Multilevel environmental assessment of regional farming activities with Life Cycle Assessment: Tackling data scarcity and farm diversity with Life Cycle Inventories based on Agrarian System Diagnosis

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Abstract

Keywords

regional Life Cycle Assessment; Agrarian System Diagnosis ; farm typology; environmental assessment; data scarcity; uncertainty

1. Introduction

The environmental impacts of agriculture are of tremendous and growing concern for decision makers involved in regional land planning, as well as for agricultural policy makers (Ripple et al., 2018). Policies aimed at achieving sustainable agriculture must be developed at the regional level, and adapted to local opportunities and constraints (Caron, 2005; Cairol et al., 2009; Benoît et al., 2012). Sustainable agriculture must both maximise productivity on existing farmland — to meet increasing global food, fuel and fibre demand — and significantly decrease its negative impacts on the environment, e.g., on climate change and biodiversity loss (Cassman and Grassini, 2020). Decision-makers need tools, methods and criteria to assess the sustainability of farming systems, despite the difficulties posed by such a challenge due to their diversity, dynamics (Quintero-Angel and González-Acevedo, 2018), and the range of environmental impacts to be assessed. The latter should be broad enough to ensure that none are overlooked and that trade-offs are recognized (Kanter et al., 2018).

Life-Cycle Assessment (LCA) was designed in the early 70s to measure the "environmental cost" of products by quantifying their potential impacts on a large range of environmental impact categories. LCA was originally dedicated to products and supply chains, and has become a central plank of the European Union's Environmental Footprint Policy (European Commission, 2012). Some authors also recommend its use for public decision-making applied to land management, e.g., for the environmental assessment of small regions (Loiseau et al., 2012) or for agricultural land planning (Payraudeau and van der Werf, 2005; Aubin, et al., 2011; Huang et al., 2014). Notwithstanding its advantages, applying LCA to farming activities at the regional level – instead of the crop or farm level- poses two main methodological challenges that need to be addressed, i.e., the huge variability of farming systems to be characterised and, on the other hand, data scarcity (Guinée et al., 2011; Avadí et al., 2016). This can lead to supplying LCA with doubtful input data, which is very detrimental to LCA outputs, as it increases their epistemic uncertainty (Nemecek et al., 2010; Chen and Corson, 2014; Teixeira, 2014). Input data uncertainties are related to several factors, e.g., non-representativeness, insufficiency, or the complete absence of data (Huijbregts, 1998). Indeed, accessing relevant data on agricultural activities at regional scales has been a focal point of attention for LCA scientists for more than 20 years. As pointed out by several LCA scientists (Dalgaard et al., 2004; Nemecek and Erzinger, 2005; Reap et al., 2008; Renaud-Gentié et al., 2014) agricultural LCAs were often conducted with data that were not representative of the system under study. Data were generally taken from statistical sources like Avadi et al, (2017), including the accountability-derived data from the Farm Accountancy Data Network (FADN), (Jan et al., 2012, Dolman et al., 2014) and agricultural census (Mishima et al., 2005) and therefore deemed "average" management practices. Other authors used technical guidelines (Basset-Mens et al., 2010; Nemecek, et al., 2011b) or pilot farms (Nemecek and Erzinger, 2005). The problem with data generated by FADN is that the European Commission intended it to be used to assess the impacts of the Common Agricultural Policy and the income of average agricultural holdings, and not for environmental purposes. It is limited to data on farm structure. Inputs and agricultural machinery are aggregated at the farm level and quantified on an economic basis (EEA, 2005). Such economic data are prone to fluctuate with market prices (Jan et al., 2012), and aggregation makes it impossible to identify the origin of environmental hotspots (EEA, 2005; Moreau et al., 2012), or assess their recycling potential (Efole Ewoukem et al., 2012). The high level of uncertainty associated with this statistical data, which stems from missing or inaccurate data, is also criticised (Dalgaard et al., 2006; Samson et al., 2012; Avadí et al., 2017). Therefore, the European Environmental Agency discourages the use of EU FADN to derive agro-environmental indicators (European Environmental Agency, 2005). Moreover, there is huge heterogeneity in the availability and precision of statistics-based data among countries. Only when primary data is not available (i.e., original data from scientific research, surveys, case studies, or monitoring with a low level of aggregation) does the World Food LCA database provide statistics-based data, i.e., aggregated generic data (Nemecek et al., 2015).

Consequently, data scarcity poses a major challenge regarding uncertainty, and researchers have searched for ways to reduce it. Lindeijer and Weidema (2000) claimed that farm typologies in LCA could be used "*to lower data variability, to allow a better selection of representative farms for detailed research, and to better determine the marginal effects of a studied change*"; the better the typology, the lower the variability within each farm type, and the higher the variability between farm types (Köbrich et al., 2003). Basset-Mens et al. (2010) highlighted the need to develop a protocol for "*designing and characterising typical farming systems at a given scale*".

The challenge is to build a method designed to tackle data scarcity - and the resulting data uncertainty in LCA - especially in cases involving highly-diverse agrarian systems. Our hypothesis is that Agrarian System Diagnosis (ASD) is a good approach for the development of such a method.

ASD was initially designed by researchers from INRAE (formerly INRA) to model-farm performances related to technical results (yield) and economical performances (gross product, revenue) (Cochet, 2015). Its multilevel approach for collecting data has already proven efficient for capturing the complexity and diversity of farming and cropping systems, despite data scarcity (Cochet, 2015). ASD has already been used for modelling environmental impacts; primarily, for assessing specific impacts such as eutrophication (Mabon et al., 2009; Moreau et al., 2012; Lacoste et al., 2016). Avadí et al. (2016) used it to build regional LCA, with farm-level data issued from a previous ASD (Mabon 2008) along with regional farm-level surveys and statistics (e.g., main production outputs, land use), and scaled-up results by using proxy data (e.g., glyphosate for pesticides).

To go a step further, our aim is to build an innovative method based on ASD to secure data collection for Life-Cycle Inventory (LCI) at a regional scale, despite data scarcity, in highly diverse agrarian systems. ASD will be used to describe the farm typology in the area, and account for the diversity of farming and cropping systems. The innovation in this method is linked to the targeted reduction in epistemic uncertainty: firstly by applying a stratified sampling to this farm typology, to target data collection on farms representative of the types, and secondly, by carefully collecting and curating data essential to LCI.

In this paper, we develop and apply this methodological framework to an irrigation zone in Tunisia. We describe the development of this new methodological framework combining ASD and LCI, which we named "ASD-based LCI". This is a novel way to streamline this highly data-intensive LCI phase. We apply this methodology to a case study, i.e., the irrigated semi-arid plain of Kairouan in Tunisia, which was part of an EU research project (Eau4Food: www.eau4food.info/). We plan to carry out the other phases of the LCA, converting LCI data into Life Cycle Impact Assessment (LCIA) outputs, to obtain the LCA assessment. The aim is twofold: first, to compare the environmental impacts of various cropping/livestock systems and farming systems as well as trend-based scenarios of the farming region; and second, to assess the contribution of farming systems and processes to regional impacts, and to identify hotspots.

2. Material and Methods

2.1 Methodological features of LCA

LCA has a 4-step framework (Figure 1) that models the potential environmental impacts of the delivery of one unit of product or service (e.g. producing food, transporting commodities, etc.), quantified in functional units (e.g., 1 kg of bell peppers harvested, 1 kg*km transported, etc.). This approach is standardised, but the manner in which LCI is obtained ("inventory analysis" phase) is specific to each study, and different impact models can be used for the "impact assessment" phase (ISO, 2006a, 2006b).

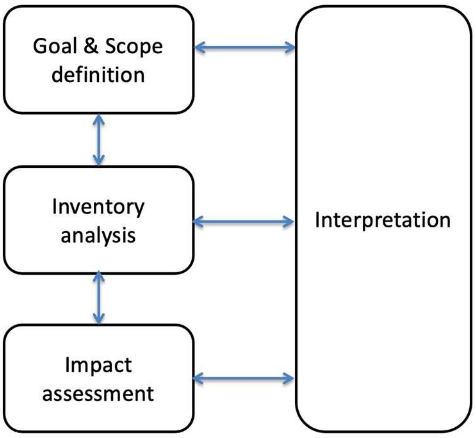

Figure 1. The four steps of the standardised Life Cycle Assessment method for modelling the environmental impact of services and products

In the first step, "Goal and scope definition", the system boundaries and functions (which determine the choice of functional unit(s)) are identified. In the second step, "Inventory Analysis", every flow of resources consumed, and of polluting emissions, is accounted for in the LCI. This is by far the most time-consuming and effort-intensive step of the whole LCA. LCI data are extracted from studied elementary flows of materials or energy consumed (e.g., kg of raw material, hours of processing, amounts of energy) or released into the environment (e.g., polluting emissions and functional units delivered), (Brentrup et al., 2004). In our case, the starting point was to build a good model of farm activities, e.g., fertilizing, irrigating, ploughing, etc. To do so, "activity data", i.e., data related to the crop/ livestock management were collected. Such activities are responsible for emissions/consumption flows and linked to two process types called Foreground and Background processes. "Foreground processes" are emissions/ consumption related to farmer choices (e.g.: the type of fertilizer, the dose, the spreader use, etc). They have a significant influence on agricultural LCA results (Cowie et al., 2012; Modahl et al., 2012). Related data must therefore be collected specifically for the system under study. Data necessary for a good modelling of foreground processes include not only "activity data", but also other "site-specific" data (e.g., soil texture, crop variety) that are useful to correctly model emissions and consumptions (Bellon-Maurel et al., 2014.; Röös et al., 2010). However, LCA also considers emissions/ consumptions which are related to the resources used for the activities of the farm, e.g., related to agricultural machinery building or to energy/ input production. Such "background processes" occur upstream or downstream (e.g., recycling steps, after resource usage) and are not described with the same accuracy as foreground processes: background data are taken from database libraries incorporated in LCA software: in our case, EcoInvent 2.2.

The third step is Impact Assessment (LCIA), in which these inventory data are processed using an environmental impact assessment model to be converted into potential environmental impacts. For instance, the 2008 LCIA ReCiPe method (Goedkoop et al., 2012) generates 18 "midpoint impacts" - including climate change, human toxicity, and water depletion - as well as three aggregated impact categories called "endpoint impacts" -i.e., human health, ecosystems and resources. In ReCiPe, water depletion is routinely modelled only up to the midpoint level in volumetric units. However, in the present work, we will model it up to the endpoint level, due to the local high water stress (Pfister et al., 2009).

Lastly, step 4 consists in interpreting the results with regards to the modelling choices made in the preceding steps.

2.2 Agrarian System Diagnosis

Agrarian System Diagnosis (ASD) is an iterative approach and method that aims at "identifying and characterising the ecological, technical and socio-economic conditions from which originates the diversity and complexity of farming systems and their evolution" (Cochet and Devienne, 2006). This is a systemic approach aimed at supporting local farmers by offering tailored support despite diversity in farming systems in terms of functioning and strategy. This is achieved by combining technical, financial and socio-economic criteria to describe each farming system.

The ASD is a multilevel approach that can be applied from the farming region to the cropping system. The "farming region" can be defined as a "geographic entity, differentiated and structured by the activities and the social groups which occupy it and interact there" (Papy, 2001; Payraudeau and Van der Werf, 2005). At the regional level, the concept of an "agrarian system" is employed to model the farming region under study as a weighted aggregation of farming systems that exchange flows among themselves, and/or between their sub-subsystems (cropping and livestock systems) (Mazoyer and Roudart, 1997; Cochet, 2012). At the farm level, the "farming system" refers to a farm archetype that represents a set of similar farms. These farms are characterised by a given combination of cropping systems and livestock systems, which rely on comparable farm resources and face comparable socio-economic constraints (Reboul, 1976). At the field level, the "cropping system" is defined as a ''subset of the farming system, characterized by crops, sequencing and planning", i.e. the logical and orderly combination of cultivation techniques (Cochet, 2012). As such, the same crop rotation, implemented with notably different levels of inputs (fertilisers, pesticides, water, etc.), may lead to two distinct cropping systems. At the herd level, the livestock system is also a subset of the farming system. It refers to "a set of dynamically interacting elements organised by humans in order to: valorise resources provided by domestic animals, and thus obtain various commodities (milk, meat, leather, workforce, manure, etc.), or fulfil other needs" (Landais, 1987).

Essentially, ASD relies on the functional typology approach. The "functional typology" of farms accounts for the farming system diversity in a region under study (Trebuil and

Dufumier, 1993; Devienne and Wybrecht, 2002; Tittonell et al., 2010; Aubron et al., 2016). Functional typology is based on criteria describing the functioning of each farm sampled, and its strategy. The hypothesis made here is that the current agrarian system in a region results from: the evolution of farms (and their adaptation to bioclimatic conditions in a given space), and the dynamics of socio-economic constraints and opportunities, including, for example, labour-force availability or market opportunities (Mazoyer and Roudart, 1997; Groppo et al., 1999). The ASD approach is comprised of 3 main steps, with some overlapping and feedback: landscape analysis, historical reconstitution of the regional agro-ecosystem management, and finally techno-economic characterisation of farming activities at the farm and field/herd levels (Ferraton and Touzard, 2009; Moreau et al., 2012).

2.3 Methodological proposal: "ASD-based LCI" to build a multilevel LCI of farming activities

The first step of the LCA is "goal and scope" definition (Figure 1). The system boundaries are those of the farming region studied and temporal boundaries are assessed on a yearly basis. The "functional unit", i.e., the unit in reference to which the impacts will be calculated, must be determined. As far as agriculture is concerned, many studies recommend choosing functional units that are either related to the areas concerned, or to product quantities (de Vries and de Boer, 2010; Nemecek, et al., 2011a; Salou et al., 2017), since they greatly influence the results of the LCA (Halberg et al., 2005; Payraudeau and Van der Werf, 2005; Cairol et al., 2009).

The next step, i.e., LCI, is the most critical. "ASD-based LCI" is the name we have given to the new approach that we have developed to build the LCI of farming activities. "ASD-based LCI" is based on a multilevel approach (Figure 2) in which the ASD is first carried out through: 1-Landscape Analysis / 2-Historical reconstitution / 3-Techno-economic characterization, to describe the farming systems (Figure 2- line 1), in order to guide farm sampling and further collection of activity data. The latter are then enriched with additional data collected at the regional scale and with specific data estimated at the field level to plug the activity data gaps. The steps in the lower part of flow chart below refer to the conversion of activity data (related to farm operations) into an emission / consumption inventory.

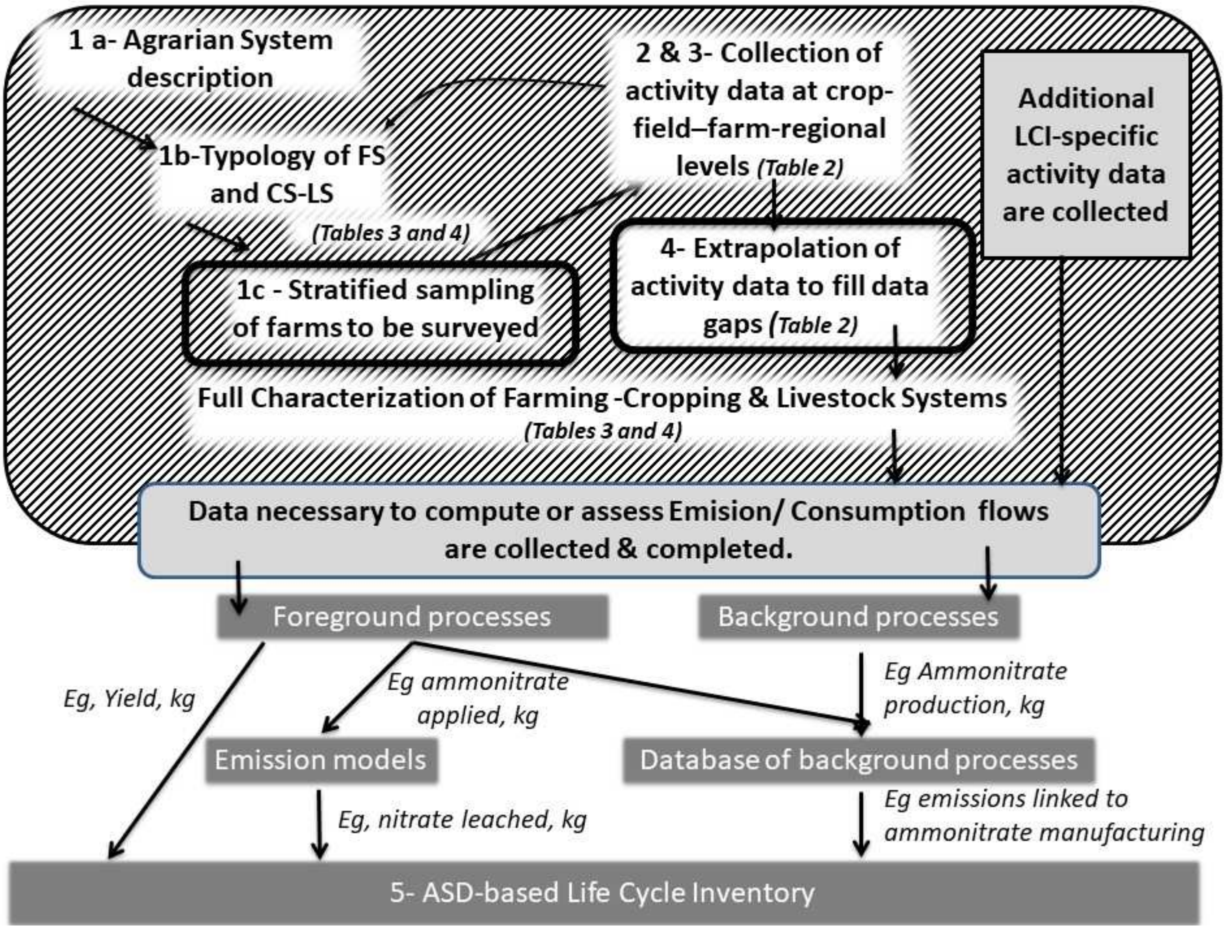

Figure 2. Main steps for building an ASD-based LCI. The dashed area corresponds to the ASD steps. Dark grey boxes relate to emission/ consumption computation; light-grey boxes correspond to data collected/ enriched by ASD to feed LCI. The two innovative steps used to reduce uncertainty of LCA outputs of the region are shown in black thick-edged boxes. FS: Farming System; CS-LS: Cropping System, Livestock System; "Tables" indicated in italics refers to the tables where data can be found.

This nested approach - using both top-down and bottom-up paths – has eight steps, which are described in more detail in Table 1.

- In Steps 1 to 3, farming and cropping systems are identified through ASD. Based on a stratified sampling of farms, activity data are collected at the: crop, field, farm and regional levels, and enriched with additional data specific to LCI requirements.
- Data gaps are checked and filled in Step 4.
- Then, LCI is built using a bottom-up approach (Steps 5 to 8). At each level, data are aggregated, and internal exchanges of material flows are accounted for. LCI are delivered for each cropping system (Step 6), farming system (Step 7), and for the whole farming region (Step 8).

#	Title	Aim	Tools & methods	Outputs
1	Regional-level ASD	To identify the Agrarian system and build the pre-typology of farming, cropping and livestock systems	= Literature, = Landscape analysis & historical reconstitution = Expert knowledge = Interviews/ Enquiries	- Agro-ecological zoning - Agrarian system history - Pre-typology of farming and cropping/livestock systems - Stratified sampling of farms - Farm survey grid
2	Farm-level ASD	To characterise farming systems and activity data	= Farm visits (1st visit) = Survey grid = Interviews/ Enquiries/ Open questions	- Typology of farming systems - Farm history and evolution of production strategy and functioning - Farm resources /Cropping pattern/Working schedule - **LCI-specific data: equipment & infrastructure lifetime

3	Field/herd-level ASD	To characterise Cropping/ Livestock Systems and activity data	= Farm visits (2nd and 3rd visits) = Survey grid = Interviews/ Enquiries/ Closed questions	- Typology of cropping system (crop rotation and sequence of farm management operations) and livestock systems - ** LCI-specific data
4	Extrapolation of activity data in crop/herd datasets	To check missing activity data and fill data gaps	= Analogies = Crop modelling = Expert knowledge = Literature	- Complete activity data at crop level (crop datasets) and herd level - ** LCI-specific data
5	LCI at Crop level: LCI of each crop (C_i LCI)	To convert Activity data into Life Cycle Inventory data	= Field emissions models = Activity data files = Database of LCI background processes (EcoInvent)	- Crop level- C_i LCI
6	LCI at Field/herd level: LCI of each Cropping System (CS_j LCI)	To aggregate crop-level Life Cycle Inventory data;	Inventory Data files; EcoInvent Databases	Field level-CS_j LCI = ∑ (Crop-level LCI C_i-CS_j)
7	LCI at Farm level: LCI of each Farming System LCI (FS_k LCI)	To aggregate field (and herd) levels Life Cycle Inventories; account for flows exchanged within farms	Inventory Data files; EcoInvent Databases	Farm level-FS_k LCI = ∑ (Field-level LCI CS_j.FS_k*weight CS_j)-internal flows
8	LCI at Regional level: LCI of the whole Farming region LCI	To aggregate farm-level Life Cycle Inventories; account for flows between	Inventory Data files; EcoInvent Databases	Regional level-LCI = ∑ (Farm level LCI FS_k*weight FS_k)-internal flows

		farms		

Table 1. The proposed method for the multilevel environmental assessment of regional farming activities with Life Cycle Assessment is based on Agrarian System Diagnosis for the second LCA phase, i.e., the Life Cycle Inventory. The multilevel LCI is built with the ASD-based LCI at nested levels, from the crop up to the farming region (CS: cropping system, LS: livestock system, LCI: Life Cycle Inventory, LCA: Life Cycle Assessment, ASD: Agrarian System Diagnosis, **: specific output flows collected with ASD for LCA purposes only

In Step 1, various sources of information are consulted to better understand local context dynamics and resulting influences on regional farming systems. Review of literature, along with field work, consisting in landscape analysis, and the historical reconstitution of local farming activities are used to sketch a preliminary typology of farming systems. Interviews are conducted with: active farmers and some retired ones, local agriculture administration officials, extension officers, and input retailers (Table 1, Step 1). Open-ended questions are preferred to closed-ended questions since the aim is to build a functional typology, reflecting the opportunities and constraints which determine the range of farming activities which are organised within the agrarian system at the regional level. Moreover, understanding the drivers of innovation is essential for drawing trend-based scenarios for the future. Usually, access to classical farm resources (land/water, capital, workforce) determines the range of actual opportunities regarding farming activities, but access to market is also a major determinant. In previous studies (Ferraton and Touzard, 2009, Belières et al., 2013), farming systems were classified into corporate/ family business/ family farming categories, mostly according to the status of the labour force (family members versus employees), farm management (commercial versus family-oriented), and ratio of self-consumed agricultural products to commercialized products. Other criteria used for differentiating farm types include: farm size, topographical constraints, cropping systems, market opportunities (local market, exports, etc.), number of workers, soil type, and access to water. This first step delivers a pre-typology of cropping/ livestock and farming systems, which is later fine-tuned with experts. A minimum of three farms are selected for interviews for each “pre-type” of farm. Representative farms are identified by local experts based on their strategies and performances (e.g. yield).

Steps 2 and 3 consist in conducting interviews in the stratified sample of farms to refine typologies of cropping/livestock and farming systems. Cropping and livestock systems are characterised during comprehensive interviews with farmers; preferably the owner or the person who manages the farm, to record the main strategy and operational information. At the farm level, the cropping plan and cropping pattern (composed of all the cultivated plots) are reconstituted and explicitly linked to crop rotation on every plot. Each cropping system is characterised by the most probable crop succession, including fallow, and the sequence of crop management operations: crop species, planting density, soil type, yield, amount and type of fertilisers, pesticides, irrigation schedule, type of machinery required, as well as irrigation duration and equipment (length of pipes, etc.). As we intend to go beyond a “standard” ASD, and to use collected data to model environmental impacts, we have endeavoured to collect activity data related to the technical functioning of cropping systems (to be converted into LCI data at Step 5) and economic performances. This notably includes: active ingredients of pesticide, fertiliser formulation, date of input application for modelling field emissions by accounting for daily climate parameters, flows of material and energy linked to farm equipment, machinery, and pumping systems. Table 2 gives examples of activity data collected at the crop level in a “standard” ASD versus what is required for an “ASD-based LCI”. With LCA in mind, priority is given to cropping systems expected to have the most environmental impacts (input-intensive or highly represented in the area), as well as to innovative systems. Obtaining the feedback of farmers interviewed is a key objective; therefore, technical and economic results are presented to them in local language: typologies of farming and cropping/livestock systems along with performances in terms of yield and gross product and revenue if possible. It is very worthwhile to discuss yield and economic results with farmers because they pay particular attention to them, and help refine these values during the meeting, which finally improves the robustness of LCI data based on activity data collected during interviews.

Step 4 consists in filling some data gaps. Certain can remain after field enquiries, particularly for crops that were not prioritized (Steps 2 and 3). Some data gaps include: non-availability of farmers, difficulties for them to quantify inputs (e.g., some used food cans to quantify fertilisers), a lack of trust in the interviewer, or exceptionally complex farm management practices. This is the case, for example, when the farm is managed by several members of the family, and part of the farm is run separately, while some activities or infrastructure elements are still shared. Data that are crucial for agricultural LCA are ranked as follows: yield, fertilisers, pesticides, irrigation and machinery (Nemecek et al., 2015). Yield directly influences LCA results, since it is used as a functional unit. Nitrogen-based fertilisers are a key driver of many impacts (Roches et al., 2010). It is essential to fill incomplete and missing data gaps. We have explored different ways to extrapolate data. First, the Unep-Setac group (Hischier et al., 2001) and Björklund (2002) recommend "analogies" or "proxies". This is fully compatible with the ASD framework and its holistic approach, which captures the diversity of farming systems while also making it possible to match different systems that are alike. Second, crop models are very useful. In this study, missing data on yield, total applied nitrogen, and irrigation water were modelled using PILOTE, a one-day time-step crop model (Mailhol et al., 1996) which has been parameterised using the soil and crop features of the case study. The last available information sources are expert knowledge and data from the literature. The methods most likely used to fill missing data gaps, i.e., analogies, crop-models, expert knowledge and literature are summarised in Table 2. Such extrapolated data—whatever the method used — lead to higher epistemic uncertainty than that associated with data collected directly during interviews. Therefore, extrapolated data will be rated lower in terms of quality in the crop dataset (supplementary information, Section S.2.1, Table S2) and in subsequent analysis regarding uncertainty propagation (Section S.2.2).

Collected Activity data	Standard ASD outputs	Additional LCI-specific data collected in ASD-based LCI	Extrapolation method
Fertilisers	Total amount of NPK units, total costs, fertiliser formulation of main ones	Formulation of every fertiliser applied, total doses, application date	CM* (predominant for N fertilisers)- A - E - L
Irrigation	Total cost, amount (m3 used) irrigation (volume per ha)	Type of water resource, Irrigation calendar, energy consumed, pumping system details (description, lifetime, maintenance details, end of life).	CM*- A - E -L
Crop	Species, plant crop density, crop calendar, yield, crop rotation, soil preparation (duration per ha),	Origin of seeds and seedlings	CM -A* - E - L
Pesticides	Total cost, commercial names, number of treatments	Active ingredients, total doses	A* - E - L
Plastic covering, greenhouse	Cost/ha	Characteristics of the greenhouse, lifetime, maintenance (elements and frequency), end of life	A* - E - L
Machinery	Type of machinery required, cost	Lifetime, duration of use/ha/yr per crop, fuel consumption, manufacturing characteristics, maintenance (elements and frequency), end of life	A* - E - L

Climate & soil properties	*Location*	*Soil properties (for modelling field emissions), weather data*	*L* -E*

Table 2. Distinction between activity data provided by a standard ASD and data specifically collected for LCI during the ASD-based LCI. Activity data can be extrapolated by: A (analogy), CM (crop model), E (expert knowledge), or L (literature), * indicates the predominant approach used for extrapolating missing data. In grey boxes, climate and soil properties are not activity data but are additional data needed to compute field emissions

Step 5, and the following steps encompass the Life Cycle Inventory and LCA. In Step 5, the LCI is built at the elementary level of the crop: the activity data related to the crops in each cropping systems are converted into LCI data or “inventory data”. Inventory data are made up of input and output flows of materials and energy involved in each elementary process. For example, "producing 1 kg of pepper" comprises material and energy flows involved in the manufacture and transportation of inputs, e.g., fertilisers and pesticides (specific molecules, active ingredients and amounts are specified), along with the output flows of polluting emissions- notably field emissions - into the air, water and soil compartments of the environment (Figure 2). Data collected at the farm level, such as machinery and water used for irrigation, are disaggregated respectively into the crop and cropping systems to which they contribute, according to the ratio of hours spent on each of them, versus total lifetime. In standard ASD, machinery data are collected to calculate economic depreciation to be deducted from the operator's turnover in order to calculate their income. Conversely, the ASD-based LCI aims to characterise not only the total lifetime of a piece of machinery, but also its quantified use in relation to each crop in order to assign to each crop the share of the environmental impacts it has caused. Lastly, field emissions are assessed based on activity data collected by ASD-based LCI, and complemented with data related to soil / weather. They are computed with dedicated models and emission factors for nitrogen emissions, in accordance with local soil and climate conditions (Brentrup et al., 2000; Bouwman and Boumans, 2002a, 2002b; IPCC, 2006; European Environmental Agency and EMEP/EEA, 2009). Details are given in Supplementary information S.1.1. The EcoInvent 2.2 LCI database was used for background processes.

Steps 6, 7 and 8 consist in aggregating LCIs computed at crop levels. Aggregation is based on typologies of cropping, livestock and farming systems, along with their regional weight. Material / energy flows exchanged within and between farms are taken into account to avoid double counting.

Hence, in Step 6, the LCI of each cropping system (at field level) is modelled by aggregating the crop-level LCIs of each crop grown in the cropping system considered. No flow exchanges were identified at this level. Next, in Step 7, the LCI of each farming system (at farm level) is modelled as an aggregation of the LCI of cropping and livestock systems, minus intra-farm flows to and from crops and livestock (e.g., forage, cereal straw, farmyard manure as shown in Figure 3). Finally, in Step 8, the LCI of the farming region is, in turn, modelled as an aggregation of the LCI of farming systems weighted according to their relative share, minus flows between farms.

The following steps are standard LCA stages that occur after LCI has been completed, i.e., modelling potential environmental impacts through LCIA and interpreting the results of the LCA (Figure 1). To summarize, ASD-based LCI allowed us to construct LCIs of farming activities based on a nested approach, using both top-down and the bottom-up approaches.

2.4 Uncertainty computation

As mentioned in the introduction, uncertainty is a serious issue in LCA, and this is particularly acute when data is scarce. Our proposal was to combine ASD and LCA to reduce uncertainty on LCI data, thanks to two original proposals: stratified sampling and data gap filling. Therefore, LCI data uncertainty must be characterized.

The pedigree matrix approach is a semi-quantitative method proposed by the LCA scientific community to characterise data uncertainty when the probability distribution of data is not available (Weidema and Wesnæs, 1996; Huijbregts, 1998; Frischknecht et al., 2005; Frischknecht et al., 2007). In most unit processes, uncertainty follows a lognormal distribution, and the pedigree matrix expresses how each source of uncertainty contributes to global uncertainty. For each item of data (e.g., NO2 and CO2 emissions, etc.), a "pedigree matrix factor" (PMF) - referring to its level of uncertainty expressed by an uncertainty factor (UF), i.e., the square of a standard geometric deviation - is set based on an "expert" approach. The uncertainty interval around the geometric mean (µg) containing 95% of values is given by: $\{\mu_g / UF_g;\ \mu_g * UF_g\}$ *with* $UF_g = \sigma^2{}_g$. For more details on this method, please consult Supplementary information S.1.2. In the present work, the pedigree matrix approach was used to compare the quality of data according to the data collection method used. We choose to compare statistic data obtained from public regional agricultural census (Centre Régional de Développement Agricole, 2010a, 2010b) with ASD-based LCI data either before or after extrapolation to fill missing data gaps (Table 1, Step 4). In the present study, uncertainty was computed for each crop within a cropping system, and assessed regarding the quality of its "crop dataset", i.e., the set of activity data related to the whole crop cycle until harvest, as in Röös et al. (2010). The global uncertainty factor (i.e., of the cropping system) is then computed as the linear combination of the squares of the geometric standard deviations of each crop included, weighted according to their share.

2.5. The case study: the irrigated plain of Kairouan, Tunisia

The study was conducted in the semi-arid to arid irrigated plain of Kairouan (180 to 420 mm annual rainfall) in central Tunisia. The plain of Kairouan covers 30,000 ha, of which 12,700 ha are irrigated. This is mostly conducted through private and partly unregulated groundwater pumping from the calcareous aquifer. Input-intensive and profitable vegetables / fruit orchards have supplanted the former model of agro-pastoralism which is currently the default choice for farmers who lack access to groundwater. In 2004, Leduc et al. reported an annual drawdown rate of the water table at between 0.25 and 1 m. During field interviews, farmers reported that the rising number of deep boreholes had increased the annual water table drawdown rate by up to 1.5m per year. Four distinct types of water pumping systems are used, whose performances sand environmental impacts were assessed with LCA by Pradeleix et al. (2014).

In this large area, a pilot area covering 6000 ha was selected as it is very input-intensive to model the environmental impacts of the "worst case" farming scenario with LCA. This area includes the highest concentration of well-resourced farms characterized by deep boreholes, and the production of profitable, but water-intensive crops, like high-density Spanish-variety olive groves, and fruit orchards. Conversely, traditional family farmers are equipped with surface wells and diesel- or electricity-fuelled pumps and need to periodically deepen their wells to reach the ever decreasing water table level. They usually practice intercropping to increase water productivity and have up to 3 crop cycles per year, which renders their production strategy diverse and complex. Farmers owning costly diesel-fuelled surface pumps suffer from water limitations and consequently leave up to 25% of their cropping area fallow.

The spatial distribution of crops is uneven and depends on the soil texture. "Sandy soils", despite their poor water storage capacity, are favoured for fruit orchard implantation by well-resourced farms. These soils are composed of a 30 cm thick layer of alluvial sand covering loamy textured soil. Conversely, "loamy soils" provide less favourable conditions for fruit orchard implantation and root development; they usually support vegetables, cereals and olive groves. Maintaining soil fertility for crops requires farmers to resort to chemical fertilisers and large amounts of farmyard manure: up to 10 tons per ha in fruit orchards. It should be highlighted that more than 99% of the manure applied originates from the surrounding hilly areas where agro-pastoralism prevails. Manual labour is far more commonplace than the intensive use of farm machinery, and there are frequent labour shortages on corporate farms and family business farms during harvesting periods.

2.6 The ASD-based LCI applied to the Kairouan plain: modelling choices

By using ASD to model LCIs, it was possible to collect relevant data in a relatively short period of time, despite the diversity and complexity of farming systems. All the fieldwork, including field interviews, was accomplished in ten weeks by two people spending about 6 hours in total per farm, during 1 or more visits (3 maximum) . Using stratified sampling, thirty farms were chosen for the survey, and twenty-four farms were selected for in-depth interviews. Particular attention was paid to the amount of water applied and consumed (via evapotranspiration) to model the potential environmental impacts of water deprivation in LCA. Water pumping impacts were also under scrutiny; since Pradeleix et al. (2014) showed that the energy used and toxicity produced vary widely depending on pumping system efficiency and energy type. The ratio between useful energy and total energy consumed ranges from 8% in diesel-powered surface pumps to 50% in electricity-powered submersible pumps. ASD results were presented in Arabic to farmers interviewed to reduce data uncertainty.

Functional units were both area and product-based. The area-based unit encompasses the area cropped by each farming system for either owned or rented land and also includes grazed rangeland used for lamb production. The second functional unit is the gross value obtained when selling products on the local market in 2012 (in Tunisian currency, the Tunisian Dinar "TD").

The allocation of impacts of multiple-outputs systems, such as cereals, was based on economic indicators, i.e., weighted by farm gate prices (Suh and Huppes, 2005; AFNOR, 2006a, 2006b).

Supplementary information on this process can be found in S.1.1 and S.1.4.

3. Results of the methodology applied to a case study

3.1 ASD outcomes: Typology of farming systems and cropping systems

Before the advent of irrigation in the 80s, which was initially destined for collective farms, and later for individual ones, rainfed olive groves and cereals with sheep rearing dominated. Irrigation allowed farmers to first develop vegetable production and, since the early 2000s, fruit orchards. Table 3 displays the farming system typology (FS1 to FS9). Nowadays once water access is sufficient - be it purchased from other farms (e.g. FS5) or not - almost every plot in the plain is irrigated. Water is the primary limiting factor and determines the cropping plan.

Modern farms (FS1 to FS4) pump groundwater from deep boreholes to irrigate high-density olive groves (Spanish high-yield varieties) and fruit orchards, which are the most economically profitable cropping system per ha. Traditional farms (FS6 to FS9) grow a wide diversity of crops and generally practice intercropping to save water. Crops are mostly local varieties of olives in groves along with vegetables and cereals to feed sheep. Within family-based FS, only FS6 can afford to invest in fruit orchards. FS6 and FS7 pump water from open wells. FS8 has a tiny plot of olive trees, whereas FS9 is landless; it exclusively relies on rangeland to feed its own sheep, and the farmer here also works as a shepherd for other FS. The resources and strategy of each farm depend on its status, whether it belongs to investors (FS1 to FS3) seeking to maximize the profit in the short-term or to family farmers (FS4 to FS9) concerned with mid- to long-term stable production and relying mostly on a family workforce. The family business FS5 is somewhat unique: it is run by inhabitants from other regions (within a 100km distance) who rent out all their cultivated land for short periods.

Average farm size varies considerably, ranging from 33 ha for FS1 down to 0.8 ha for FS8. FS1 and FS2 cultivate the biggest areas. Only FS7 adopts fallowing practices for 25% of its land due to a lack of water and either uses it for its own grazing needs, or rents it out to FS5. On these areas, FS5 applies the most input-intensive monocropping system of the whole plain (melons or watermelons) over two consecutive years maximum. Afterwards, the land is left uncropped for 6 years to restore soil fertility and eliminate pests and diseases before going back to another 2-year production period.

In our case study, sheep-rearing livestock systems rely on various feedstuffs among which rangeland for grazing, given farmers dedicated arable land to agricultural commodities for sale. Livestock in FS6 and FS7 is mostly fed with feed produced on the farm (cereals, alfalfa, crop residues), unlike FS8 and FS9 which are almost entirely - if not exclusively (FS9) - reliant on rangeland grazing. The grazing area of rangeland was estimated during on-site visits and reflects an average value of areas grazed all year round. It is included in the functional unit named "area used". Consequently, the amount of "area-based" functional units delivered is much higher for farming systems that include sheep rearing (FS6 to FS9), especially FS8 and FS9, than for crop-oriented farming systems (FS1 to FS5).

The traditional "mixed family farming system" (FS6) represents 44% of the farming region area and is responsible for 45% of agricultural gross product. Only 11% gross product originate from corporate agriculture (FS1 to FS3), which occupies 9% of the area, and 1% from the water-restricted farms FS8 and FS9, which are the least profitable per ha used, including rangeland.

	Corporate Agriculture			Family Business		Family Farming			Landless	
Farming system (FS)	FS1	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	
Main products	Fruit-Olives	Olives-Fruit	Olives-Fruit-Vegetables	Fruit > Olives	Vegetables	Mixed Farming System & Fruit Orchards	Mixed Farming System	Olive groves & Sheep	Sheep	
% of total farms	0.1 %	2.4 %	2.4 %	13.7 %	9.8 %	34.1 %	26.8 %	4.9 %	5.8 %	100 %
Cropped area per farm (ha)	33	15	8	8	1.4	8	4.5	0.8	0	
Rented area per FS (ha)	0	0	0	0	1.4	8	-1.5	0.8	0.2	
Rangeland area per farm (ha)	NA	NA	NA	NA	NA	1.1	3	13.5	13.5	
Gross Product (TD) per ha of area used**	11 173	7 673	9 768	9 180	15 967	6 933	3 375	408	312	
% of regional area used* except rangeland	0.5 %	5.9 %	3.1 %	17.6 %	2.2 %	44.0 %	25.9 %	0.6 %	0.1 %	100 %
% regional Gross Product (TD)	0.8 %	5.9 %	4.0 %	21.2 %	4.6 %	45.2 %	17.2 %	0.6 %	0.5 %	100 %
Water consumed per ha of area used* (m3)	4 908	6 463	4 286	4 806	11 063	4 992	2 477	335	256	

Table 3. Typology of farming systems (FS) and their main products, area used, and gross product generated, the two latter being functional units. Gross product is given in Tunisian Dinar. Rented area*: FS5 rents out 1.4ha from FS6 which rents in average 1.5ha to FS5 given the weight of each at regional level and their cropping plan. Area used refers to "owned area + rented area + rangeland".**

Table 4 details the typology of the most common cropping system categories, out of the 27 identified during field visits in the 9 farming systems. For example, the FS2 cropping plan is composed of five cropping systems: 15% of intermediate-density olive groves; 35% of high-density olive groves 20% of citrus of which 5% are young plants intercropped with pepper, and 30% of orchards intercropping olive trees and citrus. Even if cropping systems use the same crop rotation, they can differ from one another regarding crop variety, tree density or amount of agricultural inputs (fertilisers and pesticides). Tree density ranges from high (550 trees.ha^{-1}) to intermediate (280 trees.ha^{-1}) and low density (100 trees.ha^{-1}), the latter being mostly grown in traditional family farming systems, i.e., FS6, FS7 and FS8.

		Corporate Agriculture	Corporate Agriculture	Corporate Agriculture	Family Business	Family Business	Family Farming	Family Farming	Family Farming	Landless
	Farming System (FS)	**FS1**	**FS2**	**FS3**	**FS4**	**FS5**	**FS6**	**FS7**	**FS8**	**FS9**
	Access to water	Good	Good	Good	Good	Good	Medium	Poor	No access	No access
Land occupation	**Crop characteristics**									
Olive Groves	Intermediate density High density	35 %	15% 35%	35%						
	Low density			15 %	25%		15 %	18 %	100 %	
Citrus	Sole crop Intercropping	20%	15 % 5%	7 % 3%	8 % 3%					
Apple or Peach or Apricot	Sole crop Intercropping	45 %		20 %	51 % 3%		16 % 3%			
Intercropping Olives and Citrus	Sole crop Intercropping (with pepper)		30 %	10%	10 %		10% 5%			
Intercropping Olive-Vegetables	Input-Extensive			10 %				10 %		
	Input-Intensive						10 %	7 %		
Intercropping Vegetables	Input-Intensive					70 %				
Intercropping Olive-Vegetables-Cereals	Water-Intensive						10 %			
	Input-Intensive							10 %		
Rotation Vegetables/ Vegetables	Input-Intensive					30%		5%		
Rotation Cereals/ Vegetables	Input- Intensive							8 %		
	Input-Extensive Sole crop Intercropping						15 % 10%	2 %		
Rotations Cereals/Pulse							6 %	18 %		
Fallow								25 %		
Livestock activities										
Number of breeding ewes							7	20	15	15

Table 4. Typology of cropping systems comprising each farming system. Percentages illustrate the weight of each cropping system regarding the cropping plan. Intensity levels includes planting density, pure cropping versus intercropping, and levels of water use intensity or of other agricultural inputs (fertilisers and/or pesticides). For clarity sake, this table only reports on the most common cropping systems out of the 27 categories recorded for the area under study.

Input levels can vary widely for the same crop rotation as shown in Table 5 which compares the activity data of two different cropping systems of the category "intercropping olives-vegetables-cereals". In FS6, yield obtained is around 40% higher than in FS7. FS6 applies less pesticide and around 25% less N fertiliser, but uses 25% more water (see details in the supplementary information, Table S.3).

	Total N (kg/ha)	Pesticides: N° of treatments/N° of products	Irrigation water (m3/ha)	Planting density (plants/ha)	Yield (kg/ha)
FS6	200	9/4	3 870	5 000	19 000
FS7	270	10/6	3 050	5 500	13 300

Table 5. Comparison of activity data characterizing the melon cultivation in "intercropping olives-vegetables-cereals", in FS6 and FS7.

In most farming systems, the number of cropping systems is generally high: it reaches 12 in FS6, the most common farming system. Moreover, cropping systems are also complex: around 70 CS are reported and detailed (Table S2), for three main reasons (i) the same crop rotation in two different FS may give rise to 2 different CS due to differences in input use (see Table 5), (ii) up to three crops per year may be grown on the same plot, and (iii) intercropping is common. Each cropping system consists of several crops cultivated in a crop rotation system; for example,"intercropping olives-vegetables-cereals". CS comprises the rotation of olive, melon, watermelon, pepper, wheat and barley (see supplementary information on Table S2). Usually, young fruit-tree orchards are intercropped with vegetables (mostly pepper), until they become productive in order to maximise water and land productivity.

A final layer of complexity to be accounted for in LCI and LCA are flows exchanged between or within farms, and also through the farming region boundaries (Figure 3). FS1 to FS6 buy farmyard manure from outside the farming region while FS7 to FS9 sell it locally; more than

99% of manure is imported from outside the farming region. Farming systems FS5, FS8 and FS9 have poor access to water and buy it from others. In addition, FS5 rents land from FS7. FS8 and FS9 buy straw and the access to crop residue for grazing from FS6 whose feed production exceeds its own needs.

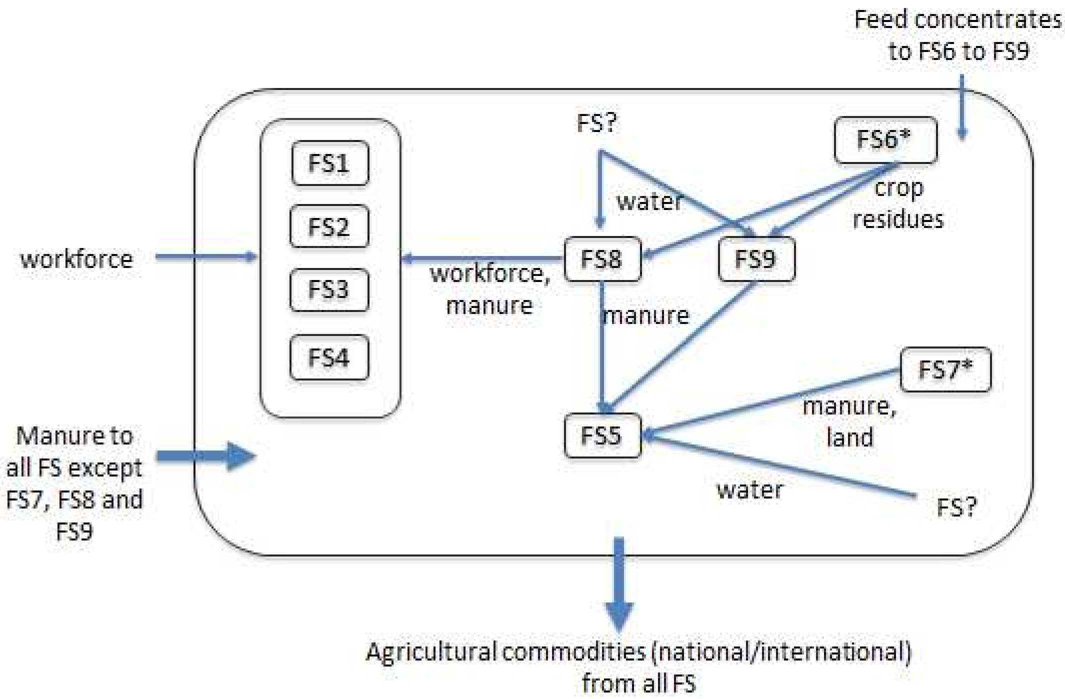

Figure 3. Flows exchanged through the farming region boundaries as well as within and between farming systems (*means internal exchanges of manure and straw); large width of arrows indicates large flows

The farming region is significantly deficient in manure required to maintain soil fertility and productive capacity of this highly exploited area. In addition, corporate farming systems suffer from labour shortages and often hire labour from outside the farming region. On the other hand, intense exchanges of by-products (cereal straw) and wastes (cereal stubbles and fava bean residues) take place in family farming, which is characterised by the highest diversity of cropping systems (olive groves, fruit orchards, vegetables and cereals, along with sheep rearing).

3.2 Data uncertainty with ASD-based LCI

When ASD is completed (Step 3), we have 70 datasets describing the activity data (and additional data) for the 70 different cropping systems. Each dataset is given a mark (from excellent to poor) according to its completeness. When more than two-thirds of the dataset is completed with activity data, the dataset is scored “excellent”. When between 1/3 and 2/3 data activities are known, the dataset is given an “intermediate" score. When less than one third of the data activity is collected, the dataset is scored “poor”. There are 19 “excellent”, 49 “intermediate” and 2 “poor” scores; for details, see supplementary information S.2.1. Intermediate- and poor-quality datasets are then extrapolated to fill the data gaps.

Table 6 shows the pedigree matrix approach, with crop datasets obtained using different data collection methods. For the sake of clarity, the single livestock system existing among all farming systems was not used for the uncertainty analysis. For each of the 6 categories encompassed by the pedigree approach, which can contribute to data quality, a score, named the “pedigree matrix factor” (PMF) is estimated by experts based on data quality. The better the data quality level, the lower the PMF score with 1 set as the lowest limit (smallest uncertainty level). The first column (0) shows ideal data and therefore receives a PMF score of 1. The second column (1) represents the PMF of the statistical data (FADN type). Columns 2 to 4 concern data collected with ASD-based LCI before extrapolation, and give PMF for “poor”, “intermediate” and “excellent” datasets respectively. Columns 5 and 6 show improvements by extrapolation of datasets previously classified as “intermediate” and “poor”. In relation to the PMF mark assigned to each type of dataset, the pedigree matrix also provides the corresponding “uncertainty factor” (Ui), which are to be combined to compute the global uncertainty factor as the square geometric standard deviation (Frischknecht et al., 2007). Details on how the PMF scores were assigned to each data quality level for each of the three data collection methods can be found in Supplementary information S.2.2.

The uncertainty factor (UF) for all the crop datasets (i.e. of the aggregation of the 70 datasets) was obtained by a linear combination of uncertainty factors obtained for each of the three quality levels in the dataset, weighted according to their share of the total: 19/70, 49/70 and 2/70 respectively, for good, intermediate and poor quality datasets.

In the ideal case, in which all PMF are optimal, the minimum UF is 1.03. The UF obtained for datasets modelled using statistics is the worst, i.e., 1.37. It is 1.20 and 1.12 for data obtained with ASD-based LCI before and after extrapolation, respectively. As the uncertainty interval around the geometric mean (µg) containing 95% of values is given by: $\{\mu_g / UF_g; \mu_g * UF_g\}$ *with* $UF_g = \sigma^2{}_g$, this means that – with regard to statistics data - the uncertainty interval obtained with ASD-based LCI (by stratified sampling) is divided approximately by two and by four before and after extrapolation, respectively,

In conclusion, the application of ASD-based LCI leads to a significant reduction in LCI data uncertainty, despite the very conservative and stringent assumptions made when assigning pedigree scores.

Data origin	**Ideal case**		**Statistical approach**		**ASD-based LCI**						**ASD-based LCI & Extrapolation**			
	0.		1.		2. Good		3. Intermediate		4. Poor		5. Intermediate		6. Poor	
Pedigree Matrix Factor and Uncertainty fac-tor (resp PMF and Ui)	PMF	Ui	PMF	Ui	PMF	Ui	PMF	Ui	PMF	Ui	PMF	Ui	PMF	Ui
Categories:														
Reliability	1	1	4	1.2	1	1	3	1.1	4	1.2	2	1.05	3	1.1
Completeness	1	1	3	1.05	2	1.02	2	1.02	4	1.1	2	1.02	2	1.02
Temporal correlation	1	1	3	1.1	1	1	1	1	1	1	1	1	2	1.03
Spatial correlation	1	1	2	1.01	1	1	1	1	1	1	1	1	1	1
Technological	1	1	5	2	1	1	3	1.2	3	1.2	1	1	3	1.2

correlation														
Sample size	1	1	2	1.02	4	1.1	4	1.1	4	1.1	4	1.1	4	1.1
Basic uncertainty		1.07		1.07		1.07		1.07		1.07		1.07		1.07
UF_g ($\sigma^2{}_g$)	1.03		1.37		1.20						1.12			
UF increase vs Ideal case	0%		33%		17%						9%			
% reduction in UF/ statistical approach	NA		0%		50%						74%			

Table 6. Application of the pedigree matrix approach to compute the uncertainty factor in crop datasets (activity data) depending on 3 sources of data: statistics (Column 1), ASD-based LCI before the data gaps are filled (Columns 2-3-4), and after filling the data gaps, (Columns 5-6). For each source of data, the pedigree matrix factor (PMF) ranges from 1 (best score) to 5 (worst score). The first column (0) shows ideal data, and therefore receives a PMF score of 1. Each PMF generates a corresponding uncertainty factor (Ui) (Frischknecht et al., 2007). In comparison with data obtained with statistics, data uncertainty is reduced by up to 74% for data obtained through ASD-based LCI and extrapolation to fill data gaps.

In addition to the pedigree matrix demonstration, simulated data have been used to show the effect of stratified sampling by comparing the variances obtained after random or stratified sampling (for details, see supplementary information section S1.3).

4. Discussion

The overall goal of applying LCA at the regional scale can be closely associated to our primary objective: to propose a method to build reliable Life Cycle Inventories in a context of data scarcity and farm diversity. To our knowledge, although many LCA studies have been carried out to assess the environmental performances of agricultural systems (Avraamides and Fatta, 2008; Basset-Mens et al., 2010, Borghino et al 2021, Notarnicola et al 2017), the question of how to practically reduce uncertainty has yet to be properly addressed, especially in contexts of very scarce data like in the case of our Tunisian study. We have designed “ASD-based LCI” to collect LCI-specific data in a context of scarce data, and to model representative farming and cropping/livestock systems, despite their diversity and complexity (e.g., intercropping, multiple output crops, etc) in a multilevel approach from the plot up to the farming region (Tables 3 and 4).

4.1 How ASD helped us to address the lack of LCI-relevant data

The first challenge was data scarcity. The issue was not only to find data related to farming systems, but also to collect data related to farming systems that could be relevant for LCA impact modelling, i.e., related to environmental impacts. Unfortunately, essential information for environmental impact modelling is often lacking in both statistics and farm accountability data. For instance, aggregated economic data are useless when computing nitrogen emissions, which are a major contributor to the environmental impact of agricultural production, i.e., the third-largest threat to our planet, after biodiversity loss and climate change (Rockström et al., 2009). Active ingredients in pesticides and other toxic chemicals are also overlooked.

Describing cropping systems at a large scale is problematic. In their review of the methods used at the regional scale to support public decision-making, Leenhardt et al. (2010) found that information collected using remote sensing (e.g., crop, plot size, density) was insufficient to describe cropping systems, and that dedicated expertise and detailed field enquiries were required to provide consistent data, particularly on the chemical properties of fertilisers and pesticides used and the quantities applied. Crop rotations and intercropping cannot be adequately described with remote sensing systems, although they are key components of farming systems, and together represent a major lever that could be used to achieve sustainable agriculture (Kassam et al., 2009; Guillou et al., 2013).

The ASD method allowed us to capture data which are crucial to LCI. Activity data related to each crop include crop management practices and were collected during field visits and interviews with different local stakeholders, mostly farmers. The survey grid is usually built ad hoc in the ASD (Jouve, 1986); this means that it can be specifically designed for the purposes of a LCA. For example, "ASD-based LCI" focuses on the chemical properties of every fertilizer and pesticide, which are major contributors to field emissions in agricultural systems (Avraamides and Fatta, 2008), beyond the standard technical and economic data (e.g., total units of NPK, input costs) usually collected in ASD (Trebuil and Dufumier, 1993; Devienne and Wybrecht, 2002; Tittonell et al., 2010).

Obviously, the typology may be easier to build, and the surveys shorter in regions where farming systems are more specialised (Dalgaard et al., 2006). It is important to mention here that the quality of data collected in interviews depends on the degree of trust the farmers have in the interviewer, which invariably increases with the frequency of contacts. Most farmers are reluctant to provide information on their economic performances. This field observation underlines the uncertainty of farm typologies built only upon questionnaires and sometimes without any field visit.

4.2 How ASD helped us to tackle the issue of diversity of farming systems at the regional scale to reduce uncertainties due to modelling errors

The second challenge was to capture the diversity and complexity of farming systems present in the region, and to mitigate the errors that a bad representation of farms in data collection can produce. This challenge was addressed by characterizing FS through typologies, built using ASD, at the field/herd and farm levels. Several authors failed to build farm typologies based upon statistical or accountability data because such data showed greater variability within each farm type than between farm types (Dalgaard et al., 2006; Samson et al., 2012; Avadí et al., 2017). Conversely, ASD typology is concerned not only with structure, but with farm functioning. Differences in management and functioning (e.g., strategic choices regarding animal feeding strategies, fertiliser type) were not reflected in the FADN accountancy data, but were significant enough to be used by ASD to identify different farm types (Dalgaard et al., 2006; Samson et al., 2012; Avadí et al., 2017). Indeed, ASD goes far beyond simply listing farm resource facilities and purchased inputs/ sold outputs, as with statistics that aggregate farm-level data. It also accounts for the farm strategy and its functioning (Tittonell et al., 2010). In our work, this helped us to better identify the different types of farming systems in the pre-typology (Step 1, Table 1). Whereas FS6 and FS7 initially belonged to the same farming system in (Step 1), it became obvious that they were distinct when analysing the cropping systems (Step 3). When ASD is employed to build LCI, other factors must be taken into account in the typology, i.e., factors that can modify field emissions. Consequently, although some FS may have similar farm structures (area cultivated, family workforce, pumping systems, etc.) and grow similar crops, they may be very different regarding their impacts. For instance, melons were grown in Olive-Vegetable-Cereal rotation in FS6 and FS7, but with less water in FS7 due to a lack of water availability. Furthermore, soil texture influences water consumption and field emissions of any cropping system (e.g., Extensive Olive-Vegetable CS is cultivated either on sandy soil in FS3 or loamy soil in FS7). Lastly, considering the same cropping system, LCI will differ depending on the machinery and pumping systems used. CS Apple orchards have different impacts in FS1 and FS6 because water is pumped with submersible pumps, or from open wells with surface pumps, respectively (Pradeleix et al., 2014).

4.3 How uncertainty could be improved by stratified sampling and extrapolation

The final uncertainty of results was reduced thanks to two strategies. The first one was to carry out a stratified sampling of farms, instead of a random sampling. The stratified sample of farms—representative of the farming region— is the output of the first step of ASD, which aims at capturing the main archetypes of regional farming activities by analysing major drivers of their diversity.

Using the pedigree matrix approach, we showed that stratified sampling reduced the uncertainty factor with regards to random sampling. In the pedigree matrix, the relative UF is respectively 1,03 for the smallest possible value (ideal case), 1,37 for the random sampling (+33%) and 1,20 for the stratified sampling (+17%). This means that the increase in uncertainty -with regards to the ideal case- could be halved when stratified sampling is used instead of random sampling. The positive effect of stratified sampling has been demonstrated mathematically on a theoretical numerical example in the supplementary data. This result concurs with those of Jayaraman (1999) and The Pennsylvania State University (2018): the variance computed in stratified sampling only accounts for the variability within each group, but not for the one between groups. Indeed, the level of optimisation depends on the ratio of "inter-group" variance to total variance.

Extrapolation allowed us to go even further: the "ASD-based LCI" UF, when supplemented with an extrapolation step, dropped to 1.12. This means that the uncertainty increase -with regards to the ideal case- could be divided by 4 when both stratified sampling and extrapolation are used instead of random sampling.

Lastly, farm stratification produced by ASD played a key role in characterising the diversity, and therefore in reducing the uncertainty of LCI data computed for the region. In fact, the accuracy performance of LCI outputs would improve in step with a rise in the number of types of farming systems identified in the farm population. However, to characterize additional farming system types a greater number of interviews would be required. Therefore, a balance must be found due to the extra time and effort required for the additional interviews (Jayaraman, 1999). Furthermore, the uncertainty related to the number of farms in each farming system affects the uncertainty of the LCI of the whole farming region. In line with the ASD, we suggest conducting a large and rapid survey based on a questionnaire to classify every farm of the farming region within the farm typology, according to a short list of qualitative and quantitative criteria (Ferraton and Touzard, 2009).

4.4. How ASD offers additional benefits regarding circular economy in agriculture

The "ASD-based LCI" has other advantages. Small-scale and diversified farming systems, in line with agro-ecological practices rely on diversity and "loop closing" based on complementary activities at the farm and regional levels (Larrère, 2006; Guillou et al., 2013), and even beyond the agricultural sector (Fernandez-Mena et al., 2016; Maina et al., 2017; Fabien et al., 2018). Such flow exchanges are illustrated by our case study, and especially by FS6 and FS7 (see Figure 3), which implement intercropping. Owing to limited resources, these farming systems tend to optimize their use and foster internal material recycling (Efole Ewoukem et al., 2012) in addition to exchanging flows with their neighbours. Such flows are often overlooked by accountability networks, despite being of great interest with regards to resource recycling. Moreover, data related to by-products or near-to zero values are often overlooked in statistics (Lindeijer and Weidema, 2000), but such material flows are at the heart of the circular economy (Toop et al, 2017).

5. Conclusion

Our main objective was to build a robust method to carry out regional LCA of farming activities, despite the high diversity of farming systems and data scarcity, two factors which increase the uncertainty of input data (and therefore outputs) in LCA. To overcome this dual challenge, which is of critical importance at the regional scale, we propose an innovative method, which combines ASD and LCA to conduct the first and most difficult step, of LCA:

Life Cycle Inventory. This method, which we have named "ASD-based LCI" was applied to a 6000 ha pilot area, characterized by intensive irrigated farming in the Kairouan plain, Tunisia, to build a Life Cycle Inventory that reflected the diversity of farming activities at the regional scale. ASD was used to characterize the farming systems and their inner functioning, a necessary step before a stratified sampling of farms that were chosen for each archetype to conduct data collection on farm activities. The "activity data" collected suffer from incompleteness, which led us to propose an innovative step, named "data extrapolation" to fill gaps, based on 4 processes, e.g., analogies, crop modelling, expert knowledge and literature findings.

First, this study allowed us to characterize, in detail, the farming systems of the Kairouan irrigated plain. Nine typical farming systems archetypes were identified which are related to (i) corporate agriculture (all with good access to water but differing in their production), (ii) family farming (differentiated according to water access and their production) and (iii) landless farmers (livestock breeders). The categories above accounted for three, five and one farming system archetypes, respectively. Activity data of seventy cropping and livestock systems encountered in these nine farming systems were collected through interviews and completed with the extrapolation process.

Second, the new ASD-based LCI methodology was assessed with regards to our objective of uncertainty reduction on LCA input data. The pedigree matrix approach was used in LCA to compare uncertainty of input data obtained using 3 data collection protocols, i.e., i.) the full ASD-based LCI methodology (including stratified sampling and extrapolation), ii.) partial ASD-based methodology (including stratified sampling but without extrapolation) and iii.) classical statistics-based input data. This work showed that stratified sampling played a key role in reducing LCI data uncertainty: uncertainty (when compared to the ideal case) was halved when switching from the statistics-based LCI to the ASD-based LCI using stratified sampling (and no extrapolation). When the full ASD-based LCI methodology was applied (i.e., with stratified sampling and extrapolation), uncertainty (when compared to the ideal case) was reduced by a factor of 4 when switching from data extracted from statistics to those obtained by extrapolated ASD-based LCI.

Finally, the strength of this new methodology that couples ASD and LCA is that smart and efficient data collection is carried out: ASD helps us to carry out the stratified sampling and therefore to concentrate efforts on the most typical farms, and on data relevant for LCA (e.g., those that can have big environmental footprints such as the active ingredients used in pesticides, etc.) are well taken into account. ASD also improves farmer involvement in the comprehensive interviews, upon which our methodology is built, and thereby increases LCI data quality.

Lastly, ASD was used to quantify material and energy flows, including by-products and wastes, exchanged over farming region boundaries, but also between or within farming systems. This knowledge is crucial for agroecology and the circular economy, but difficult and even impossible to obtain from standard databases.

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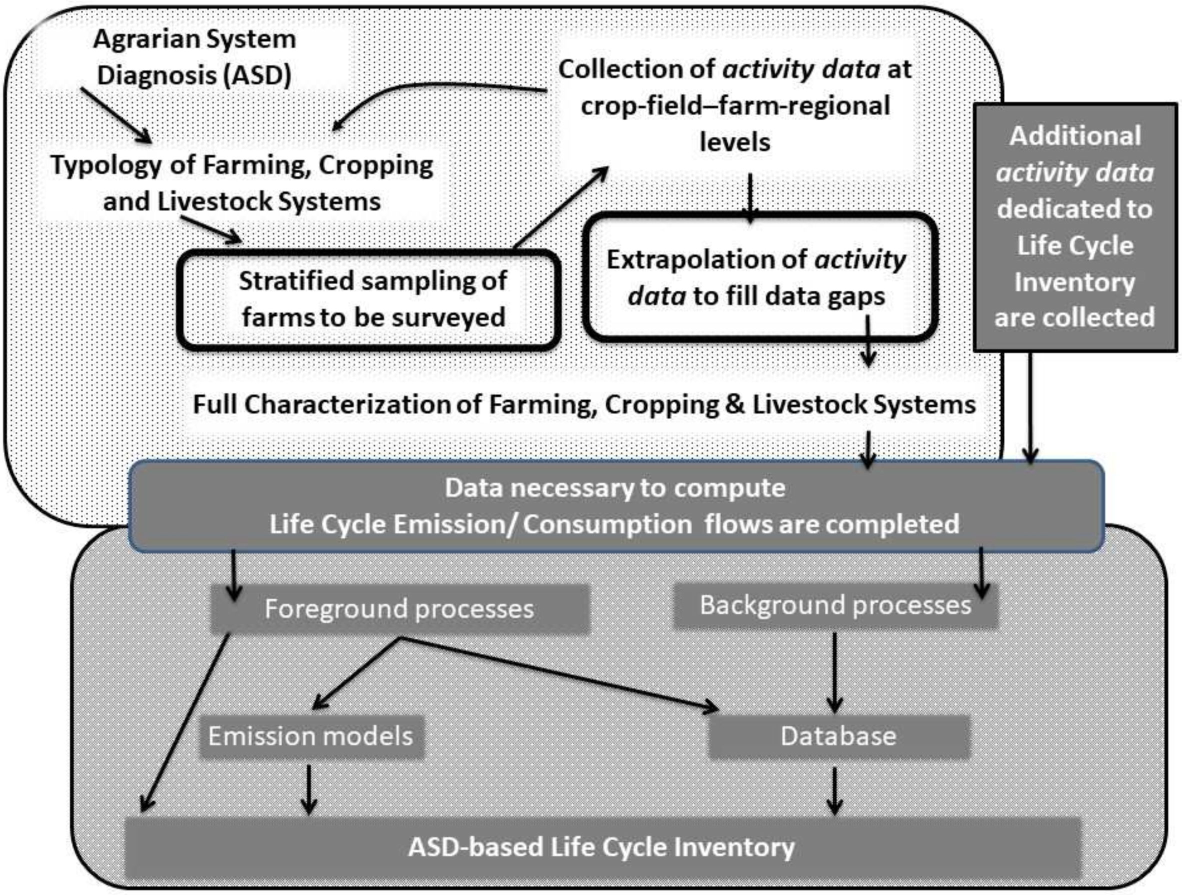
Graphical abstract

Multilevel environmental assessment of regional farming activities with Life Cycle Assessment and Agrarian System Diagnosis: Part I - Tackling data scarcity and farm diversity with ASD-based LCI



Coupling Agrarian System Diagnosis (ASD) with LifeCycle Assessment to improve and facilitate LifeCycle Inventory.The light-grey box/ white labels corresponds to the ASD steps. The dark-grey box / grey labels corresponds to emission/ consumption computed for the Life Cycle Inventory. The two black thick-edged boxes outline the innovative steps proposed to reduce uncertainty of LifeCycle Assessment outputs.