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Characterisation model approach for LCA to estimate land use impacts on pollinator abundance and illustrative characterisation factors

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ABSTRACT

This study presents the first approach to characterise relative land use impacts on pollinator abundance for life cycle assessment (LCA). Pollinators make an essential contribution to global crop production and in recent years evidence of declines has raised concerns on how land use, among other factors, affects pollinators. Our novel method assesses land use impacts on pollinator abundance and proposes a new impact category that is compatible with the current framework of life cycle impact assessment (LCIA). While a systematic literature research showed the existence of multiple models that could assess pollinator abundance impacts, their parameterization is too complicated for applications in LCA. Therefore, a simplified method based on expert knowledge is presented. The practical application of the method is illustrated through the connection to, and characterisation of, relevant land use types derived from the widely used LCA database, ecoinvent. The illustrative characterisation factors demonstrate that key differences among land use types can be reflected through the proposed approach. Further development of robust characterisation factors through a larger sample of pollinator abundance estimates, and improvements to the model, such as considerations of spatial differentiation, will contribute to the identification of impacts of agricultural practices in LCA studies, helping prevent further pollinator abundance decline.

1. Introduction

In recent years, pollinators have attracted wide attention due to their alarming decline rates and their essential role in global food security (IPBES, 2016). Around three quarters of the leading food crops around the world depend, at least in part, on insect pollination (Klein et al., 2007; Stein et al., 2017). Pollinators include many groups of insects, though bees are recognized as the most important taxa of crop pollinators across the globe (Klein et al., 2007; Potts et al., 2016) and their service has a positive influence not only on crop yield but also on the quality of pollinator-dependent crops, increasing fruit and seed production (Garratt et al., 2018; Motzke et al., 2015; Stein et al., 2017). Pollinator declines are due to a variety of factors, with the main drivers considered to be land use change (Carvalheiro et al., 2010; Koh et al., 2016), agricultural intensification, including the use of agrochemicals such as pesticides (Kennedy et al., 2007; Samson-Robert et al., 2017; Stanley and Raine, 2017), climate change (Hannah et al., 2017; Radenković et al., 2017), pathogens and alien invasive species (Crenna et al., 2017; Potts et al., 2016). Understanding the effect and intensity of impact drivers is essential to prevent further decline of pollinators and their associated negative consequences.

Global food security, already affected by impact drivers such as climate change, waste, increasing demand and soil degradation (Dhankher and Foyer, 2018; McCarty, 2018) might be further jeopardized by the severe declines observed of wild pollinators in parts of Europe and North America, and which could potentially be happening in other parts of the world as well (Hallmann et al., 2017; Novais et al., 2016; Vasiliev and Greenwood, 2020). To help prevent further decline, impact assessments can be a useful tool to show environmental impacts associated with a variety of production systems and industries (Alejandre et al., 2019; Crenna et al., 2019). Nowadays the most commonly applied method is Life Cycle Assessment (LCA). This method has been standardized by the International Organization for Standardization (ISO 14040–14044) and it allows to quantify the potential environmental impacts associated with a product system over its entire life cycle (Guinée et al., 2002; Hellweg and Canals, 2014; ISO, 2006). Product systems are defined in LCA as the set of unit processes interlinked by material, energy, product, waste or service flows, performing one or

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more defined functions (Guinée et al., 2002). During the impact assessment phase, environmental interventions are translated into potential impacts with the use of characterisation factors that are provided by impact assessment methods. However, current impact assessment methods used for LCA, such as ReCiPe2016 (Goedkoop et al., 2013; Huijbregts et al., 2016), LC-Impact (Verones et al., 2016) and Impact World+ (Bulle et al., 2019) do not account for impacts on pollinators or pollination. Given the essential role of pollination in global food security and the ability and wide use of LCA to evaluate a wide range of environmental interventions and potential impacts, it is crucial to address this omission by proposing a new impact category that focuses on pollinators, and to develop an impact assessment model to produce the aforementioned characterisation factors for use in LCA.

To produce new impact categories for LCA, one of the biggest challenges is to connect highly specific and complex impact models to LCA inventories which are often coarse and over-simplified (Schmidt, 2008). This paper tackles this specific challenge and addresses the development of a new impact model on pollinators. This new model includes pollinators as an impact category and provides the related characterisation model in LCA. Based on the review of Crenna et al. (2017) on potential impact drivers on insect pollinators, this study focusses on pollinator impacts driven by land occupation. To exemplify the operationalization of the characterisation model proposed, this study presents more than 50 illustrative characterisation factors for a range of land use types that are compatible with one of the most extensively used databases for LCA, ecoinvent (Wernet et al., 2016).

To achieve this aim, the general requirements for new impact categories in LCA are discussed first and it is analysed if and how pollination impact pathways fit within the general structure of LCIA (Life Cycle Impact Assessment). Next, the selection of a suitable pollinator impact models is discussed. This selection explicitly accounts for complications that may arise from the geospatial incompatibilities between the pollinator impact model and the geographical scales available in LCA inventories (Mutel et al., 2019; de Baan et al., 2013). The most feasible way to develop applicable characterisation factors for land use impacts on pollinators, accounted for this spatial mismatch is presented. The applicability of the approach is illustrated by showing globally applicable characterisation factors based on relative estimates of pollinator abundance for a variety of land types as provided by expert knowledge. Finally, possible improvements regarding this topic as provided in the discussion section.

2. Methods

The steps taken in this study to develop a novel method for assessing land use impacts on pollinator abundance, are summarized in three main sections below (See Fig. 1): the selection of an impact category taking into consideration the limitations and current structure of LCA is followed by the selection and derivation of a characterisation impact model, and finally by the calculation of characterisation factors that can be used in LCA.

2.1. Selection of a midpoint impact category

2.1.1. Key characteristics and considerations for LCA

Any proposal for a new impact category for LCA should follow the general structure of the life cycle impact assessment (LCIA) phase and ensure the new category is compatible with existing impact assessment methods to guarantee applicability (a detailed description of LCIA can be found in the Supplementary material S1). To achieve this compliance, the most appropriate indicator for a midpoint impact category was determined. When it comes to pollination, this service is a function of supply and demand that varies depending on the location, type of crop, type of pollinators and season, among other aspects (IPBES, 2016). Currently most of this data is completely absent from the LCA inventory, making the high spatial variability of pollination services one of the main constraints for their estimation in LCAs. However, instead of assessing the service of pollination as midpoint, the pollinator abundance can be used. The capacity to provide pollination services has been shown to be strongly correlated with pollinator abundance (Koh et al., 2016; Lonsdorf et al., 2009). Assessing impacts on pollinator abundance is thus an appropriate alternative. This alternative is feasible and compatible with the current LCIA structure since pollinator abundance can be directly estimated based on the land use/cover types for which information is available in LCA. Moreover, pollinator abundance as a midpoint category resembles an environmental property and as such complies to general definitions of midpoint impact categories (Othoniel et al., 2016; Rugani et al., 2019). Thus, the scope of our study is to present an impact model that can estimate pollinator abundance impacts associated with land use/cover types, specifically focusing on wild pollinators (See Fig. 2).

Land use impacts are usually characterised in LCA for two types of interventions: occupation and transformation (Koellner et al., 2013). Occupation impacts refer to the change in quality of a given land during its time of use, while transformation impacts refer to the change in quality due to land use or cover change. The impact of these land use interventions is calculated amongst others by estimating the change of an ecosystem quality (ΔQ) over a certain period of time, with the characterisation factor (CF) for occupation impacts calculated as the change in the quality ($CF_O = \Delta Q$), and for transformation impacts as the change in quality multiplied by a regeneration time (Treg) and assuming a linear recovery between the two states ($CF_T = \Delta Q \times t_{reg} \times 0.5$). If the same ΔQ value is used for the calculation of both occupation and transformation impacts, there is a risk of incurring on double counting. Currently, most agricultural background processes in ecoinvent present a link to both occupation and transformation flows of the same size (See Supplementary material S3), with most processes presenting the same land use type in the transformation from-and-to flows. Taking into

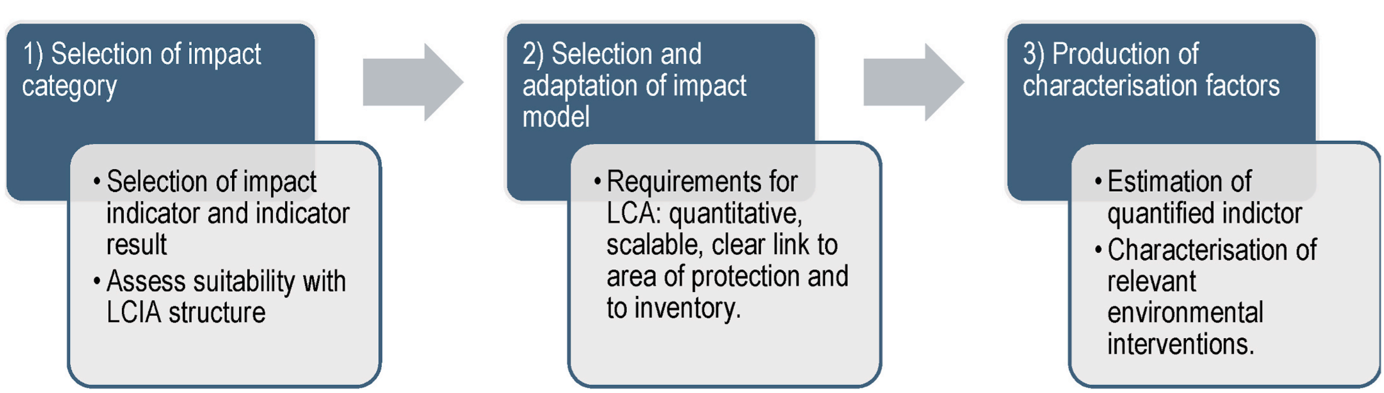

Fig. 1. Methodological steps and considerations.

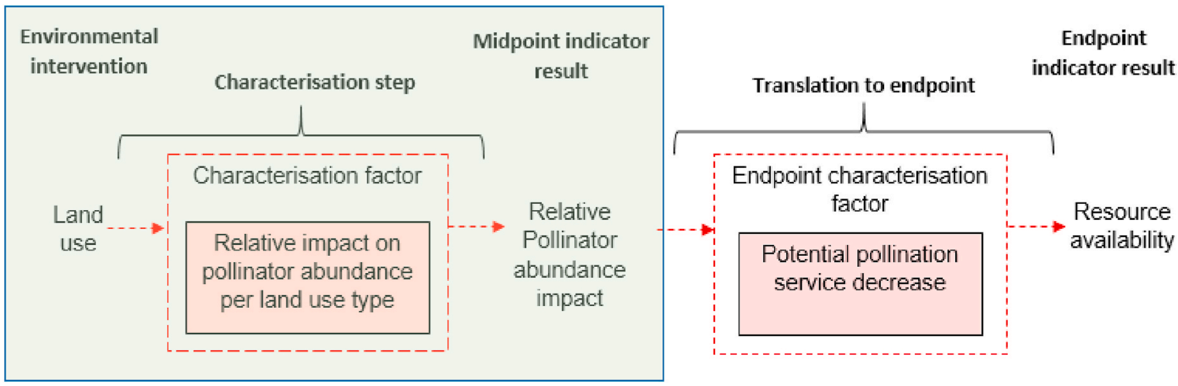

Fig. 2. Conceptual diagram of the structure for a new impact category assessing land use impacts on pollinator abundance. The scope of this study is delimited within the green box. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

consideration the risk of double counting, this study focuses on land use occupation impacts to illustrate the characterisation model proposed and the derivation of CFs.

2.1.2. Connection to background inventory

It is important that new impact categories, related models and characterisation factors, are compatible with 'background processes'. Background processes define the relationship between unit processes, which are the smallest portion of a product system for which data are collected in a LCA (Guinée et al., 2002) and products based on databases, without needing input from a LCA practitioner. One of the most widely used databases around the world for LCA is the ecoinvent database (https://www.ecoinvent.org/), which contains several thousands of interlinked background processes that can have a substantial weight in the LCA results (Heijungs, 2012). Therefore, compatibility with the inventory of background processes is an important consideration when developing characterisation models, to avoid the resulting characterisation factors to be limited to foreground processes (i.e., processes defined by the LCA practitioner).

To illustrate the operationalization of the proposed model with existent background processes, we analysed relevant land use processes and inventory data from ecoinvent. For this, the ecoinvent database version 3.4 'cut off' (https://www.ecoinvent.org/) was assessed with Open LCA version 1.8.0 for Windows (http://www.openlca.org/). Every process in the database includes 'elementary flows' reflecting an emission, a use of a resource or land use, either entering (resource and land use) or leaving (emissions) the product system under study (Guinée et al., 2002). These elementary flows allow tracing and accounting of the total emissions and resources related to a product system, and are translated by characterisation factors into potential environmental impacts. We created an inventory of the relevant land use types found in elementary flows (Table 1). We only included elementary flows that were already linked to background processes and relate to agriculture and/or natural land (full list in Supplementary material S2). We did not include flows relating to the occupation of industrial sites, construction areas, or mineral extraction sites, since the pollinators abundance of those land use types can be assumed to be null.

Table 1
Summary of the land use types derived from elementary flows connected to agricultural processes in ecoinvent.

Elementary flows	
"Occupation"	
1	Annual crop
2	Natural grassland
3	Man-made pasture
4	Permanent crop
5	Shrub land
6	Forest

2.2. Impact models in the literature targeting pollinator abundance

To retrieve impact models from the literature that can be used to estimate pollinator abundance based on land use types, we conducted a bibliometric analysis in the ISI Web of Science (WoS) published by Thomson Reuters, using as keywords 'pollinator abundance' AND 'impact model' (accessed on 19/11/2018). This provided models from both the ecological and the LCA scientific community. To be selected, models had to comply with the specific criteria in order to be considered for a new LCA impact category (see Box 1).

Models that did not fulfil all of these basic requirements were not considered for LCIA within the scope of this research.

2.3. Characterising pollinator abundance

Once a suitable impact model was found and derived from the literature, we proceeded to analyse how it could be used as a characterisation model within the LCIA framework while complying with the LCA requirements (described in the previous sections). Characterisation models link and quantify the potential contribution of elementary flows to a specific impact with the use of characterisation factors (CFs; see section 2.1.1). The elementary flows of ecoinvent represent coarse land use types such as for example 'permanent crop', 'forest', etc. However, independent of elementary flows, ecoinvent contains more detailed information at a processes level, such as type of crops. To utilize this additional information, we characterized both the list of coarse land use types from elementary flows, and the additional categories derived from the agricultural processes available for non-perennial and perennial crops (Fig. 3). For non-perennial crops, the database contains 45 type of crop processes, ranging from cereals to fibre crops, and there are 29 perennial crops available, ranging from fruits to spices. Additionally, considering the current limitations for biogeographical differentiation in LCA, we will focus on presenting a global characterisation model and derive the preliminary characterisation factors world generic estimates.

3. Results

3.1. Impact model selected from the literature

The bibliographical search resulted in 65 studies. From these, studies targeting climate change or toxicity by pesticides in their impact model were out of the scope of this study. We found that the majority of studies assessing pollinator abundance based on land systems have applied the Lonsdorf model (Lonsdorf et al., 2009) or an adaptation of it. The Lonsdorf model is a spatially explicit model that predicts relative bee abundance based on the composition of habitats and their floral and

Box 1
Criteria used to select impact models for a new impact category in LCA:

1) The model should allow for quantitative estimations: LCIA is a phase of LCA where potential contributions of environmental interventions from LCI (e.g., emissions, resources use, land use) to impact categories (e.g., climate change, acidification, resource depletion, pollination) are quantified by multiplying these interventions with characterisation factors derived from scientific impact models and aggregating the results into indicator results for each impact category.
2) The model can be linked with inventory data: During the inventory phase the product system is defined and the data for each unit process is collected. However, a crucial limitation of LCA is the availability of data. The impact model proposed should be able to use data that are currently present in LCA inventories or that can be added in a way compatible with LCA inventories (UNEP/SETAC, 2016).
3) A clear link to an area of protection: The three areas of protection (AoP) currently assessed in LCA are Ecosystem quality, Human health and Resource availability. Within each, there are multiple endpoint categories that could be developed and represent impacts in one or multiple AoP (UNEP/SETAC, 2016).
4) Scalable with a functional unit: A functional unit is the quantified function provided by the product system(s) under study, for use as a reference basis in an LCA (Guinée et al., 2002). All impact results are scaled in a linear way in accordance to the functional unit defined for each study (Heijungs, 2020).

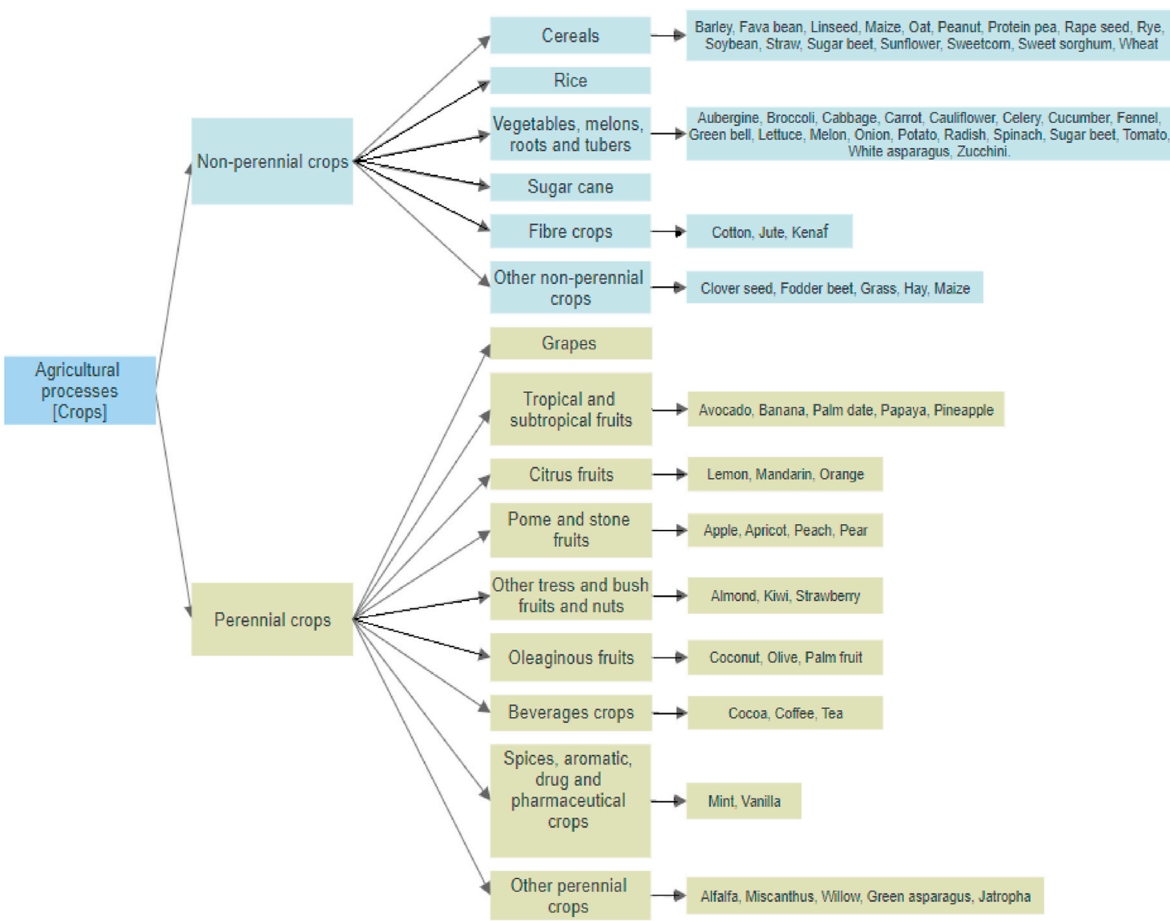

Fig. 3. Inventory of agricultural crop processes found in ecoinvent (https://www.ecoinvent.org/).

nesting resources, and it relies on simple land cover data and established pollinator behaviour as governed by a few key parameters.

Based on the criteria described in section 2.2 we found that the Lonsdorf model complies with the general requirements for LCA: 1) The model allows a quantitative estimate of pollinator abundance with a linear model; 2) The relation between land use (type and amount) and pollinator abundance can be directly linked with inventory data which provides information on the land use type and amount of land used; 3) The link between pollinator abundance and at least one of the areas of protection covered with LCA can be modelled through either 'Resource availability' and/or 'Ecosystem quality'; and 4) the environmental intervention assessed with this model and its estimated impact is scalable to a functional unit. Given compliance to these main four criteria, we concluded that the model could theoretically be used to calculate characterisation factors for a midpoint impact category for LCA.

3.1.1. The Lonsdorf model

The first part of the Lonsdorf model consists of using the landscape structure and vegetation community of a given area to determine the possible community of pollinators available and their abundance. The result of this first part is a spatially explicit estimate of the relative abundance for each species or guild across a given landscape. This first part of the model can be applied to estimate the pollinator abundance of, for example, land use/cover type 'x'. The resulting estimate can be used as the characterisation factor for land use type 'x', which would represent the pollinator abundance associated to land use type 'x'. Alternatively, if there is enough information of a certain land use type at two different states (e.g., before and during land use 'x'), the first part of the Lonsdorf model can be used to estimate the pollinator abundance at the two states of land to derive the change in quality (ΔQ) due to a specific land use or management. The result would correspond to the characterisation factor.

Using the Lonsdorf model to determine the potential change in pollinator abundance associated with land use can provide robust results in terms of spatial and temporal representativeness. However, exact application of the model would require a large standardization and quantification of data to produce harmonized and comparable results. Given the high number of location-specific parameters in the model, representative CFs should be the product of a meta-analysis that can adhere to the model assumptions, use standardised data (e.g., standard land cover maps), and preferably validated with field observations. Additionally, it would be necessary that a panel of experts evaluates the nesting suitability for each of the bee nesting guilds (e.g., ground, cavity, stem, and wood-nesting bees) and floral resource availability for the foraging seasons considered (e.g., spring, summer, fall), for each land use type studied. Such evaluation was beyond the scope of this study and therefore we derived a simplified method.

3.2. Alternative approach

3.2.1. The simplified method

Considering the demands for application of a pollinator impact model within an LCA context, we derived an alternative approach that minimizes the number of parameters to be characterised by "bypassing" the Lonsdorf model and utilizing expert input to obtain relative pollinator abundance values. This approach also allows the CFs to be linked with background processes by specifically characterising the land use types derived from the ecoinvent database. We refer to this approach as the simplified method. Similar to the Lonsdorf model, it relies on expert knowledge to determine pollinator abundance for each land cover data. To do this, our method requires experts to assign a score of pollinator abundance to each land use/cover type. Since LCA results are relative values and not absolute, we can use an averaged pollinator abundance per land use/cover type to derive the CFs and portray the differences among product systems by accounting for the types of land use/cover involved on each system.

To illustrate the simplified method, the inventory of relevant elementary flows and of agricultural crop processes was characterised by a pollinators' expert who attributed a mean estimate of the pollinator abundance (denominated here as S_x) that can be expected or associated with each land use type (this 'mean' estimate refers to the most predominant values and not specifically to the statistical mean, therefore it refers to the 'mode' of pollinator abundance values). Assigning each land use type with a quantitative score, serves as a proxy to represent its capacity to provide an ecosystem service or function. In this case, the quantitative score was given to each land type to reflect their relative pollinator abundance. The estimates varied from 0 to 100, starting by assigning the highest value to a reference state of optimal pollinator abundance. Open phrygana (also called *garrigue*) in Mediterranean ecosystems had a value of 100 and thus coincided in terms of pollinator abundance with the reference state, but is not to be confused with a potential natural vegetation. Values between 50 and 100 were attributed to land use types that have a high relative pollinator abundance, while values between 0 and 50 correspond to land use types that are likely to present low to none pollinator abundance. The estimates thus describe the relative impact on pollination associated with each land use type. Additionally, a score for low and high rates of pollinator abundance was given for each land use type (the full table of pollinator abundance estimates for each land use type can be found in Supplementary material **S4**) to account for impacts of differences in management within a land use type.

While several reference states can be used for the characterisation of impacts, such as potential natural vegetation (PNV), the prior land use state, or a mix (Koellner et al., 2013), the CFs produced through this approach express relative pollinator abundance decrease in reference to an optimal state, which in this study corresponds to a land use type of open phrygana. Given that the CFs produced in this study are for occupation impacts and world generic, the reference state is only used during the characterisation of the relative impact that is attributed to each land use type, and unlike the PNV, it does not imply that the land would naturally regenerate to the optimal state.

3.3. Application for LCA

3.3.1. The quantified indicator

The quantified indicator for this newly proposed impact category is then pollinator abundance (*PA*) in reference to the land use type with the maximum value (100) of pollinator abundance (PA_{ref}), which in this case coincides with open phrygana. The value of 100 represents an undetermined number of pollinators per m^2 of reference land use type, written as α:

$$PA_{ref} = \alpha$$

The number α is expressed in pollinator individuals per m^2. This number is difficult to specify exactly, but there is no need to do that as we define pollinator abundance only relatively. For any other land use type, say x, we express the pollinator abundance as (PA_x, in pollinators/m^2):

$$PA_x = \frac{S_x}{100}\alpha$$

with S_x as an expert estimate of the pollinator density on a scale from 0 to 100, relative to the reference state, which in this study corresponds to open phrygana. This quantified indicator is used to derive characterisation factors.

3.3.2. Deriving characterisation factors

To derive the characterisation factors for impacts of land use (occupation) on pollinator abundance, we analysed the change in number of pollinators per unit area of land use type x, compared to the reference state:

$$CF_{O,x} = \Delta PA_x = \alpha - \frac{S_x}{100}\cdot\alpha = \left(1 - \frac{S_x}{100}\right)\cdot\alpha$$

Because the number α is unknown, we prefer to work with CFs relative to a reference condition of optimal pollinator abundance. This then yields:

$$CF_{O,x} = 1 - \frac{PA_x}{PA_{ref}} = 1 - \left(\frac{\left(S_x/100\right)\cdot\alpha}{\alpha}\right) = 1 - \frac{S_x}{100}$$

The CF for open phrygana is 0, while for complete pollinator-free land use types, it is 1, and for land use x with $S_x = 40$ the CF will be 0.6 indicating 60% lower pollination abundance compared to the reference state. These CFs are dimensionless in the same way as the IPCC (2013) global warming potentials (GWPs) are dimensionless: The GWPs express the time-integrated increased infrared absorption due to an emission of 1 kg of a given greenhouse gas (GHG) relative to an equal emission of carbon dioxide, which results in dimensionless characterization factors (kg GHG/kg CO_2). The GWPs are then multiplied with inventory emissions of GHGs (kg GHG) and aggregated to an indicator result for climate change expressed in kg of CO_2 equivalents. In the same way, our CFs are 'dimensionless' ($m^2 \cdot year/m^2 \cdot year$ reference land) and relative, expressing the time-integrated decrease of areal pollinator abundance (expressed in terms of number of pollinators per m^2) of, for example, land occupation x, relative to the time-integrated areal pollinator abundance of the reference land:

$$\frac{\frac{pollinators}{m^2}\,_x \Big/ m^2 \cdot year_{O,\,x}}{\frac{pollinators}{m^2}\,_{ref} \Big/ m^2 \cdot year_{O,\,ref}} = \frac{m^2 \cdot year_{\;O,\;ref}}{m^2 \cdot year_{\;O,x}}$$

The CFs ($m^2 \cdot year/m^2 \cdot year$ reference land) are multiplied with their corresponding land occupation interventions (*in* $m^2 \cdot year$), that results in an indicator result in $m^2 \cdot year$ reference land (further described in Section 3.3.4).

3.3.3. Illustrative characterisation factors for impacts on pollinator abundance

To illustrate the simplified method, we present the characterisation procedure and illustrative CFs that are obtained for the land use types evaluated in this study. The pollinator abundance estimates were provided by one pollinator expert based on existing literature, consistent with general trends prevailing in pollination assessments (e.g., IPBES, 2016). These values should thus not be interpreted as a consensus of expert knowledge on the scores of each land use type.

The CFs for the aggregated land use types derived from elementary flows are presented in Table 2. These aggregated values allow directly connecting to current background processes and were estimated directly by expert assessment (i.e., considering all possible land use within each category). To additionally present the CFs of the 42 non-perennial and perennial crops, we derived and aggregated values of each crop within sub-categories as shown in Fig. 3, and present them in Tables 3 and 4, accordingly.

These CFs express the potential contribution to the impact category of pollinator abundance, relative to a reference state. The result can thus not be used for absolute decisions (Guinée et al., 2017). One should thus only use the CFs for comparing alternative products. Furthermore, it is important to consider the full suite of environmental implications when interpreting LCA results, to identify potential trade-offs.

3.3.4. Implementation in LCA: the indicator result

For calculating the indicator result for all land occupation flows related to a specific LCA case study, all occupation flows (O_x) are multiplied by their respective characterisation factors $CF_{O,x}$ and their results are aggregated into the indicator result *PAO*:

$$Pollinator\ Abundance\ Occupation\ (PAO) = \sum_{x=1}^{x=n} (CF_{O,x} \times O_x)$$

where O_x is the time integrated area of occupation in $m^2 \cdot year$. The unit of the indicator result *PAO* is thus also $m^2 \cdot year$. The indicator result allows to compare the relative pollinator abundance decrease that is associated with each product system, as a result of the land use types involved in each. For example, systems relying mainly in non-perennial crops will present a higher pollinator decrease compared with systems relying mainly on permanent crops.

Table 2
Illustrative characterisation factors for aggregated land use types derived from **elementary flows** from ecoinvent.

Aggregated land use types	Pollinator abundance (PA)	Characterisation factor $\left(CF = 1 - \frac{S_x}{100}\right)$
Annual crops	20	0.80
Natural grasslands	70	0.30
Man-made pastures	35	0.65
Permanent crops	40	0.60
Scrubland	60	0.40
Cropland fallow	50	0.50
Forest	40	0.60

Table 3
Illustrative characterisation factors for **non-perennial crops** derived from **agricultural processes** present in ecoinvent.

Non-perennial crops	Pollinator abundance (PA)	Characterisation factor $\left(CF = 1 - \frac{S_x}{100}\right)$
Cereals	17	0.82
Rice	10	0.90
Vegetables, melons, roots and tubers	25	0.75
Sugar cane	10	0.90
Fibre crops	40	0.60
Other non-perennial crops	16	0.84

Table 4
Illustrative characterisation factors for **perennial crops** derived from **agricultural processes** present in ecoinvent.

Perennial crops	Pollinator abundance (PA)	Characterisation factor $\left(CF = 1 - \frac{S_x}{100}\right)$
Grapes	25	0.75
Tropical and subtropical fruits	25	0.75
Citrus fruits	35	0.65
Pome and stone fruits	35	0.65
Other trees and bush fruits and nuts	28	0.72
Oleaginous fruits	25	0.75
Beverage crops	25	0.75
Spices, aromatic, drug and pharmaceutical crops	35	0.65
Other perennial crops	32	0.68

4. Discussion

4.1. Scientific and methodological advances

This study proposes a modelling approach that is compatible and applicable with current LCA methods and inventories, and form the basis for future improvements for the assessment of impacts on pollination. One of the first innovations was to define pollinator abundance as the target for a midpoint category, instead of targeting pollination service at endpoint as it had been proposed in the literature (Crenna et al., 2017). While pollination service delivery is highly correlated with the abundance of the most common pollinators, it is also correlated with pollinator diversity (IPBES, 2016). We made a pragmatic decision to address only pollinators abundance at midpoint since models such as Lonsdorf et al. (2009) correlate landscape characteristics with pollinators abundance. Species richness may be included in the translation from abundance into service delivery, which we propose to be the target for the endpoint category. By targeting pollinator abundance, we were able to integrate a new impact category in LCA that is compatible with the current structure of LCIA and that can be linked with existing information from LCA inventories.

The connection to background processes is currently essential to aim for a wide applicability of the CFs produced. This study is one of the first to address this particular issue when proposing new land use related impact models for LCA. The lack of connection to background processes can render new models to fall behind as the potential impact results cannot reflect the influence of the grand majority of processes within the product system studied. For our study, we specifically characterised land use types retrieved from the widely used LCA database ecoinvent. While these land use types are coarse and lack important biogeographical differentiations, they present an opportunity to utilize the existing data available in LCA inventories and allow characterising the potential impact to pollinator abundance by using a simplified approach based on expert knowledge. Through expert knowledge, empirical knowledge regarding observed trends of pollinator abundances were integrated, consistent with results found in the literature that rely on both predicted and sampled data. The results indicate that the CFs reflect key differences among land use types. Further validation tests will be done in follow up research projects aimed at further improving the accuracy of the characterisation factors with input from a broader range of experts.

4.2. Limitations and potential improvements

While the simplified approach allows us to characterise current inventory flows from ecoinvent related to agricultural lands, the approach does not allow to capture critical local sources of variation through its use of broad land use types and crop processes. It also does not take into account the full range of drivers of pollinator communities such as local management, the local species pool and impact sources such as mortality caused by pesticides or pathogens. As part of our bibliographical search for impact models targeting pollinators, we found that climate change impacts depend highly on indirect effects linked for example with temperature and precipitation changes, forest health, and soil attributes (Hannah et al., 2017; Radenković et al., 2017), and the pesticides impact models are highly specific to the case studies in which they are applied, which is an inherent characteristic of toxicity impacts on pollinators (Godfray et al., 2014). Therefore, these models were not considered to be yet readily compatible and applicable within an LCA context and therefore these impact drivers were not considered in our current proposed model. Furthermore, we found several studies assessing the influence of landscape on pollinator abundance (Brandt et al., 2017; Kennedy et al., 2007; Matteson et al., 2013; Ricketts and Lonsdorf, 2013; Sárospataki et al., 2016). Other studies addressed specific aspects that can influence pollinator abundance such as pollinator body size (Benjamin et al., 2014), pollinator habitat and its effect on visitation probability (Schulp et al., 2014), and the influence of bees species traits (De Palma et al., 2015). However, the Lonsdorf was found to be the most widely used landscape-pollination model in the literature and its application for LCA is suitable, which is why we focused our study on this single model. Looking into specific characteristics of the models and the land use types assessed, both the Lonsdorf model and the simplified method assume that the population of pollinators is static. This can be seen as both a limitation and an advantage, since it cannot reflect the changes of population size across time, but it allows both methods to be applied within the LCA framework where temporal scales are currently not available in inventory data. Further improvements could target the inclusion of additional impact models regarding pesticide use and/or climate change impacts on pollinators. Such may be achieved by increasing the detail of inventory background processes to include, even if it is generalized, data on management practices regarding for example pesticide application rates, irrigation, seasonal rotations or connectivity in the landscape, would allow to derive CFs that can take these differences into consideration when providing the pollinator abundance estimates without having their application limited to foreground processes.

The characterisation approach is illustrated in this study through the world generic CFs. To produce regionalized CFs for this new impact category, it would be necessary to select the appropriate geographical scale, the additional reference state per geographical unit (e.g., PNV), and matching of land use categories depending on the data sources used. It is recommended for future research to complement the development of regionalized characterisation factors with a clear overview of the connection to background processes and the necessary adaptations (if any) of the LCA inventories for the application of regionalized CFs.

Additionally, while wild pollinator abundance is driven (at least in part) by land use, the abundance of managed honeybees, the most important global pollinator species, is primarily driven by beekeeper and farmer decision making (which may be indirectly linked to land use, but not always). Therefore, it is important to recognise that our proposed method only addresses wild pollinators and not managed pollinators. This is an important first step towards a comprehensive model, given that wild pollinators are widely documented as being at least as important, and often more important than managed honeybees for crop pollination (IPBES, 2016). Further improvements can be aimed at incorporating new inventory processes in ecoinvent that can include managed pollinators and remediation practices, for which the characterisation factors would be negative values indicating positive impacts. That way, comparisons in LCA of agricultural practices could explore possibilities for prevention and remediation in the design of their product systems or in sensitivity analyses, allowing LCA practitioners to recommend changes or better strategies to reduce impacts on pollinators.

4.3. Outlook

Identifying the potential effects of land use on pollinators is an indispensable aspect to consider during decision making, and impact assessments can be instrumental to raise awareness and help prevent further decline rates. We have been able to further expand the reach of LCIA, by allowing LCA practitioners to consider pollinator impacts when assessing the potential environmental interventions of a product system. Through the development and integration of this new impact category and its corresponding impact model to produce robust CFs, we provide LCA practitioners with a prior account of impacts while comparing among product systems. This will be beneficial, for example, when comparing between crops for biofuels purposes, for food production systems, or when assessing different scenarios for land management. This will facilitate the identification of product systems with high impacts on pollinator abundance and allow practitioners to recommend preventive or remediation actions. In addition to allowing a comparison of product systems, based on their potential environmental impacts including those on pollinators, it also allows the identification of impact hot spots within product systems. In addition to preventing environmental impacts, such actions will likely also provide economic benefits given the critical role of pollination in securing crop productivity (REF). Therefore, securing pollination will increase the competitiveness of agriculture and its resilience to future change.

Before such large-scale application, the model proposed in this study needs further evaluation. Our method was operationalized by producing illustrative CFs that reflect key differences among crops and land use types. However, it is important to bear in mind that these values were obtained from the expert knowledge of one pollinator expert who provided the scores for each of the land use/cover types assessed in this study. Further improvements will target the collection of data from multiple experts to increase robustness and assess the associated uncertainty of the characterisation factors. The same approach for the derivation of relative quantitative values proposed in this study can be also adapted to other impact categories for which absolute values are too complex to calculate at a worldwide level for an LCA application. This will allow incorporating knowledge from diverse fields, e.g., by multidisciplinary research groups. This will help to further improve the robustness of life cycle impact assessments and make it more comprehensive by adding highly relevant environmental impacts such as pollination.

5. Conclusions

This research highlights the need for incorporating pollination impacts within the assessment of LCA, due to their relevance in our current global food security and the urgent need to prevent further decline. We present a novel way to overcome current limitations in the structure of LCIA and the available LCA inventories by proposing an approach to account for pollinator impacts. We provide the required steps for the characterisation of impacts, and illustrate the operationalization by producing preliminary characterisation factors that are compatible with the ecoinvent LCA database. These characterisation factors reflect key differences on the pollinator abundance associated with each land use type, including for the coarse land use types derived from elementary flows. Therefore, the application of the proposed approach and derivation of characterisation factors from a larger sample of experts will result in applicable characterisation factors compatible with background processes. Our novel approach could be further extended to incorporate other crucial components of biodiversity underpinning food and nutritional security, such as the effect of managed pollinators and potential spatial differentiations. The results of this study contribute towards the continuous improvement of the impact assessment methods for LCA, providing tools to assess key environmental impacts as comprehensively as possible.

CRediT authorship contribution statement

Elizabeth M. Alejandre: Idea, Study design, Writing – original draft. **Simon G. Potts:** Pollinator abundance estimates. **Jeroen B. Guinée:** Idea, Study design, Writing – original draft. **Peter M. van Bodegom:** Idea, Study design, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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