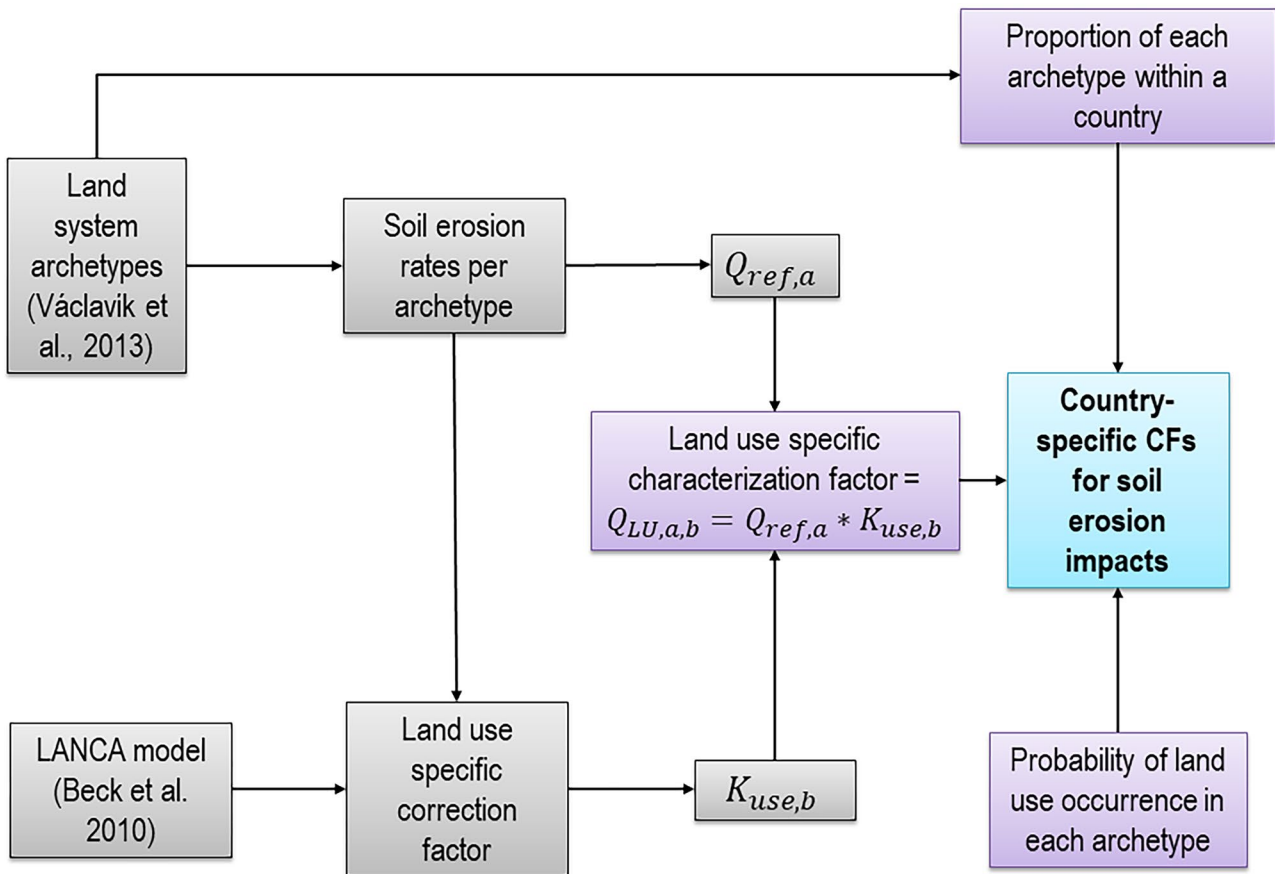
$$CF_{a,b} = Q_{LU,a,b} - Q_{ref,a}$$

where  $Q_{ref,a}$  is the soil erosion rate of archetype  $a$ , and  $Q_{LU,a,b}$  is the soil erosion rate associated with land use  $b$ , calculated by multiplying the soil erosion rate of archetype

$a$  ( $Q_{ref,a}$ ), by a “correction factor” of land use type  $b$  ( $K_{use,b}$ ) that is adapted from the LANCA method by Beck et al. (2010) (Fig. 1). Thus:

$$Q_{LU,a,b} = Q_{ref,a} \times K_{use,b}$$

These “correction factors” ( $K_{use}$ ) reflect the relative degree of soil erosion impact that can be attributed to each



**Fig. 1** Study design for the calculation of country-specific characterization factors for land use soil erosion impacts

land use type. The factors are dimensionless numbers ranging from 0.5 to 10, and available for 36 land use types (Beck et al. 2010). These correction factors represent a considerable simplification of soil erosion mechanisms. While alternative approaches have utilized additional correction factors to incorporate relative differences due not only to land cover but also management practices, for the comparative and illustrative purposes of this study, we assume the correction factor  $K_{use}$  from Beck et al. (2010) as an applicable approximation to estimate land use-specific soil erosion rates.

The specific land use types to assess in this study were selected based on their compatibility with land use elementary flows used in background processes of the ecoinvent database (<https://www.ecoinvent.org/>), given that this is one of the most predominantly used database in the LCA field (Wernet et al. 2016). To select the land use types, we compared the list of land use types for which Beck et al. provide  $K_{use}$  factors, with the detailed list of relevant background processes in ecoinvent (Version 3.4, “cut off”). This comparison (detailed in Supplementary material A) led to the following selection of land use types assessed in this study: “forest,” “permanent crops,” “farmland,” “fallow ground,” “urban, industrial, and transport,” “grassland, meadow,” “moorland, lawn, or fallow with vegetation,” and “mining and landfill.”

Furthermore, the characterization of land use impacts is commonly done for two types of impacts, occupation and transformation. Occupation describes the influence of land use over an area for a given amount of time ( $CF_{occ} = Q_{ref} - Q_{LU}$ ) while transformation is described as the change in quality of an area from one land use to another, including the regeneration time ( $CF_{trans} = (Q_{ref} - Q_{LU}) \times 0.5 \times t_{reg}$ ) (Koellner et al. 2013; Milà i Canals et al. 2007b). If the same  $\Delta Q$  is incorrectly assumed to be applicable to the calculation of CFs for both occupation and transformation impacts, there is a risk of incurring on double counting during the impact assessment of a product system. Additionally, most land use processes in ecoinvent were found to have the same magnitude of flows for both occupation and transformation (Supplementary material A). While land occupation always follows land transformation, the reverse is not always the case. Therefore, the current connection of flows inevitably increases the risk of incorrect double counting. Based on these considerations and for the comparative purposes of this study, we will illustrate the production of characterization factors focusing on occupation impacts only.

As an additional consideration for the case of sealed soils, which occur in roads, industrial and urban areas for example, the procedure by Beck et al. (2010) assigns a high erosion correction factor to represent the permanent damage done to the quality of soil. However, for land use occupation impacts, the soil erosion is neither improved nor decreased

by the effect of sealing. While sealing has a negative effect on other soil properties such as mechanical and physico-chemical filtration, the soil erosion is not actively increasing nor decreasing due to the sealing during occupation impacts. To address this methodological artifact, we attribute the neutral value of 1 as the correction factor  $K_{use}$  for sealed soils corresponding to urban/industrial/transport land use types, this results in a characterization factor of value 0, representing no change of erosion during occupation. The impact of soil sealing would be reflected as a transformation impact. However, the production of CFs for transformation impacts are currently left out of the scope of this study. For the land use types of mining and landfill, the maximum value of 10 was used as  $K_{use}$  factors for occupation impacts.

### 2.3 Producing country-specific characterization factors

To aggregate towards country-specific characterization factors for each land use type, we produced characterization factors for occupation impacts for each land use type, e.g.  $b$ , in country  $c$  ( $CF_{OCC,b,c}$ ) based on a weighting process taking into account the impact potential of land use type  $b$  on each archetype present in country  $c$  ( $CF_{a,b,c}$ ), the probability of the land use  $b$  occurring on each archetype present in country  $c$  ( $PO_{a,b,c}$ ), and the area of each archetype  $a$  within a country  $c$  ( $Ar_{a,c}$ ), which results in:

$$CF_{OCC,b,c} = \frac{\sum_{a=1}^{12} (Ar_{a,c})(CF_{a,b,c})(PO_{a,b,c})}{\sum_{a=1}^{12} Ar_{a,c}}$$

For example, the probability of using the land as “forest” is considered to be minimal in archetypes such as LSA5 (High density urban agglomeration) and LSA12 (Barren lands in the developing world), and quite high in archetypes such as LSA1 (forest systems in the tropics) and LSA3 (Boreal systems of the western world). These probabilities estimates ranged between three values (0.1, 0.5, and 1), and were based on rule of thumb expert estimations (Supplementary material B).

### 2.4 The indicator result

Characterization factors are used to translate environmental interventions into potential environmental impacts, commonly referred to in LCA as the indicator results. The characterization factors produced, translate occupation flows for land use type  $b$  in country  $c$  ( $OF_{b,c}$ ) into potential soil erosion impacts by multiplying the land use flows by their respective characterization factors ( $CF_{OCC,b,c}$ ). The impact results are aggregated across all land use types into an indicator result:

**Table 2** Land use-specific characterization factors (in ton/(m<sup>2</sup>·year)), for each combination of land use type and land system archetype

Land system archetype		Land use type							
		Grassland	Forest	Farmland	Fallow ground	Permanent crops	Mining/landfill	Urban/industrial	Moorland
LSA 1	Forest systems in the tropics	-1.30E-04	-1.30E-04	5.20E-04	2.34E-03	1.30E-03	2.34E-03	0	0
LSA 2	Degraded forest/cropland systems in the tropics	-6.02E-03	-6.02E-03	2.41E-02	1.08E-01	6.02E-02	1.08E-01	0	0
LSA 3	Boreal systems of the western world	-1.00E-05	-1.00E-05	4.00E-05	1.80E-04	1.00E-04	1.80E-04	0	0
LSA 4	Boreal systems of the eastern world	-5.00E-06	-5.00E-06	2.00E-05	9.00E-05	5.00E-05	9.00E-05	0	0
LSA 5	High-density urban agglomerations	-1.55E-04	-1.55E-04	6.20E-04	2.79E-03	1.55E-03	2.79E-03	0	0
LSA 6	Irrigated cropping systems with rice yield gap	-3.10E-04	-3.10E-04	1.24E-03	5.58E-03	3.10E-03	5.58E-03	0	0
LSA 7	Extensive cropping systems	-2.95E-04	-2.95E-04	1.18E-03	5.31E-03	2.95E-03	5.31E-03	0	0
LSA 8	Pastoral systems	-9.00E-05	-9.00E-05	3.60E-04	1.62E-03	9.00E-04	1.62E-03	0	0
LSA 9	Irrigated cropping systems	-1.20E-04	-1.20E-04	4.80E-04	2.16E-03	1.20E-03	2.16E-03	0	0
LSA 10	Intensive cropping systems	-1.40E-04	-1.40E-04	5.60E-04	2.52E-03	1.40E-03	2.52E-03	0	0
LSA 11	Marginal lands in the developed world	-3.50E-05	-3.50E-05	1.40E-04	6.30E-04	3.50E-04	6.30E-04	0	0
LSA 12	Barren lands in the developing world	-1.50E-05	-1.50E-05	6.00E-05	2.70E-04	1.50E-04	2.70E-04	0	0

$$\text{Soil Erosion Occupation (SEO)} = \sum_{x=1}^{x=n} (CF_{Occ,b,c} \times OF_{b,c})$$

The impact indicator, which in LCA refers to the quantifiable representation of an impact, corresponds to the tons of soil eroded due to land use impacts, where  $OF_{b,c}$  is the time-integrated area of occupation (in m<sup>2</sup>·year). The unit of the estimated impact, the indicator result ( $SEO$ ) is thus in tons, which represents the tons of soil eroded that can be associated with the functional unit of a studied system.

### 3 Results

#### 3.1 Land use-specific characterization factors

The land use-specific impacts on soil erosion rates were characterized for each combination of land use and archetype, presented in Table 2. For the categories “moorland” and “Urban and industrial,” the land use-specific characterization factors (in ton/(m<sup>2</sup>·year)) result in values of 0, due to the fact that the correction factors had a value of 1, indicating that these land use type do not increase or decrease soil erosion.

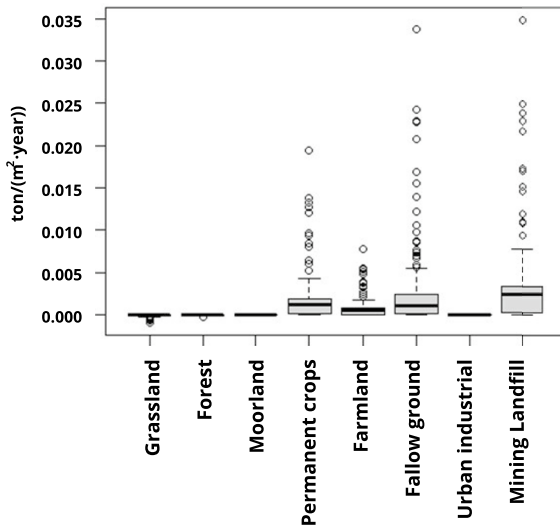
The land use-specific characterization factors for the categories grassland and forest have negative values, which indicate a reduction in soil erosion across all archetypes. The categories of permanent crops, farmland, and fallow ground present positive values, indicating a negative impact to the soil by increasing erosion rates. The values of these

land use-specific impacts vary across archetypes, with LSA2 (Degraded forest/cropland systems in the tropics) being disproportionately higher than the rest, due to the fact that this archetype is present in areas of the world characterized with the highest soil erosion rate (Table 1).

#### 3.2 Country-specific characterization factors

The characterization factors were derived for 263 countries and for 8 land use types, resulting in 2,104 values expressed in terms of ton/(m<sup>2</sup>·year) (data generated and full list of CFs available in Supplementary material B). The country-specific characterization factors allow to distinguish between land use types, and present a wide range of variation for permanent crops, fallow ground, and mining and landfill, with mean values around 0.002ton/(m<sup>2</sup>·year), and reaching max values, including outliers, of up to 0.035ton/(m<sup>2</sup>·year) (Figs. 2a and 3). To compare the CFs, we also calculated country-specific characterization factors based only on the most predominant archetype per country (and without applying probability of occurrence factors) (Fig. 2b). The CFs based on the most predominant archetype per country ranged between 0 and 0.003ton/(m<sup>2</sup>·year) for permanent crops and between 0 and 0.005 ton/(m<sup>2</sup>·year) for fallow ground and Mining landfill, indicating these CFs could underestimate impacts of up to 0.020ton/(m<sup>2</sup>·year) for permanent crops and of up to 0.035 ton/(m<sup>2</sup>·year) for fallow ground and mining and landfill. The benefits of grassland are underestimated as well when only accounting for the most predominant archetype in

a) CFs accounting for all archetypes within a country



b) CFs based on most predominant archetype per country

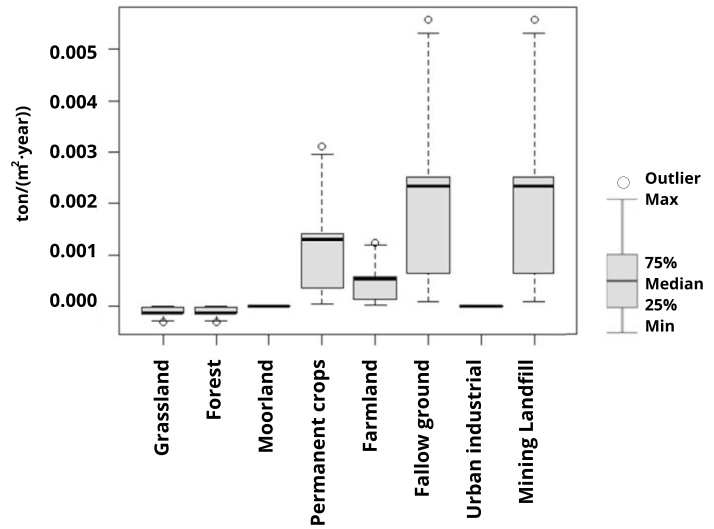


Fig. 2 Country-specific characterization factors for soil erosion potential impacts (in ton/(m<sup>2</sup>·year))

comparison to CFs weighting all archetypes within a country, with a difference of  $6.26 \times 10^{-4}$  ton/(m<sup>2</sup>·year). Similarly, for forest, the mean CFs indicate lower benefits in comparison to weighted values. However, these CFs have a slightly larger range (from 0 to -0.0031) than weighted values (0 to -0.00022), due to the influence of the probability of occurrence estimates.

Furthermore, when accounting only for the most predominant archetype per country, not all archetypes are represented in the CF results. This was the case for LSA 2 (Degraded forest/

cropland systems in the tropics) and LSA 5 (High-density urban agglomerations), which are not predominant in any country. Considering the high soil erosion rate and impact potential associated with LSA2 (Table 2), the use of country-specific CFs based only on most predominant archetypes as reference does not allow to reflect key land use impacts on highly vulnerable areas. The countries characterized as some of the most vulnerable in terms of soil erosion impacts for permanent crops, farmland, and fallow ground (e.g., Rwanda, Guatemala, Philippines, Swaziland, New Zealand, Malaysia, Burundi, Sri Lanka,

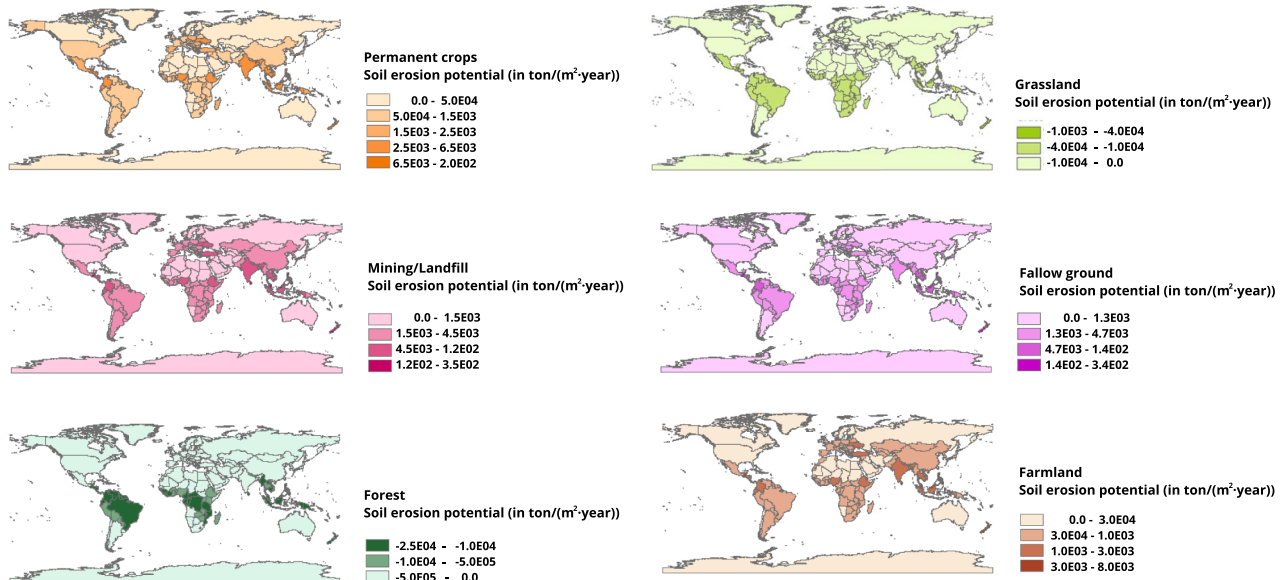
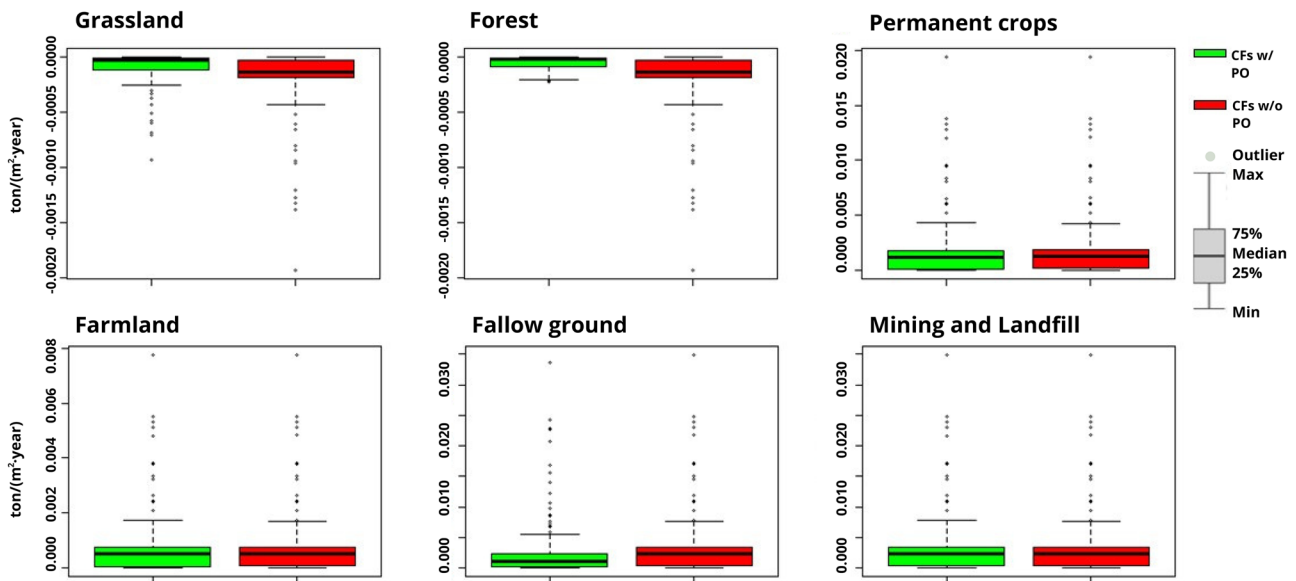


Fig. 3 Global maps of country-specific characterization factors for soil erosion potential impacts by land use occupation (in ton/(m<sup>2</sup>·year))



**Fig. 4** Comparison of the resulting characterization factors when accounting for probability of occurrence estimates (in green) and without (in red)

Albania, and Dominican Republic) present as common feature an archetype composition mainly dominated by a combination of LSA1 (forest systems in the tropics), LSA2 (Degraded forest/cropland systems in the topics) and LSA7 (Extensive cropping systems). Therefore, the use of weighted values for the production of characterization factors results in a more comprehensive representation of intra-national impacts.

The probabilities of land use occurrence (PO) were rule of thumb expert estimates (of value 0.1, 0.5, and 1) based on the assumption that not all land use types have the same probability of occurring across all archetypes. To assess the influence of these probability estimates, we compared the results with CFs produced without taking into account the probability estimates (assuming  $PO=1$  across all land types and archetypes). The results of this comparison (Fig. 4) indicate that the use of probability estimates allow to identify differences between grassland and forest, which would otherwise be represented by the same values, given that both land use types use the same correction factor of 0.5. The mean benefits of grassland and forest are slightly decreased by the use of the probability estimates. The variation range is also smaller, due to the fact that we assumed a low probability ( $=0.1$ ) of these natural landscapes occurring in archetypes describing urban or highly agglomerated areas. By taking into account the occurrence probabilities, the potential bias due to unlikely combinations is decreased. For example, while grassland represents the highest potential benefits when assessed for LSA2 (Table 2), the probability of grassland occurring in LS2 was attributed a probability estimate of 0.5, thus decreasing the influence of LS2 in the total CFs for grassland by half. For farmland, permanent

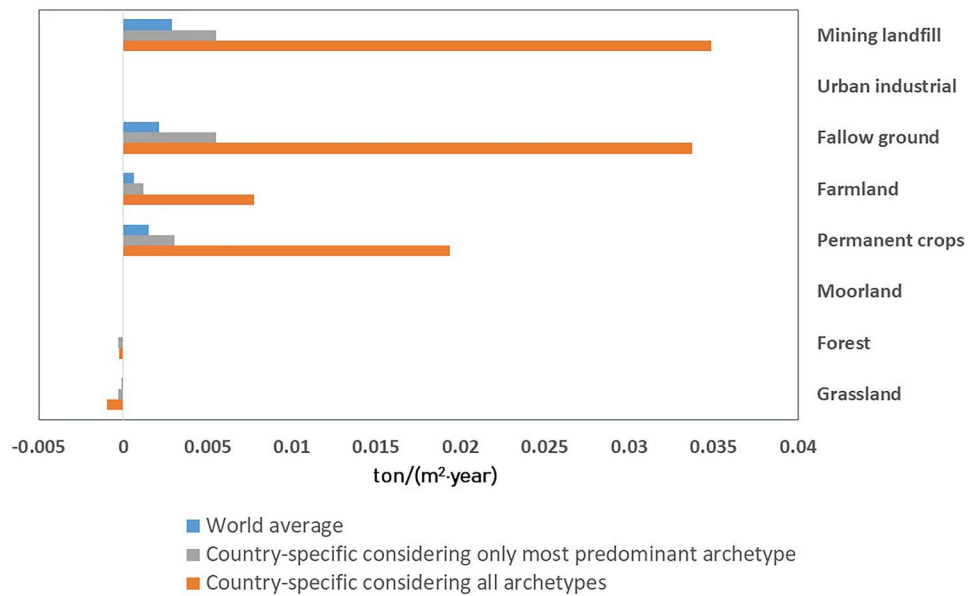
crops, and mining and landfill, there were no substantial differences between the results, while the mean impacts for fallow ground are slightly increased when no probability of occurrence is assumed. Furthermore, a comparison of CFs obtained with world generic estimates based on the mean of each land use type (Fig. 5) shows that world generic estimates can underestimate over ten times the degree of potential impact associated with land use types such as mining and landfill, fallow ground, and permanent crops.

## 4 Discussion

### 4.1 Considerations for country-specific characterization factors

The compatibility of characterization factors with the information present in LCA inventory databases is, as previously mentioned, generally a limiting factor to the applicability of new regionalized impact methods that need to reconcile with coarse geographical scales available in inventory data. In the case of land use impacts, this reconciliation generally leads to the production of country-specific characterization factors that are commonly derived by considering the most predominant biome per country as representative of the whole. While moving from world generic estimates to country-specific values might seem like a sufficient compromise, the great variation shown by the resulting characterization factors demonstrate further evidence of the need to improve the representation of intra-national variations during impact characterization, as illustrated in this study with the use of land system archetypes.

**Fig. 5** Comparison of the characterization factors values for world generic (blue), country-specific considering only most predominant biome (grey), and considering all archetypes within a country (orange)



Furthermore, the use of occurrence probabilities in the calculation of characterization factors allowed us to evaluate additional differences between land use impacts by taking into account the characteristics of each land system archetype. The risk of potentially underestimating benefits or potential impacts will depend on the assumptions made for each occurrence probability. This risk may be reduced by obtaining occurrence probabilities based on a wider consensus of expert knowledge, or by coupling land use and urban planning data for more accurate predictions. We suggest that using coarse probability estimates might be better than using none, as further evidenced when comparing our results with those from Saad et al. (2013), where the characterization factors for grassland and forest present the same values and are therefore unable to reflect differences between these two land use types, a shortcoming that can be overcome with the use of occurrence probabilities.

## 4.2 Advantages of land system archetypes

The land system archetypes used in this study were produced by Václavík et al. (2013) using a self-organized map (SOM), which relies on a non-supervised neural network algorithm that decreases dimensionality by eliminating redundancy among indicators and allowing to visualize complex datasets. The output is a map where a given amount of archetypes is determined to be a representative amount of categories to represent land use systems (Václavík et al. 2013). The resulting archetypes reflect patterns clustered in consistent groups based on the similarity of the available indicators. There are several potential benefits of utilizing unsupervised data driven methods to further develop archetypes that can be used for impact characterization, as they allow to cluster large amount of data without

the need of expert rules or a priori classification thresholds. The archetypes by Václavík et al. (2013), reflect regional patterns that take into account several land use intensity indicators and temporal trends to account for changing dynamics of land systems, and therefore might be better suited to reflect land use potential impacts in contrast with estimates based solely on land cover maps where only a few biogeographical parameters are considered. For example, while CFs for soil erosion impacts are usually heavily influenced by soil texture and geographical slope data, the land system archetypes that were particularly vulnerable to further soil damage were characterized by factors such as a high degree of agricultural inputs, low GDP and strong dependence on agricultural production (Václavík et al. 2013). Therefore, accounting for socioeconomic factors besides biogeographical parameters seems indispensable to improve representativeness of characterization factors for land use impacts.

## 4.3 General recommendations for LCA application

For a practical application of archetypes in LCA, it is recommendable to apply or develop an archetype classification that can be used across several impact categories, to keep consistency and minimize the proliferation of category-specific archetypes (Mutel et al. 2019). The land system archetypes used in this study, by Václavík et al. (2013), account for a variety of parameters such as crop yield, fertilizer input, species richness, irrigation, among several others factors that present opportunities for their use in other impact categories. However, this should be further studied by for example, a meta-analysis focusing on the different data requirements across categories. Further integration of environmental and socioeconomic indicators with the use of archetypes presents

potential advantages for the characterization of environmental impacts in LCA and in particular of ecosystem services. Ecosystem services have gained attention during the last decade due to their key role sustaining quality of life throughout the world (EEA 2016; FAO 2015; IPBES 2019). The severe degree of anthropogenic impact found across several key services globally, has fueled increased efforts for their incorporation in impact assessment methods (Blanco et al. 2017; Zhang et al. 2010, Beck et al. 2010; Bos et al. 2016; Mutel et al. 2019; Cao et al. 2015; Milà i Canals et al. 2007a; Núñez et al. 2013; Othoniel et al. 2019). However, their assessment still remains highly underrepresented in common LCA studies (Othoniel et al. 2016; Alejandro et al. 2019). The complex dynamics that influence ecosystem services and their high spatial variability present multiple characterization challenges. The archetypes approach outlined in this study is highly suitable to address these issues, precisely for its capacity to incorporate a range of multidimensional aspects while allowing to characterize impacts for LCA.

Additionally, while general recommendations have been made in the literature regarding uncertainty (Igos et al. 2019; Muller et al. 2016), assessing and merging the several sources of uncertainty associated with characterization factors presents major challenges for impact assessment developers (Mutel et al. 2019). In the case of the land system archetypes, the nature of the data and methods applied to produce the resulting archetype classification introduces several levels of uncertainty. Additional uncertainty sources for the characterization factors are related with the characterization model assumptions, inherent spatial variability, among others. To include an estimate of uncertainty for regionalized CFs, developers usually provide measures of dispersion along with their resulting CFs to reflect the uncertainty associated with the spatial variability, for example, by estimating the average absolute deviation to show how far is a CF from the central tendency (e.g. median value). However, further research is necessary to determine the best approach for harmonizing uncertainty guidelines for both LCI databases and impact assessment developers.

## 5 Conclusion

The results of this study illustrate how the use of land system archetypes present a practical and representative approach to characterize land use impacts while accounting for intranational differences in country-specific CFs. The hypothesis was that by utilizing land system archetypes we could better reflect spatial variability that can be driven by biogeographical and socioeconomic factors, than by simply assessing the most predominant archetype as the representative per country. This was confirmed by the comparison of country-specific CFs, which presented a considerably larger variation when accounting through a weighting process all the archetypes present

within a country, than those assuming only the most predominant archetype as representative. The resulting CFs yielded estimates of up to ten times higher magnitude compared with world generic values, reflecting considerable regional differences. Moreover, our use of land system archetypes as reference state avoided potential biases in impacts of land use change, as it accounts for prevailing general soil degradation – in contrast to the commonly used potential natural vegetation as reference state. A wider application of archetypes for regionalization of impacts in LCA is recommended for further research as a practical approach to bridge the gap between impact models that require finer spatial and multidimensional data with currently available LCA inventories.

**Supplementary information** The online version contains supplementary material available at <https://doi.org/10.1007/s11367-022-02037-w>.

**Acknowledgements** We would like to thank Carlos Felipe Blanco for input, and to the anonymous reviewers for their contribution to the manuscript and Tomáš Václavík, who provided the land system archetypes data used in this study.

**Funding** The project was financed by the Mexican National Council for Science and Technology (CONACyT).

## Declarations

**Conflict of interest** The authors declare no competing interests.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

## References

- Alejandro EM, van Bodegom PM, Guinée JB (2019) Towards an optimal coverage of ecosystem services in LCA. *J Clean Prod* 231:714–722. <https://doi.org/10.1016/j.jclepro.2019.05.284>
- Bare J (2011) TRACI 2.0: The tool for the reduction and assessment of chemical and other environmental impacts 2.0. *Clean Technol Environ Policy* 13:687–696. <https://doi.org/10.1007/s10098-010-0338-9>
- Beck T, Bos U, Bastian W et al (2010) LANCA ® Land Use Indicator Value Calculation in Life Cycle Assessment Assessment - v2.0, Fraunhofer-Institut für Bauphysik IBP. 166
- Blanco CF, Marques A, van Bodegom PM (2017) An integrated framework to assess impacts on ecosystem services in LCA demonstrated by a case study of mining in Chile. *Ecosyst Serv*
- Bos U, Horn R, Beck T et al (2016) LANCA - Characterization Factors for Life Cycle Impact

- Bos U, Maier SD, Horn R et al (2020) A GIS based method to calculate regionalized land use characterization factors for life cycle impact assessment using LANCA®. *Int J Life Cycle Assess* 25:1259–1277. <https://doi.org/10.1007/s11367-020-01730-y>
- Bulle C, Margni M, Patouillard L et al (2019) IMPACT World+: a globally regionalized life cycle impact assessment method. *Int J Life Cycle Assess*. <https://doi.org/10.1007/s11367-019-01583-0>
- Cao V, Margni M, Favis BD, Deschênes L (2015) Aggregated indicator to assess land use impacts in life cycle assessment (LCA) based on the economic value of ecosystem services. *J Clean Prod* 94:56–66. <https://doi.org/10.1016/j.jclepro.2015.01.041>
- EEA (2016) The direct and indirect impacts of EU policies on land. 118. <https://doi.org/10.2800/05464>
- FAO (2015) Nuestro futuro: Un mundo sin hambre. FAO Publ 83
- Gandhi N, Huijbregts MA, van de Meent D, Peijnenburg WJG, Guinée J, Diamond ML (2011) Implications of geographic variability on Comparative Toxicity Potentials of Cu, Ni and Zn in freshwaters of Canadian ecoregions. *Chemosphere* 82:268–277. <https://doi.org/10.1016/j.chemosphere.2010.09.046>
- Heijungs R (2012) Spatial Differentiation. GIS-Based Regionalization, Hyperregionalization, and the Boundaries of LCA. <https://doi.org/10.1016/j.ecoser.2017.11.011>
- Igos E, Benetto E, Meyer R, Baustert P, Othoniel B (2019) How to treat uncertainties in life cycle assessment studies?. *Int J Life Cycle Assess* 24:794–807. <https://doi.org/10.1007/s11367-018-1477-1>
- IPBES (2019) Summary for policymakers of the global assessment report on biodiversity and ecosystem services of the Intergovernmental Science- Policy Platform on Biodiversity and Ecosystem Services
- Koellner T, de Baan L, Beck T et al (2013) UNEP-SETAC guideline on global land use impact assessment on biodiversity and ecosystem services in LCA. *Int J Life Cycle Assess* 18:1188–1202. <https://doi.org/10.1007/s11367-013-0579-z>
- Kounina A, Margni M, Shaked S et al (2014) Spatial analysis of toxic emissions in LCA: a subcontinental nested USEtox model with freshwater archetypes. *Environ Int* 69:67–89. <https://doi.org/10.1016/j.envint.2014.04.004>
- Milà i Canals L, Bauer C, Depestele J, Dubreuil A, Freiermuth Knuchel R, Gaillard G, Rydgren B (2007a) Key elements in a framework for land use impact assessment within LCA. *Int J Life Cycle Assess* 12:5–15. <https://doi.org/10.1065/lca2006.05.250>
- Milà i Canals L, Romanya J, Cowell SJ (2007b) Method for assessing impacts on life support functions (LSF) related to the use of “fertile land” in Life Cycle Assessment (LCA). *J Clean Prod* 15:1426–1440. <https://doi.org/10.1016/j.jclepro.2006.05.005>
- Muller S, Lesage P, Samson R (2016) Giving a scientific basis for uncertainty factors used in global life cycle inventory databases: an algorithm to update factors using new information. *Int J Life Cycle Assess* 21:1185–1196. <https://doi.org/10.1007/s11367-016-1098-5>
- Mutel C, Liao X, Patouillard L et al (2019) Overview and recommendations for regionalized life cycle impact assessment. *Int J Life Cycle Assess* 24:856–865. <https://doi.org/10.1007/s11367-018-1539-4>
- Nordborg M, Sasu-Boakye Y, Cederberg C, Berndes G (2017) Challenges in developing regionalized characterization factors in land use impact assessment: impacts on ecosystem services in case studies of animal protein production in Sweden. *Int J Life Cycle Assess* 22:328–345. <https://doi.org/10.1007/s11367-016-1158-x>
- Núñez M, Antón A, Muñoz P, Rieradevall J (2013) Inclusion of soil erosion impacts in life cycle assessment on a global scale: application to energy crops in Spain. *Int J Life Cycle Assess* 18:755–767. <https://doi.org/10.1007/s11367-012-0525-5>
- Othoniel B, Rugani B, Heijungs R et al (2016) Assessment of life cycle impacts on ecosystem services: promise, problems, and prospects. *Environ Sci Technol* 50:1077–1092. <https://doi.org/10.1021/acs.est.5b03706>
- Othoniel B, Rugani B, Heijungs R et al (2019) An improved life cycle impact assessment principle for assessing the impact of land use on ecosystem services. *Sci Total Environ* 693:133374. <https://doi.org/10.1016/j.scitotenv.2019.07.180>
- Pavan ALR, Ometto AR (2016) Regionalization of land use impact models for life cycle assessment: Recommendations for their use in the global scale and their applicability to Brazil. *Environ Impact Assess Rev* 60:148–155. <https://doi.org/10.1016/j.eiar.2016.05.001>
- Rosenbaum RK, Bachmann TM, Gold LS et al (2008) USEtox - The UNEP-SETAC toxicity model: Recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. *Int J Life Cycle Assess*. <https://doi.org/10.1007/s11367-008-0038-4>
- Saad R, Koellner T, Margni M (2013) Land use impacts on freshwater regulation, erosion regulation, and water purification: A spatial approach for a global scale level. *Int J Life Cycle Assess*. <https://doi.org/10.1007/s11367-013-0577-1>
- Václavík T, Lautenbach S, Kuemmerle T, Seppelt R (2013) Mapping global land system archetypes. *Glob Environ Chang* 23:1637–1647. <https://doi.org/10.1016/j.gloenvcha.2013.09.004>
- Van Oost K, Quine TA, Govers G et al (2007) The impact of agricultural soil erosion on the global carbon cycle. *Science* (80-) 318:626–629. <https://doi.org/10.1126/science.1145724>
- Verones F, Hellweg S, Antón A et al (2020) LC-IMPACT: A regionalized life cycle damage assessment method. *J Ind Ecol* 24:1201–1219. <https://doi.org/10.1111/jiec.13018>
- Wernet G, Bauer C, Steubing B et al (2016) The ecoinvent database version 3 (part I): overview and methodology. *Int J Life Cycle Assess* 21:1218–1230. <https://doi.org/10.1007/s11367-016-1087-8>
- Yang Y (2016) Toward a more accurate regionalized life cycle inventory. *J Clean Prod* 112:308–315. <https://doi.org/10.1016/j.jclepro.2015.08.091>
- Zhang Y, Singh S, Bakshi BR (2010) Accounting for ecosystem services in life cycle assessment, part I: a critical review. *Environ Sci Technol* 44:2232–2242. <https://doi.org/10.1021/es9021156>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.