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

4

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6

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13

14 **Abstract**

15

16 **Keywords**

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

19

20

21 **1. Introduction**

22 The environmental impacts of agriculture are of tremendous and growing concern for  
23 decision makers involved in regional land planning, as well as for agricultural policy makers  
24 (Ripple et al., 2018). Policies aimed at achieving sustainable agriculture must be developed  
25 at the regional level, and adapted to local opportunities and constraints (Caron, 2005; Cairol  
26 et al., 2009; Benoît et al., 2012). Sustainable agriculture must both maximise productivity on

1

27 existing farmland — to meet increasing global food, fuel and fibre demand — and  
28 significantly decrease its negative impacts on the environment, e.g., on climate change and  
29 biodiversity loss (Cassman and Grassini, 2020). Decision-makers need tools, methods and  
30 criteria to assess the sustainability of farming systems, despite the difficulties posed by such  
31 a challenge due to their diversity, dynamics (Quintero-Angel and González-Acevedo, 2018),  
32 and the range of environmental impacts to be assessed. The latter should be broad enough  
33 to ensure that none are overlooked and that trade-offs are recognized (Kanter et al., 2018).

34 Life-Cycle Assessment (LCA) was designed in the early 70s to measure the “environmental  
35 cost” of products by quantifying their potential impacts on a large range of environmental  
36 impact categories. LCA was originally dedicated to products and supply chains, and has  
37 become a central plank of the European Union’s Environmental Footprint Policy (European  
38 Commission, 2012). Some authors also recommend its use for public decision-making  
39 applied to land management, e.g., for the environmental assessment of small regions  
40 (Loiseau et al., 2012) or for agricultural land planning (Payraudeau and van der Werf, 2005;  
41 Aubin, et al., 2011; Huang et al., 2014). Notwithstanding its advantages, applying LCA to  
42 farming activities at the regional level – instead of the crop or farm level- poses two main  
43 methodological challenges that need to be addressed, i.e., the huge variability of farming  
44 systems to be characterised and, on the other hand, data scarcity (Guinée et al., 2011; Avadí  
45 et al., 2016). This can lead to supplying LCA with doubtful input data, which is very  
46 detrimental to LCA outputs, as it increases their epistemic uncertainty (Nemecek et al., 2010;  
47 Chen and Corson, 2014; Teixeira, 2014). Input data uncertainties are related to several  
48 factors, e.g., non-representativeness, insufficiency, or the complete absence of data  
49 (Huijbregts, 1998). Indeed, accessing relevant data on agricultural activities at regional scales  
50 has been a focal point of attention for LCA scientists for more than 20 years. As pointed out  
51 by several LCA scientists (Dalgaard et al., 2004; Nemecek and Erzinger, 2005; Reap et al.,

52 2008; Renaud-Gentié et al., 2014) agricultural LCAs were often conducted with data that  
53 were not representative of the system under study. Data were generally taken from  
54 statistical sources like Avadi et al, (2017), including the accountability-derived data from the  
55 Farm Accountancy Data Network (FADN), (Jan et al., 2012, Dolman et al., 2014) and  
56 agricultural census (Mishima et al., 2005) and therefore deemed “average” management  
57 practices. Other authors used technical guidelines (Basset-Mens et al., 2010; Nemecek, et al.,  
58 2011b) or pilot farms (Nemecek and Erzinger, 2005). The problem with data generated by  
59 FADN is that the European Commission intended it to be used to assess the impacts of the  
60 Common Agricultural Policy and the income of average agricultural holdings, and not for  
61 environmental purposes. It is limited to data on farm structure. Inputs and agricultural  
62 machinery are aggregated at the farm level and quantified on an economic basis (EEA,  
63 2005). Such economic data are prone to fluctuate with market prices (Jan et al., 2012), and  
64 aggregation makes it impossible to identify the origin of environmental hotspots (EEA, 2005;  
65 Moreau et al., 2012), or assess their recycling potential (Efole Ewoukem et al., 2012). The  
66 high level of uncertainty associated with this statistical data, which stems from missing or  
67 inaccurate data, is also criticised (Dalgaard et al., 2006; Samson et al., 2012; Avadí et al.,  
68 2017). Therefore, the European Environmental Agency discourages the use of EU FADN to  
69 derive agro-environmental indicators (European Environmental Agency, 2005). Moreover,  
70 there is huge heterogeneity in the availability and precision of statistics-based data among  
71 countries. Only when primary data is not available (i.e., original data from scientific research,  
72 surveys, case studies, or monitoring with a low level of aggregation) does the World Food  
73 LCA database provide statistics-based data, i.e., aggregated generic data (Nemecek et al.,  
74 2015).

75

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

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

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

98 To go a step further, our aim is to build an innovative method based on ASD to secure data  
99 collection for Life-Cycle Inventory (LCI) at a regional scale, despite data scarcity, in highly  
100 diverse agrarian systems. ASD will be used to describe the farm typology in the area, and

101 account for the diversity of farming and cropping systems. The innovation in this method is  
102 linked to the targeted reduction in epistemic uncertainty: firstly by applying a stratified  
103 sampling to this farm typology, to target data collection on farms representative of the  
104 types, and secondly, by carefully collecting and curating data essential to LCI.

105

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

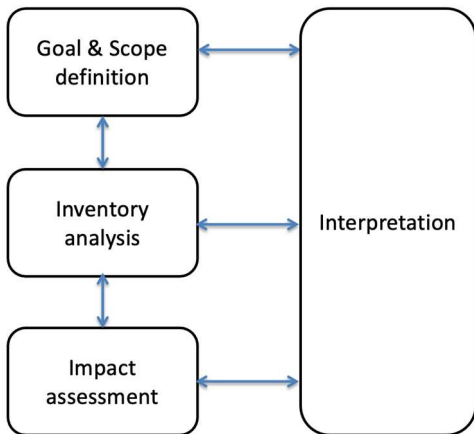
117

## 118 **2. Material and Methods**

### 119 **2.1 Methodological features of LCA**

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

126



127

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

130

131 In the first step, "Goal and scope definition", the system boundaries and functions (which  
132 determine the choice of functional unit(s)) are identified. In the second step, "Inventory  
133 Analysis", every flow of resources consumed, and of polluting emissions, is accounted for in  
134 the LCI. This is by far the most time-consuming and effort-intensive step of the whole LCA.  
135 LCI data are extracted from studied elementary flows of materials or energy consumed (e.g.,  
136 kg of raw material, hours of processing, amounts of energy) or released into the  
137 environment (e.g., polluting emissions and functional units delivered), (Brentrup et al., 2004).  
138 In our case, the starting point was to build a good model of farm activities, e.g., fertilizing,  
139 irrigating, ploughing, etc. To do so, "activity data", i.e., data related to the crop/ livestock  
140 management were collected. Such activities are responsible for emissions/consumption flows  
141 and linked to two process types called Foreground and Background processes. "Foreground  
142 processes" are emissions/ consumption related to farmer choices (e.g.: the type of fertilizer,  
143 the dose, the spreader use, etc). They have a significant influence on agricultural LCA results  
144 (Cowie et al., 2012; Modahl et al., 2012). Related data must therefore be collected specifically

145 for the system under study. Data necessary for a good modelling of foreground processes  
146 include not only "activity data", but also other "site-specific" data (e.g., soil texture, crop  
147 variety) that are useful to correctly model emissions and consumptions (Bellon-Maurel et al.,  
148 2014.; Rööös et al., 2010). However, LCA also considers emissions/ consumptions which are  
149 related to the resources used for the activities of the farm, e.g., related to agricultural  
150 machinery building or to energy/ input production. Such "background processes" occur  
151 upstream or downstream (e.g., recycling steps, after resource usage) and are not described  
152 with the same accuracy as foreground processes: background data are taken from database  
153 libraries incorporated in LCA software: in our case, Ecolnvent 2.2.

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

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

164

## 165 **2.2 Agrarian System Diagnosis**

166 Agrarian System Diagnosis (ASD) is an iterative approach and method that aims at  
167 "identifying and characterising the ecological, technical and socio-economic conditions from  
168 which originates the diversity and complexity of farming systems and their evolution"  
169 (Cochet and Devienne, 2006). This is a systemic approach aimed at supporting local farmers



170 by offering tailored support despite diversity in farming systems in terms of functioning and  
171 strategy. This is achieved by combining technical, financial and socio-economic criteria to  
172 describe each farming system.

173 The ASD is a multilevel approach that can be applied from the farming region to the  
174 cropping system. The "farming region" can be defined as a "geographic entity, differentiated  
175 and structured by the activities and the social groups which occupy it and interact there"  
176 (Papy, 2001; Payraudeau and Van der Werf, 2005). At the regional level, the concept of an  
177 "agrarian system" is employed to model the farming region under study as a weighted  
178 aggregation of farming systems that exchange flows among themselves, and/or between  
179 their sub-subsystems (cropping and livestock systems) (Mazoyer and Roudart, 1997; Cochet,  
180 2012). At the farm level, the "farming system" refers to a farm archetype that represents a  
181 set of similar farms. These farms are characterised by a given combination of cropping  
182 systems and livestock systems, which rely on comparable farm resources and face  
183 comparable socio-economic constraints (Reboul, 1976). At the field level, the "cropping  
184 system" is defined as a "subset of the farming system, characterized by crops, sequencing  
185 and planning", i.e. the logical and orderly combination of cultivation techniques (Cochet,  
186 2012). As such, the same crop rotation, implemented with notably different levels of inputs  
187 (fertilisers, pesticides, water, etc.), may lead to two distinct cropping systems. At the herd  
188 level, the livestock system is also a subset of the farming system. It refers to "a set of  
189 dynamically interacting elements organised by humans in order to: valorise resources  
190 provided by domestic animals, and thus obtain various commodities (milk, meat, leather,  
191 workforce, manure, etc.), or fulfil other needs" (Landais, 1987).

192

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

195 Dufumier, 1993; Devienne and Wybrecht, 2002; Tiftonell et al., 2010; Aubron et al.,  
196 2016). Functional typology is based on criteria describing the functioning of each farm  
197 sampled, and its strategy. The hypothesis made here is that the current agrarian system in a  
198 region results from: the evolution of farms (and their adaptation to bioclimatic conditions in  
199 a given space), and the dynamics of socio-economic constraints and opportunities,  
200 including, for example, labour-force availability or market opportunities (Mazoyer and  
201 Roudart, 1997; Groppo et al., 1999). The ASD approach is comprised of 3 main steps, with  
202 some overlapping and feedback: landscape analysis, historical reconstitution of the regional  
203 agro-ecosystem management, and finally techno-economic characterisation of farming  
204 activities at the farm and field/herd levels (Ferraton and Touzard, 2009; Moreau et al., 2012).

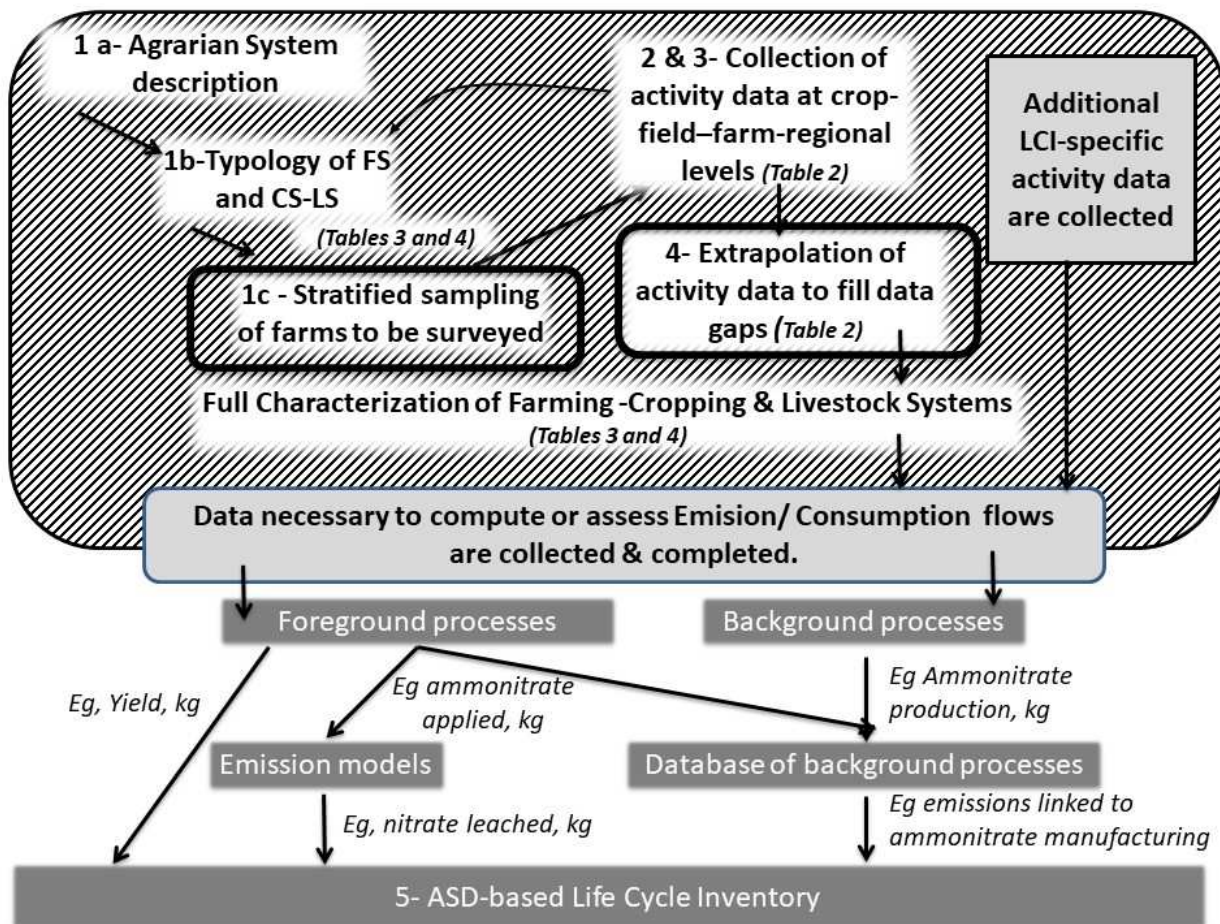
205

### 206 **2.3 Methodological proposal: "ASD-based LCI" to build a multilevel LCI of** 207 **farming activities**

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

216 The next step, i.e., LCI, is the most critical. "ASD-based LCI" is the name we have given to  
217 the new approach that we have developed to build the LCI of farming activities. "ASD-based  
218 LCI" is based on a multilevel approach (Figure 2) in which the ASD is first carried out  
219 through: 1-Landscape Analysis / 2-Historical reconstitution / 3-Techno-economic

220 characterization, to describe the farming systems (Figure 2- line 1), in order to guide farm  
 221 sampling and further collection of activity data. The latter are then enriched with additional  
 222 data collected at the regional scale and with specific data estimated at the field level to plug  
 223 the activity data gaps. The steps in the lower part of flow chart below refer to the  
 224 conversion of activity data (related to farm operations) into an emission / consumption  
 225 inventory.



226  
 227 **Figure 2. Main steps for building an ASD-based LCI.** The dashed area corresponds to the ASD steps. Dark  
 228 grey boxes relate to emission/ consumption computation; light-grey boxes correspond to data collected/  
 229 enriched by ASD to feed LCI. The two innovative steps used to reduce uncertainty of LCA outputs of the  
 230 region are shown in black thick-edged boxes. FS: Farming System; CS-LS: Cropping System, Livestock  
 231 System; “Tables” indicated in italics refers to the tables where data can be found.

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

- 234
- In Steps 1 to 3, farming and cropping systems are identified through ASD. Based on
- 235 a stratified sampling of farms, activity data are collected at the: crop, field, farm and
- 236 regional levels, and enriched with additional data specific to LCI requirements.
- 237
- Data gaps are checked and filled in Step 4.
- 238
- Then, LCI is built using a bottom-up approach (Steps 5 to 8). At each level, data are
- 239 aggregated, and internal exchanges of material flows are accounted for. LCI are
- 240 delivered for each cropping system (Step 6), farming system (Step 7), and for the
- 241 whole farming region (Step 8).
- 242

#	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 (1 <sup>st</sup> 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 (2 <sup>nd</sup> and 3 <sup>rd</sup> 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 <sub>i</sub> LCI)	To convert Activity data into Life Cycle Inventory data	= Field emissions models = Activity data files = Database of LCI background processes (EcolInvent)	- Crop level- C <sub>i</sub> LCI
6	LCI at Field/herd level: LCI of each Cropping System (CS <sub>j</sub> LCI)	To aggregate crop-level Life Cycle Inventory data;	Inventory Data files; EcolInvent Databases	Field level-CS <sub>j</sub> LCI = $\sum (\text{Crop-level LCI } C_i - CS_j)$
7	LCI at Farm level: LCI of each Farming System LCI (FS <sub>k</sub> LCI)	To aggregate field (and herd) levels Life Cycle Inventories; account for flows exchanged within farms	Inventory Data files; EcolInvent Databases	Farm level-FS <sub>k</sub> LCI = $\sum (\text{Field-level LCI } CS_j \cdot \text{weight } CS_j) - \text{internal flows}$
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; EcolInvent Databases	Regional level-LCI = $\sum (\text{Farm level LCI } FS_k \cdot \text{weight } FS_k) - \text{internal flows}$

		farms		
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243

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

250 In Step 1, various sources of information are consulted to better understand local context  
 251 dynamics and resulting influences on regional farming systems. Review of literature, along  
 252 with field work, consisting in landscape analysis, and the historical reconstitution of local  
 253 farming activities are used to sketch a preliminary typology of farming systems. Interviews  
 254 are conducted with: active farmers and some retired ones, local agriculture administration  
 255 officials, extension officers, and input retailers (Table 1, Step 1). Open-ended questions are  
 256 preferred to closed-ended questions since the aim is to build a functional typology,  
 257 reflecting the opportunities and constraints which determine the range of farming activities  
 258 which are organised within the agrarian system at the regional level. Moreover,  
 259 understanding the drivers of innovation is essential for drawing trend-based scenarios for  
 260 the future. Usually, access to classical farm resources (land/water, capital, workforce)  
 261 determines the range of actual opportunities regarding farming activities, but access to  
 262 market is also a major determinant. In previous studies (Ferraton and Touzard, 2009,  
 263 Belières et al., 2013), farming systems were classified into corporate/ family business/ family  
 264 farming categories, mostly according to the status of the labour force (family members  
 265 versus employees), farm management (commercial versus family-oriented), and ratio of self-  
 266 consumed agricultural products to commercialized products. Other criteria used for

267 differentiating farm types include: farm size, topographical constraints, cropping systems,  
268 market opportunities (local market, exports, etc.), number of workers, soil type, and access  
269 to water. This first step delivers a pre-typology of cropping/ livestock and farming systems,  
270 which is later fine-tuned with experts. A minimum of three farms are selected for interviews  
271 for each "pre-type" of farm. Representative farms are identified by local experts based on  
272 their strategies and performances (e.g. yield).

273 Steps 2 and 3 consist in conducting interviews in the stratified sample of farms to refine  
274 typologies of cropping/livestock and farming systems. Cropping and livestock systems are  
275 characterised during comprehensive interviews with farmers; preferably the owner or the  
276 person who manages the farm, to record the main strategy and operational information. At  
277 the farm level, the cropping plan and cropping pattern (composed of all the cultivated plots)  
278 are reconstituted and explicitly linked to crop rotation on every plot. Each cropping system  
279 is characterised by the most probable crop succession, including fallow, and the sequence of  
280 crop management operations: crop species, planting density, soil type, yield, amount and  
281 type of fertilisers, pesticides, irrigation schedule, type of machinery required, as well as  
282 irrigation duration and equipment (length of pipes, etc.). As we intend to go beyond a  
283 "standard" ASD, and to use collected data to model environmental impacts, we have  
284 endeavoured to collect activity data related to the technical functioning of cropping systems  
285 (to be converted into LCI data at Step 5) and economic performances. This notably includes:  
286 active ingredients of pesticide, fertiliser formulation, date of input application for modelling  
287 field emissions by accounting for daily climate parameters, flows of material and energy  
288 linked to farm equipment, machinery, and pumping systems. Table 2 gives examples of  
289 activity data collected at the crop level in a "standard" ASD versus what is required for an  
290 "ASD-based LCI". With LCA in mind, priority is given to cropping systems expected to have  
291 the most environmental impacts (input-intensive or highly represented in the area), as well

292 as to innovative systems. Obtaining the feedback of farmers interviewed is a key objective;  
293 therefore, technical and economic results are presented to them in local language:  
294 typologies of farming and cropping/livestock systems along with performances in terms of  
295 yield and gross product and revenue if possible. It is very worthwhile to discuss yield and  
296 economic results with farmers because they pay particular attention to them, and help refine  
297 these values during the meeting, which finally improves the robustness of LCI data based on  
298 activity data collected during interviews.

299 Step 4 consists in filling some data gaps. Certain can remain after field enquiries, particularly  
300 for crops that were not prioritized (Steps 2 and 3). Some data gaps include: non-availability  
301 of farmers, difficulties for them to quantify inputs (e.g., some used food cans to quantify  
302 fertilisers), a lack of trust in the interviewer, or exceptionally complex farm management  
303 practices. This is the case, for example, when the farm is managed by several members of  
304 the family, and part of the farm is run separately, while some activities or infrastructure  
305 elements are still shared. Data that are crucial for agricultural LCA are ranked as follows:  
306 yield, fertilisers, pesticides, irrigation and machinery (Nemecek et al., 2015). Yield directly  
307 influences LCA results, since it is used as a functional unit. Nitrogen-based fertilisers are a  
308 key driver of many impacts (Roches et al., 2010). It is essential to fill incomplete and missing  
309 data gaps. We have explored different ways to extrapolate data. First, the Unep-Setac group  
310 (Hischier et al., 2001) and Björklund (2002) recommend "analogies" or "proxies". This is fully  
311 compatible with the ASD framework and its holistic approach, which captures the diversity  
312 of farming systems while also making it possible to match different systems that are alike.  
313 Second, crop models are very useful. In this study, missing data on yield, total applied  
314 nitrogen, and irrigation water were modelled using PILOTE, a one-day time-step crop model  
315 (Mailhol et al., 1996) which has been parameterised using the soil and crop features of the  
316 case study. The last available information sources are expert knowledge and data from the



317 literature. The methods most likely used to fill missing data gaps, i.e., analogies, crop-  
 318 models, expert knowledge and literature are summarised in Table 2. Such extrapolated  
 319 data—whatever the method used — lead to higher epistemic uncertainty than that  
 320 associated with data collected directly during interviews. Therefore, extrapolated data will  
 321 be rated lower in terms of quality in the crop dataset (supplementary information, Section  
 322 S.2.1, Table S2) and in subsequent analysis regarding uncertainty propagation (Section S.2.2).

323

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

<i>Climate &amp; soil properties</i>	<i>Location</i>	<i>Soil properties (for modelling field emissions), weather data</i>	<i>L* -E</i>
--------------------------------------	-----------------	--	--------------

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

329

330 Step 5, and the following steps encompass the Life Cycle Inventory and LCA. In Step 5, the  
331 LCI is built at the elementary level of the crop: the activity data related to the crops in each  
332 cropping systems are converted into LCI data or "inventory data". Inventory data are made  
333 up of input and output flows of materials and energy involved in each elementary process.  
334 For example, "producing 1 kg of pepper" comprises material and energy flows involved in  
335 the manufacture and transportation of inputs, e.g., fertilisers and pesticides (specific  
336 molecules, active ingredients and amounts are specified), along with the output flows of  
337 polluting emissions- notably field emissions - into the air, water and soil compartments of  
338 the environment (Figure 2). Data collected at the farm level, such as machinery and water  
339 used for irrigation, are disaggregated respectively into the crop and cropping systems to  
340 which they contribute, according to the ratio of hours spent on each of them, versus total  
341 lifetime. In standard ASD, machinery data are collected to calculate economic depreciation  
342 to be deducted from the operator's turnover in order to calculate their income. Conversely,  
343 the ASD-based LCI aims to characterise not only the total lifetime of a piece of machinery,  
344 but also its quantified use in relation to each crop in order to assign to each crop the share  
345 of the environmental impacts it has caused. Lastly, field emissions are assessed based on  
346 activity data collected by ASD-based LCI, and complemented with data related to soil /  
347 weather. They are computed with dedicated models and emission factors for nitrogen

348 emissions, in accordance with local soil and climate conditions (Brentrup et al., 2000;  
349 Bouwman and Boumans, 2002a, 2002b; IPCC, 2006; European Environmental Agency and  
350 EMEP/EEA, 2009). Details are given in Supplementary information S.1.1. The EcolInvent 2.2  
351 LCI database was used for background processes.

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

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

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

369

## 370 **2.4 Uncertainty computation**

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

375 The pedigree matrix approach is a semi-quantitative method proposed by the LCA scientific  
376 community to characterise data uncertainty when the probability distribution of data is not  
377 available (Weidema and Wesnæs, 1996; Huijbregts, 1998; Frischknecht et al., 2005;  
378 Frischknecht et al., 2007). In most unit processes, uncertainty follows a lognormal  
379 distribution, and the pedigree matrix expresses how each source of uncertainty contributes  
380 to global uncertainty. For each item of data (e.g., NO<sub>2</sub> and CO<sub>2</sub> emissions, etc.), a “pedigree  
381 matrix factor” (PMF) - referring to its level of uncertainty expressed by an uncertainty factor  
382 (UF), i.e., the square of a standard geometric deviation - is set based on an “expert”  
383 approach. The uncertainty interval around the geometric mean ( $\mu_g$ ) containing 95% of  
384 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  
385 consult Supplementary information S.1.2. In the present work, the pedigree matrix approach  
386 was used to compare the quality of data according to the data collection method used. We  
387 choose to compare statistic data obtained from public regional agricultural census (Centre  
388 Régional de Développement Agricole, 2010a, 2010b) with ASD-based LCI data either before  
389 or after extrapolation to fill missing data gaps (Table 1, Step 4). In the present study,  
390 uncertainty was computed for each crop within a cropping system, and assessed regarding  
391 the quality of its “crop dataset”, i.e., the set of activity data related to the whole crop cycle  
392 until harvest, as in Rööös et al. (2010). The global uncertainty factor (i.e., of the cropping  
393 system) is then computed as the linear combination of the squares of the geometric  
394 standard deviations of each crop included, weighted according to their share.

395

396

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

397 The study was conducted in the semi-arid to arid irrigated plain of Kairouan (180 to 420  
398 mm annual rainfall) in central Tunisia. The plain of Kairouan covers 30,000 ha, of which  
399 12,700 ha are irrigated. This is mostly conducted through private and partly unregulated  
400 groundwater pumping from the calcareous aquifer. Input-intensive and profitable vegetables  
401 / fruit orchards have supplanted the former model of agro-pastoralism which is currently the  
402 default choice for farmers who lack access to groundwater. In 2004, Leduc et al. reported an  
403 annual drawdown rate of the water table at between 0.25 and 1 m. During field interviews,  
404 farmers reported that the rising number of deep boreholes had increased the annual water  
405 table drawdown rate by up to 1.5m per year. Four distinct types of water pumping systems  
406 are used, whose performances and environmental impacts were assessed with LCA by  
407 Pradeleix et al. (2014).

408

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

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

431

## 432 **2.6 The ASD-based LCI applied to the Kairouan plain: modelling choices**

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

444 pumps. ASD results were presented in Arabic to farmers interviewed to reduce data  
445 uncertainty.

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

451 The allocation of impacts of multiple-outputs systems, such as cereals, was based on  
452 economic indicators, i.e., weighted by farm gate prices (Suh and Huppès, 2005; AFNOR,  
453 2006a, 2006b).

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

455

### 456 **3. Results of the methodology applied to a case study**

#### 457 **3.1 ASD outcomes: Typology of farming systems and cropping systems**

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

465 Modern farms (FS1 to FS4) pump groundwater from deep boreholes to irrigate high-density  
466 olive groves (Spanish high-yield varieties) and fruit orchards, which are the most  
467 economically profitable cropping system per ha. Traditional farms (FS6 to FS9) grow a wide  
468 diversity of crops and generally practice intercropping to save water. Crops are mostly local

469 varieties of olives in groves along with vegetables and cereals to feed sheep. Within family-  
470 based FS, only FS6 can afford to invest in fruit orchards. FS6 and FS7 pump water from  
471 open wells. FS8 has a tiny plot of olive trees, whereas FS9 is landless; it exclusively relies on  
472 rangeland to feed its own sheep, and the farmer here also works as a shepherd for other FS.  
473 The resources and strategy of each farm depend on its status, whether it belongs to  
474 investors (FS1 to FS3) seeking to maximize the profit in the short-term or to family farmers  
475 (FS4 to FS9) concerned with mid- to long-term stable production and relying mostly on a  
476 family workforce. The family business FS5 is somewhat unique: it is run by inhabitants from  
477 other regions (within a 100km distance) who rent out all their cultivated land for short  
478 periods.

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

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



493 much higher for farming systems that include sheep rearing (FS6 to FS9), especially FS8 and  
494 FS9, than for crop-oriented farming systems (FS1 to FS5).

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

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

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

505 Table 4 details the typology of the most common cropping system categories, out of the 27  
506 identified during field visits in the 9 farming systems. For example, the FS2 cropping plan is  
507 composed of five cropping systems: 15% of intermediate-density olive groves; 35% of high-  
508 density olive groves 20% of citrus of which 5% are young plants intercropped with pepper,  
509 and 30% of orchards intercropping olive trees and citrus. Even if cropping systems use the  
510 same crop rotation, they can differ from one another regarding crop variety, tree density or  
511 amount of agricultural inputs (fertilisers and pesticides). Tree density ranges from high (550  
512 trees.ha<sup>-1</sup>) to intermediate (280 trees.ha<sup>-1</sup>) and low density (100 trees.ha<sup>-1</sup>), the latter being  
513 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
<b>Land occupation</b>	<b>Crop characteristics</b>									
<b>Olive Groves</b>	Intermediate density	35 %	15%	35%						
	High density		35%							
	Low density			15 %	25%		15 %	18 %	100 %	
<b>Citrus</b>	Sole crop	20%	15 %	7 %	8 %					
	Intercropping		5%	3%	3%					
<b>Apple or Peach or Apricot</b>	Sole crop Intercropping	45 %		20 %	51 %		16 %			
					3%		3%			
<b>Intercropping Olives and Citrus</b>	Sole crop Intercropping (with pepper)		30 %	10%	10 %		10%			
							5%			
<b>Intercropping Olive-Vegetables</b>	Input-Extensive			10 %				10 %		
	Input-Intensive						10 %	7 %		
<b>Intercropping Vegetables</b>	Input-Intensive					70 %				
<b>Intercropping Olive-Vegetables-Cereals</b>	Water-Intensive						10 %			
	Input-Intensive							10 %		
<b>Rotation Vegetables/ Vegetables</b>	Input-Intensive					30%		5%		
<b>Rotation Cereals/ Vegetables</b>	Input- Intensive							8 %		
	Input-Extensive Sole crop Intercropping						15 %	2 %		
							10%			
<b>Rotations Cereals/Pulse</b>							6 %	18 %		
<b>Fallow</b>								25 %		
<b>Livestock activities</b>										
<b>Number of breeding ewes</b>							7	20	15	15

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

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

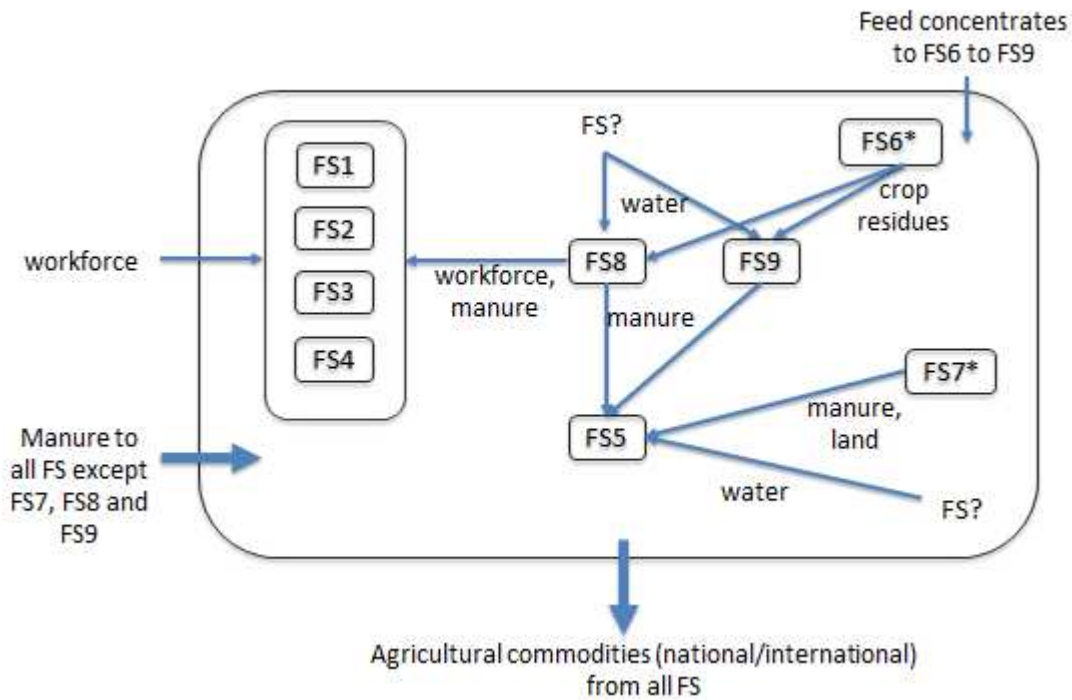
	Total N (kg/ha)	Pesticides: N° of treatments/N° of products	Irrigation water (m3/ha)	Planting density (plants/ha)	Yield (kg/ha)
FS6	200	9/4	3 870	5 000	19 000
FS7	270	10/6	3 050	5 500	13 300

524 **Table 5. Comparison of activity data characterizing the melon cultivation in “intercropping olives-**  
 525 **vegetables-cereals”, in FS6 and FS7.**

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

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

540 99% of manure is imported from outside the farming region. Farming systems FS5, FS8 and  
 541 FS9 have poor access to water and buy it from others. In addition, FS5 rents land from FS7.  
 542 FS8 and FS9 buy straw and the access to crop residue for grazing from FS6 whose feed  
 543 production exceeds its own needs.



544  
 545  
 546 **Figure 3. Flows exchanged through the farming region boundaries as well as within and between farming**  
 547 **systems (\*means internal exchanges of manure and straw); large width of arrows indicates large flows**

548  
 549 The farming region is significantly deficient in manure required to maintain soil fertility and  
 550 productive capacity of this highly exploited area. In addition, corporate farming systems  
 551 suffer from labour shortages and often hire labour from outside the farming region. On the  
 552 other hand, intense exchanges of by-products (cereal straw) and wastes (cereal stubbles and  
 553 fava bean residues) take place in family farming, which is characterised by the highest  
 554 diversity of cropping systems (olive groves, fruit orchards, vegetables and cereals, along with  
 555 sheep rearing).

### 557 3.2 Data uncertainty with ASD-based LCI

558 When ASD is completed (Step 3), we have 70 datasets describing the activity data (and  
559 additional data) for the 70 different cropping systems. Each dataset is given a mark (from  
560 excellent to poor) according to its completeness. When more than two-thirds of the dataset  
561 is completed with activity data, the dataset is scored "excellent". When between 1/3 and 2/3  
562 data activities are known, the dataset is given an "intermediate" score. When less than one  
563 third of the data activity is collected, the dataset is scored "poor". There are 19 "excellent",  
564 49 "intermediate" and 2 "poor" scores; for details, see supplementary information S.2.1.  
565 Intermediate- and poor-quality datasets are then extrapolated to fill the data gaps.

566 Table 6 shows the pedigree matrix approach, with crop datasets obtained using different  
567 data collection methods. For the sake of clarity, the single livestock system existing among  
568 all farming systems was not used for the uncertainty analysis. For each of the 6 categories  
569 encompassed by the pedigree approach, which can contribute to data quality, a score,  
570 named the "pedigree matrix factor" (PMF) is estimated by experts based on data quality. The  
571 better the data quality level, the lower the PMF score with 1 set as the lowest limit (smallest  
572 uncertainty level). The first column (0) shows ideal data and therefore receives a PMF score  
573 of 1. The second column (1) represents the PMF of the statistical data (FADN type). Columns  
574 2 to 4 concern data collected with ASD-based LCI before extrapolation, and give PMF for  
575 "poor", "intermediate" and "excellent" datasets respectively. Columns 5 and 6 show  
576 improvements by extrapolation of datasets previously classified as "intermediate" and  
577 "poor". In relation to the PMF mark assigned to each type of dataset, the pedigree matrix  
578 also provides the corresponding "uncertainty factor" ( $U_i$ ), which are to be combined to  
579 compute the global uncertainty factor as the square geometric standard deviation  
580 (Frischknecht et al., 2007). Details on how the PMF scores were assigned to each data



581 quality level for each of the three data collection methods can be found in Supplementary  
 582 information S.2.2.

583

584 The uncertainty factor (UF) for all the crop datasets (i.e. of the aggregation of the 70  
 585 datasets) was obtained by a linear combination of uncertainty factors obtained for each of  
 586 the three quality levels in the dataset, weighted according to their share of the total: 19/70,  
 587 49/70 and 2/70 respectively, for good, intermediate and poor quality datasets.

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

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

598

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
<b>Categories:</b>														
<b>Reliability</b>	1	1	4	1.2	1	1	3	1.1	4	1.2	2	1.05	3	1.1
<b>Completeness</b>	1	1	3	1.05	2	1.02	2	1.02	4	1.1	2	1.02	2	1.02
<b>Temporal correlation</b>	1	1	3	1.1	1	1	1	1	1	1	1	1	2	1.03
<b>Spatial correlation</b>	1	1	2	1.01	1	1	1	1	1	1	1	1	1	1
<b>Technological</b>	1	1	5	2	1	1	3	1.2	3	1.2	1	1	3	1.2

<b>correlation</b>														
<b>Sample size</b>	1	1	2	1.02	4	1.1	4	1.1	4	1.1	4	1.1	4	1.1
<b>Basic uncertainty</b>		1.07		1.07		1.07		1.07		1.07		1.07		1.07
<b>UF<sub>g</sub> (<math>\sigma^2_g</math>)</b>	1.03		1.37		1.20				1.12					
<b>UF increase vs Ideal case</b>	0%		33%		17%				9%					
<b>% reduction in UF/ statistical approach</b>	NA		0%		50%				74%					

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

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

609

## 610 **4. Discussion**

611 The overall goal of applying LCA at the regional scale can be closely associated to our  
612 primary objective: to propose a method to build reliable Life Cycle Inventories in a context  
613 of data scarcity and farm diversity. To our knowledge, although many LCA studies have been  
614 carried out to assess the environmental performances of agricultural systems (Avraamides  
615 and Fatta, 2008; Basset-Mens et al., 2010, Borghino et al 2021, Notarnicola et al 2017 ), the  
616 question of how to practically reduce uncertainty has yet to be properly addressed,  
617 especially in contexts of very scarce data like in the case of our Tunisian study. We have  
618 designed "ASD-based LCI" to collect LCI-specific data in a context of scarce data, and to  
619 model representative farming and cropping/livestock systems, despite their diversity and

620 complexity (e.g., intercropping, multiple output crops, etc) in a multilevel approach from the  
621 plot up to the farming region (Tables 3 and 4).

622

#### 623 **4.1 How ASD helped us to address the lack of LCI-relevant data**

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

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

642 The ASD method allowed us to capture data which are crucial to LCI. Activity data related to  
643 each crop include crop management practices and were collected during field visits and  
644 interviews with different local stakeholders, mostly farmers. The survey grid is usually built

645 ad hoc in the ASD (Jouve, 1986); this means that it can be specifically designed for the  
646 purposes of a LCA. For example, "ASD-based LCI" focuses on the chemical properties of  
647 every fertilizer and pesticide, which are major contributors to field emissions in agricultural  
648 systems (Avraamides and Fatta, 2008), beyond the standard technical and economic data  
649 (e.g., total units of NPK, input costs) usually collected in ASD (Trebuil and Dufumier, 1993;  
650 Devienne and Wybrecht, 2002; Tiftonell et al., 2010).

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

658

#### 659 **4.2 How ASD helped us to tackle the issue of diversity of farming systems at the** 660 **regional scale to reduce uncertainties due to modelling errors**

661 The second challenge was to capture the diversity and complexity of farming systems  
662 present in the region, and to mitigate the errors that a bad representation of farms in data  
663 collection can produce. This challenge was addressed by characterizing FS through  
664 typologies, built using ASD, at the field/herd and farm levels. Several authors failed to build  
665 farm typologies based upon statistical or accountability data because such data showed  
666 greater variability within each farm type than between farm types (Dalgaard et al., 2006;  
667 Samson et al., 2012; Avadí et al., 2017). Conversely, ASD typology is concerned not only with  
668 structure, but with farm functioning. Differences in management and functioning (e.g.,  
669 strategic choices regarding animal feeding strategies, fertiliser type) were not reflected in

670 the FADN accountancy data, but were significant enough to be used by ASD to identify  
671 different farm types (Dalgaard et al., 2006; Samson et al., 2012; Avadí et al., 2017). Indeed,  
672 ASD goes far beyond simply listing farm resource facilities and purchased inputs/ sold  
673 outputs, as with statistics that aggregate farm-level data. It also accounts for the farm  
674 strategy and its functioning (Tittonell et al., 2010). In our work, this helped us to better  
675 identify the different types of farming systems in the pre-typology (Step 1, Table 1).  
676 Whereas FS6 and FS7 initially belonged to the same farming system in (Step 1), it became  
677 obvious that they were distinct when analysing the cropping systems (Step 3). When ASD is  
678 employed to build LCI, other factors must be taken into account in the typology, i.e., factors  
679 that can modify field emissions. Consequently, although some FS may have similar farm  
680 structures (area cultivated, family workforce, pumping systems, etc.) and grow similar crops,  
681 they may be very different regarding their impacts. For instance, melons were grown in  
682 Olive-Vegetable-Cereal rotation in FS6 and FS7, but with less water in FS7 due to a lack of  
683 water availability. Furthermore, soil texture influences water consumption and field emissions  
684 of any cropping system (e.g., Extensive Olive-Vegetable CS is cultivated either on sandy soil  
685 in FS3 or loamy soil in FS7). Lastly, considering the same cropping system, LCI will differ  
686 depending on the machinery and pumping systems used. CS Apple orchards have different  
687 impacts in FS1 and FS6 because water is pumped with submersible pumps, or from open  
688 wells with surface pumps, respectively (Pradeleix et al., 2014).

689

#### 690 **4.3 How uncertainty could be improved by stratified sampling and extrapolation**

691 The final uncertainty of results was reduced thanks to two strategies. The first one was to  
692 carry out a stratified sampling of farms, instead of a random sampling. The stratified sample  
693 of farms—representative of the farming region— is the output of the first step of ASD,

694 which aims at capturing the main archetypes of regional farming activities by analysing  
695 major drivers of their diversity.

696 Using the pedigree matrix approach, we showed that stratified sampling reduced the  
697 uncertainty factor with regards to random sampling. In the pedigree matrix, the relative UF  
698 is respectively 1,03 for the smallest possible value (ideal case), 1,37 for the random sampling  
699 (+33%) and 1,20 for the stratified sampling (+17%). This means that the increase in  
700 uncertainty -with regards to the ideal case- could be halved when stratified sampling is used  
701 instead of random sampling. The positive effect of stratified sampling has been  
702 demonstrated mathematically on a theoretical numerical example in the supplementary data.  
703 This result concurs with those of Jayaraman (1999) and The Pennsylvania State University  
704 (2018): the variance computed in stratified sampling only accounts for the variability within  
705 each group, but not for the one between groups. Indeed, the level of optimisation depends  
706 on the ratio of "inter-group" variance to total variance.

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

711 Lastly, farm stratification produced by ASD played a key role in characterising the diversity,  
712 and therefore in reducing the uncertainty of LCI data computed for the region. In fact, the  
713 accuracy performance of LCI outputs would improve in step with a rise in the number of  
714 types of farming systems identified in the farm population. However, to characterize  
715 additional farming system types a greater number of interviews would be required.  
716 Therefore, a balance must be found due to the extra time and effort required for the  
717 additional interviews (Jayaraman, 1999). Furthermore, the uncertainty related to the number  
718 of farms in each farming system affects the uncertainty of the LCI of the whole farming

719 region. In line with the ASD, we suggest conducting a large and rapid survey based on a  
720 questionnaire to classify every farm of the farming region within the farm typology,  
721 according to a short list of qualitative and quantitative criteria (Ferraton and Touzard, 2009).

722

#### 723 **4.4. How ASD offers additional benefits regarding circular economy in** 724 **agriculture**

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

737

## 738 **5. Conclusion**

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

744 Life Cycle Inventory. This method, which we have named "ASD-based LCI" was applied to a  
745 6000 ha pilot area, characterized by intensive irrigated farming in the Kairouan plain, Tunisia,  
746 to build a Life Cycle Inventory that reflected the diversity of farming activities at the regional  
747 scale. ASD was used to characterize the farming systems and their inner functioning, a  
748 necessary step before a stratified sampling of farms that were chosen for each archetype to  
749 conduct data collection on farm activities. The "activity data" collected suffer from  
750 incompleteness, which led us to propose an innovative step, named "data extrapolation" to  
751 fill gaps, based on 4 processes, e.g., analogies, crop modelling, expert knowledge and  
752 literature findings.

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

761 Second, the new ASD-based LCI methodology was assessed with regards to our objective of  
762 uncertainty reduction on LCA input data. The pedigree matrix approach was used in LCA to  
763 compare uncertainty of input data obtained using 3 data collection protocols, i.e., i.) the full  
764 ASD-based LCI methodology (including stratified sampling and extrapolation), ii.) partial  
765 ASD-based methodology (including stratified sampling but without extrapolation) and iii.)  
766 classical statistics-based input data. This work showed that stratified sampling played a key  
767 role in reducing LCI data uncertainty: uncertainty (when compared to the ideal case) was  
768 halved when switching from the statistics-based LCI to the ASD-based LCI using stratified



769 sampling (and no extrapolation). When the full ASD-based LCI methodology was applied  
770 (i.e., with stratified sampling and extrapolation), uncertainty (when compared to the ideal  
771 case) was reduced by a factor of 4 when switching from data extracted from statistics to  
772 those obtained by extrapolated ASD-based LCI.

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

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

784

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792

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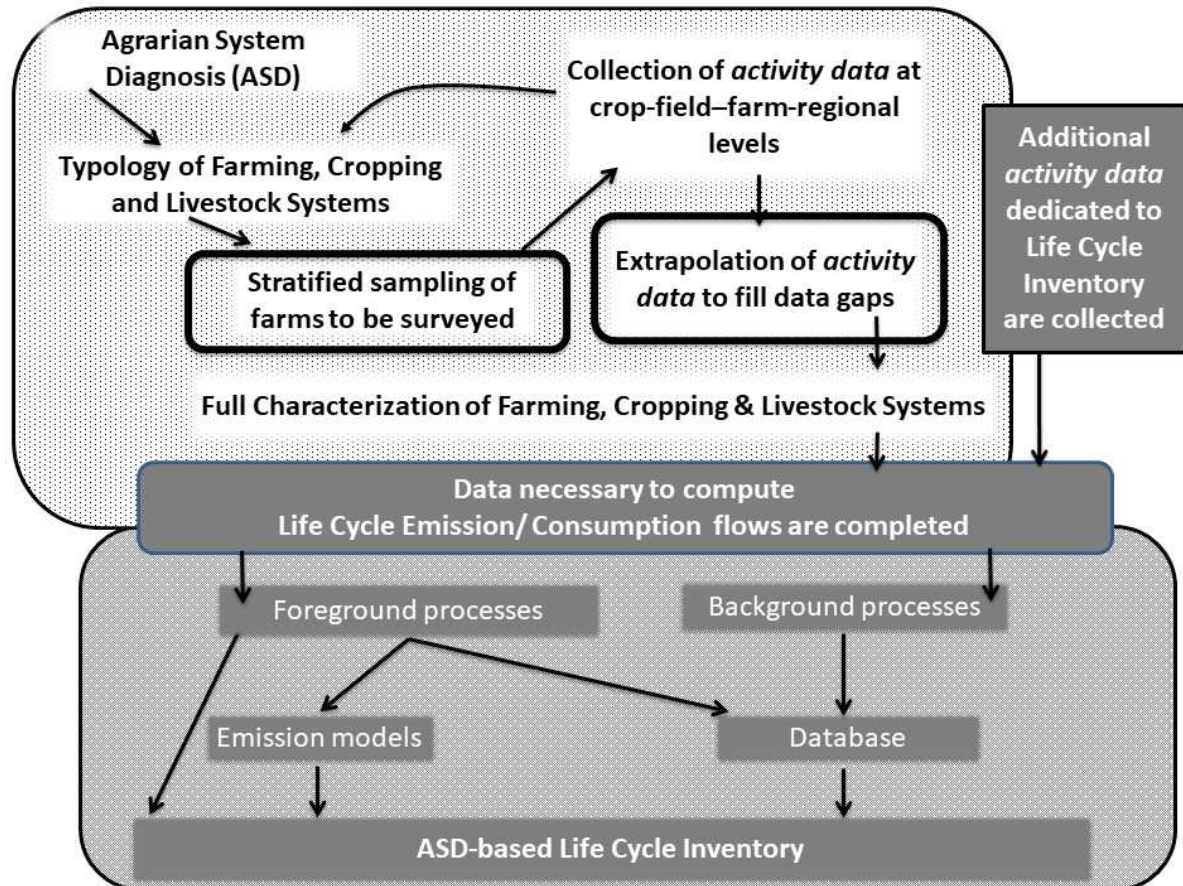
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## Graphical abstract

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.