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An approach to regionalise the life cycle inventories of Spanish agriculture: Monitoring the environmental impacts of orange and tomato crops

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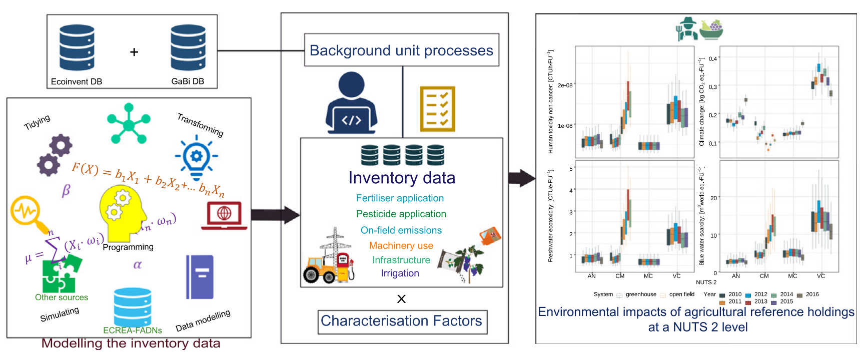
HIGHLIGHTS

- Economic data from Spanish ECREA-FADN allow regionalised LCAs to be developed.
- Temporal variability scatters more the impacts than the input data uncertainty.
- Issues to adapt ECREA-FADN to the farm-to-fork strategy requirements are identified.

GRAPHICAL ABSTRACT



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ABSTRACT

Agricultural life cycle assessment (LCA) at the sub-national regional level may be a valuable input for the decision-makers. Obtaining representative and sufficient data to develop life cycle inventories (LCIs) at that level is a relevant challenge. This study aims to contribute to the development of LCIs representative Spanish crops based on economic and operational information available in official sources to assess the average environmental impacts of these crops in the main producing regions. A comprehensive approach is proposed considering both the temporal variability and uncertainty of input data by using different methods (e.g. linear programming, weighted averages, Monte Carlo simulation, forecasted irrigation, etc.) to estimate the inventory data of reference holdings. From these inventories, the environmental assessment of those reference holdings is carried out. Two case studies are developed, on orange and tomato crops in the main producing regions, where climate change (CC), freshwater scarcity (WS), human toxicity non-cancer (HTnc), and freshwater ecotoxicity (ET) are evaluated. The environmental scores obtained differ significantly from region to region. The highest environmental scores of orange reference holdings correspond to Comunidad Valenciana for CC ($1.94 \cdot 10^{-1}$ kg CO_2 eq.) HTnc ($4.16 \cdot 10^{-11}$ CTUh) and ET ($7.45 \cdot 10^{-3}$ CTUe), and to Andalucia in WS (17.4 m^3 world eq.). As to greenhouse tomatoes, the highest scores correspond to Comunidad Valenciana in the four categories analysed (CC = 3.18 kg CO_2 eq., HTnc = $3.6 \cdot 10^{-9}$ CTUh, ET = 1.5 CTUe and WS = 13.3 m^3 world eq.). The environmental scores estimated in this study are consistent with the literature, showing that the approach is useful to obtain a representative description of the environmental profile of crops from official statistical data and other information sources. Widening the data gathered in ECREA-FADN, and also that from other data sources used, would increase the quality of the environmental impact estimation.

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1. Introduction

Agricultural food production addresses one of the most important and basic human needs. Notwithstanding this, agriculture represents a relatively small share of both the European Union's economy and also Spain's (1.9 % and 3 % of the gross domestic product on average, respectively) due to the strong growth of the industrial and service sectors (Eurostat, 2022). Many studies highlight the significant contribution of agriculture to natural resource depletion, namely water depletion, biodiversity loss, soil erosion, and environmental pollution, such as greenhouse gas emissions and other pollutants (Notarnicola et al., 2017). Thus, the Common Agricultural Policy (CAP), the most important political and economic instrument of European agriculture (EP, 2022b) that was initially constituted to guarantee food security and other social rural matters in Europe, has been modified in the latest proposals to integrate the current environmental challenges of the European Green Deal (e.g. no net emissions of greenhouse gases by 2050). Within the Green Deal framework, the Farm-to-Fork Strategy aims to obtain fair, healthy, and environmentally-friendly food systems (EC, 2022a). In this respect, the Post-2020 CAP Strategic Plan of Spain (MAPA, 2021), among other issues, aims to intensify the environmental concerns and the actions on climate change to contribute to the EU objectives.

As a first step to addressing the environmental sustainability of agriculture under this new political framework (EC, 2022b), assessing the environmental impacts of agricultural systems and products using an attributional approach can help account for and understand their environmental profile. Along these lines, farmers can estimate the impacts of their products (or farms) individually as a basis for the implementation of changes. Another possibility is that of carrying out representative estimations of the impacts of a crop in a region to have a reference average impact in order to propose improvements in the sector and to establish benchmarks. In this regard, under the life cycle thinking focus, life cycle assessment (LCA) is accepted as a powerful approach for the holistic assessment of the environmental impacts of anthropogenic activities that provides valuable environmental indicators to policymakers and other economic agents (Gava et al., 2020; Sala et al., 2021). LCA is preferred over other environmental tools because it aims to assess products and considers all the environmental burdens caused by production and consumption systems (Dai et al., 2020; Roches et al., 2010).

The available literature on agri-food LCA is extensive. Many case studies analysing the environmental impacts of different agri-food systems and products have been developed (e.g. Aguilera et al., 2015; Bosco et al., 2011; Sinisterra-Solís et al., 2020; Villanueva-Rey et al., 2014). Other studies review and propose methodological aspects so as to enable and improve the estimation of the environmental impacts with different levels of detail (e.g. Brentrup et al., 2000; Cayuela et al., 2017; Dijkman et al., 2012; Huijbregts et al., 2017; Roches et al., 2010; Rosenbaum et al., 2008).

Life cycle inventory (LCI) is one of the most relevant challenges in LCAs because an accurate analysis requires accurate data of all inputs and outputs at every stage of the product's life cycle (Meron et al., 2020). In fact, different researchers consider LCI as the most complex step when developing an LCA (e.g. Dai et al., 2020; Kuka et al., 2020; Yang, 2016). A dilemma is, thus, presented between working with global and generic data (less effort needed to obtain the data but more inaccuracy in the results) versus site-specific data (greater effort to obtain the data but greater accuracy in the results), which, in turn, determines how data are collected (Meron et al., 2020). The ideal situation is that in which all the inventory flows of the foreground system correspond with primary data from on-site measurements or representative surveys. Nevertheless, data gaps together with budget and time constraints can lead LCA professionals to use secondary data from different information alternatives (official statistics, LCA databases, etc.) or to estimate the data by using modelling approaches to represent upstream and downstream processes or to determine input consumption and subsequent emissions (Dai et al., 2020; Turner et al., 2020).

Primary data from on-site measurements or representative surveys are practical when applying LCA at the farm level; however, data representativeness is the main challenge when evaluating agriculture at the regional level (Avadí et al., 2016; Pradeleix et al., 2022). The features of agri-food products tend to differ greatly between regions and systems, and thus the use of generic and global data is not recommended in LCAs (Meron et al., 2020; Turner et al., 2020). This difficulty increases substantially when large portfolios of agri-food products and systems are evaluated (Roches et al., 2010). Different alternatives have been proposed to gather more accurate information when developing representative site-specific LCIs. For instance, Roches et al. (2010) propose an extrapolation method to estimate life cycle impact assessment (LCIA) results for a crop from a specific country using LCA data from the same crop in another country. Meron et al. (2020) present a methodology based on mathematical and statistical techniques to systematically select the best approximations of a data set. Dai et al. (2020) develop a new data processing method to facilitate the compilation of regionalised LCI databases and the characterisation of uncertainty, whereas Dai et al. (2022) propose a gaussian process regression to carry out both the inventory and the uncertainty analysis when data are lacking or of poor quality. Pradeleix et al. (2022) develop a method for building LCI of agricultural regions, able to capture the diversity of farming systems in a context of data scarcity.

Farm Accountancy Data Networks (FADN) have been used to develop agri-environmental indicators for monitoring the integration of environmental concerns within the Common Agricultural Policy (CAP) in the European Union showing that statistical sources provide harmonised regional information (EEA, 2005). However, Pradeleix et al. (2022) discourage using the FADN because these are estimated on an economic basis tending to assess the impacts of the Common Agricultural Policy (CAP) and the income of average agricultural holdings, and not for environmental purposes. This study adopts the hypothesis that, although data such as those from FADN may lack specificity, thereby contributing to epistemic uncertainty (Chen and Corson, 2014; Teixeira, 2015), in the absence of more precise data, they can be a useful basis, together with other official sources and scientific literature, to develop attributional LCAs at the regional farm-level. Based on a decision taken in an accounting context (EC-JRC, 2010), FADN allows not only the income levels of agricultural holdings to be accounted for but also the environmental effects derived from those incomes. Along these lines, this study aims to contribute to the development of regional LCIs representative of the Spanish crops based on average economic and operational information available in official sources at the farm level (reference holdings), in order to assess the average environmental impacts of these crops in the main producing regions. For that purpose, two case studies are developed studying tomato and orange crops in the main producing regions in Spain. The results can be useful for decision-makers, both locally and nationally, aiming to monitor the environmental sustainability of the agri-food sector in Spain.

2. Methodological approach

This proposal corresponds to an attributional LCA, according to the ISO standards (ISO, 2006a, 2006b, 2017) and the ILCD (EC-JRC, 2010), considering an accounting situation in which the environmental impacts of a series of reference holdings at a NUTS 2 level in the Spanish agriculture are monitored.

Different approaches to estimating the consumption of the main inputs for crop production are used to develop the LCIs of Spanish agriculture. Agricultural inputs, namely fertilisers, pesticides, fuel, electricity and irrigation water, are identified as transversal elements of the LCIs. When used, greenhouse and irrigation infrastructure, together with greenhouse management, are also accounted for, as previous research (Antón et al., 2013, 2014; Romero-Gámez et al., 2017; Torrellas et al., 2012) has highlighted the relevance of these capital goods in agricultural LCA results. However, the production of other capital goods, such as machinery, is not considered because their impacts are not usually significant in attributional LCAs (Frischknecht et al., 2007).

The proposed approach takes the annual studies of costs and incomes of agricultural holdings as the central source of information, known as ECREA according to the Spanish acronym (MAGRAMA, 2012b, 2013g, 2013d, 2013c, 2013f, 2013e, 2014g, 2014f, 2014c, 2014b, 2014e, 2014d, 2015e, 2015d, 2015b, 2015c; MAPA, 2018f, 2018e, 2018d, 2019c, 2019b, 2019a, 2020a, 2020b; MAPAMA, 2015, 2017). ECREA (from now on ECREA-FADN), differs from the Spanish FADN (RECAN according to the Spanish acronym). On the one hand, RECAN reports are part of the statistical obligations of the Spanish government, as a member of the EU; therefore, both the sample design and the accounting methodology must follow the EU regulations. Beyond methodological differences and sample design, the main difference between ECREA and RECAN is that in the former, the data correspond to the holding level, instead of to specific productions, such as EU FADNs, like the Spanish RECAN. Summarising, ECREA is a type of farm accountancy detailed for a number of reference holdings at the NUTS 2 level, developed by the Spanish Ministry of Agriculture, Fisheries and Food. On the other hand, ECREA-FADN reports mainly gather information on the economic results of the selected reference holdings (e.g. incomes, expenses and profit indicators) together with the description of the agricultural practices and some activity data (e.g. amount of macronutrient supplied, yield). These reports include the main crops produced at the Spanish NUTS 2 level, according to the common classification of territorial units for statistics (EP, 2022a). ECREA-FADN comprises currently unbalanced annual panel data, corresponding to the period 2010 to 2017, for 64 different crops and 9 of the 17 NUTS 2 of the Spanish territory. The use of data from different years allows the interannual variability in the input parameters (e.g. amount and price of fertilisers, price of fuel, etc.) to be accounted for.

Based on average data from ECREA-FADN, the reference holdings to be assessed are defined according to the management systems used in the corresponding NUTS 2, namely open-field irrigated, open-field rainfed and greenhouse irrigated. As to the crops chosen for the case study in Spain, orange groves correspond to the irrigated open-field system (from now on, orange); whereas tomatoes can be grown in open-field irrigated farms (from now on, open-field tomato) and in irrigated greenhouses (from now on, greenhouse tomato). Since the ECREA-FADN does not specify whether conventional or organic practices are applied, conventional farming is assumed for every system, which is the prevailing system in Spain. In 2017, the last year considered in this study, only 12 % of the Spanish cultivated surface area corresponded to organic farming, and, concerning the case studies, 9.15 % and 4.07 % of the vegetables and citrus surface area was devoted to organic vegetables and citrus fruit (MAPA, 2017, 2018a). The raw data from ECREA-FADN used to assess orange and tomato production in Spain for each management system is detailed in SM-1.

2.1. System boundaries and functional unit

The approach is restricted to the farming stage; system boundaries are, thus, set at the farm gate, including all the relevant stages from the production of raw materials to the farm gate (Fig. 1). To consider yield effects, results are expressed on a mass basis, taking 1 kg of the product as the functional unit (FU). Transport of agricultural inputs from the production and/or selling points to the farm is not taken into account due to lack of information (e.g. distance travelled, type of vehicle used). In addition, LCA literature on agricultural products shows that the contribution of this transport to the total environmental loads is not relevant (Escobar et al., 2022; Tassielli et al., 2018; Vázquez-Rowe et al., 2017).

2.2. Estimation of activity data for the life cycle inventory

The activity data for the LCI of each assessed system (i.e. input consumption and on-field emissions) have been estimated from ECREA-FADN data, supplemented with information from other official sources and scientific literature. The approach applied to develop the LCI is described below.

2.2.1. Greenhouse and irrigation system structure

To estimate the environmental burdens from building and managing the greenhouse structure, as well as from setting up the irrigation system, inventory data on the consumption of material needed to build the greenhouse frame are taken from Antón et al. (2013). According to personal communication with experts in irrigation and greenhouse infrastructures, steel "*Parral*" frame is considered for the reference holdings in the region of Andalucía and multi-tunnel frame for the remaining NUTS 2. Assuming that the ventilation is naturally supplied, only the electricity to operate the vents is taken into account in the management of the greenhouse structure.

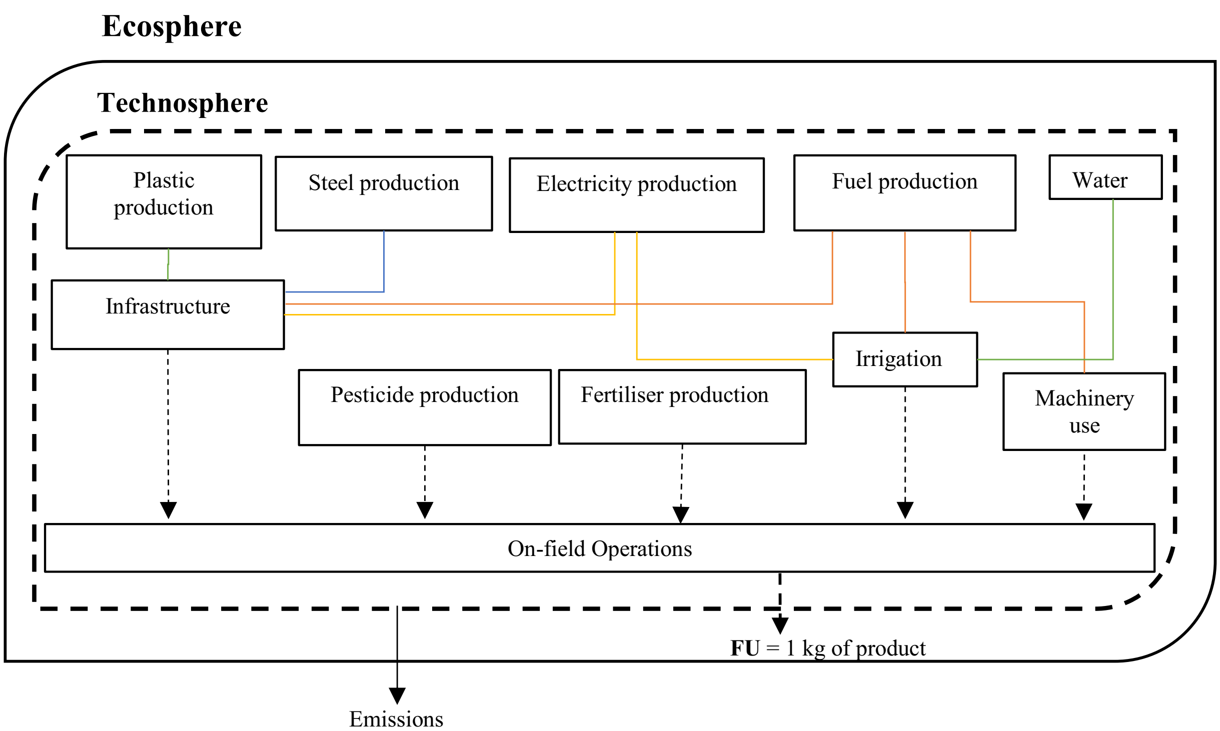

Fig. 1. System boundaries for the environmental assessment of the orange and tomato crops in Spain in the period 2010–2017.

This energy consumption, as well as the consumption of materials necessary for the building of the irrigation system for greenhouse crops, is taken from Antón et al. (2014). For irrigated open-field crops, the consumption of the materials required to build the irrigation system is taken from Martin-Gorriz et al. (2020).

2.2.2. Fertiliser consumption

A linear programming method is applied to estimate the quantity of fertiliser products required to satisfy the macronutrient supplied to the crops, as the type of fertiliser used is not specified in ECREA-FADN reports. The optimisation is constrained to the fertiliser expenses paid on each reference holding, while minimising the overall cost for that crop. To this end, in this study the "linprog" package (Henningsen, 2022), available for R v4.1.3 programming language is used.

To configure the linear programme, the amount spent on fertilisers and the amount of macronutrient applied to each reference holding (nitrogen, phosphorus, and potassium) are taken from ECREA reports, together with price paid by farmers to purchase the fertilisers available at the Spanish market in the corresponding year (MAPA, 2022a, 2022b) and the macronutrient content of each fertiliser taken from MARM (2010). The volatility of the market is a critical issue that could affect the impact estimation when using economic data (Pradeleix et al., 2022). For that reason, the average price of the fertilisers for each year assessed was used. In turn, the intra-annual volatility of the fertilisers' price was evaluated and it was found that, on average, the standard deviation relative to the mean (RSD) of the monthly price paid by farmers is 3 % and that the maximum RSD found is 14 %. These RSD values suggest a low intra-annual volatility of fertilisers' price; in consequence, for each year assessed, the corresponding average price paid by farmers to purchase the fertiliser was used as the value in the linear programmes. Manure and other organic fertilisers are not considered due to the lack of systematic information on their market value. The linear programme (Eqs. (2.1) to (2.6)) follows the structure below:

$$Min\, f\ (X_1 \ldots X_n) = C_1X_1 + \ldots + C_nX_n \tag{2.1}$$

Subject to:

$$a_{11}X_1 + \ldots + a_{1n}X_n \geq b_1 \tag{2.2}$$

$$a_{21}X_1 + \ldots + a_{2n}X_n \geq b_2 \tag{2.3}$$

$$a_{31}X_1 + \ldots + a_{3n}X_n \geq b_3 \tag{2.4}$$

$$a_{41}X_1 + \ldots + a_{4n}X_n \leq b_4 \tag{2.5}$$

$$X_1, \ldots, X_n \geq 0 \tag{2.6}$$

being:

$f\ (X_1 \ldots X_n)$: goal function, which represents the minimum cost (€·ha^{-1}·yr^{-1}) of fertilisers necessary to satisfy the macronutrients supplied to the studied crops, which cannot be higher than the fertiliser expenses from ECREA-FADN.

X_i: quantity of fertiliser i (kg of fertiliser·ha^{-1}·yr^{-1}).

C_i: coefficient of the goal function, which represents the price paid by farmers to purchase the fertiliser i (€·kg of fertiliser^{-1}).

a_{ji}: technical coefficients that represent the N, P_2O_5 and K_2O content (in kg·kg of fertiliser^{-1}) and cost (in €·kg of fertiliser^{-1}) of fertiliser i.

b_j: column vector that represents the minimum kg of N, P_2O_5, and K_2O supplied to the crop (in kg·ha^{-1}·yr^{-1}) and the total fertiliser expenses (€·ha^{-1}·yr^{-1}).

The quantity of each fertiliser is divided by the crop yield (kg of cropping product·ha^{-1}·yr^{-1}) so it may be expressed according to the functional unit (kg of fertiliser·FU^{-1}).

2.2.3. Pesticide consumption

Although ECREA-FADN provides information on the total expense on pesticides for each crop, in this case, linear programming is not used to estimate pesticide consumption because its application responds to complex and variate goal decisions compared to those considered in the linear programmes for fertiliser consumption. Pesticide consumption is, thus, obtained from the most up-to-date survey available when the study was performed. This survey was developed by the Spanish Ministry of Agriculture, Fisheries and Food (MAPA, 2021) and shows the mean consumption per hectare of different active substances applied to a set of crops (barley, citrus, sunflower, vegetables, olive, wheat and grape). In this survey, the active substances are rated in six categories, namely, fungicides and bactericides, herbicides, insecticides and miticides, molluscicides, growth vegetables regulators and other pesticides. For the sake of simplicity, 75 % of the most widely-used substances are taken for each type of crop. As the only available database concerns the year 2019, each active substance has been checked against the regulation in force in Spain for each studied year to check if it was permitted (MAPA, 2022c).

2.2.4. On-field operations

This section describes the methods used to estimate the emissions to air, soil and freshwater from fertiliser and pesticide applications. Machinery use and irrigation activities also imply natural resource consumption and emissions to the environment during field operations. However, these activities are considered separately in Sections 2.2.5 and 2.2.6.

2.2.4.1. On-field fertiliser emissions. On-field emissions from fertiliser application are estimated following different approaches. Ammonia (NH_3) and nitrogen oxide (NO_x) emissions to air are calculated following Tier 2 and Tier 1, respectively, of the most recent air pollutant emission inventory guidebook of the European monitoring and evaluation programme of the European Environmental Agency (EMEP/EEA) (Hutchings et al., 2019). PO_4^{3-} and NO_3^- emissions to surface and underground waters are estimated by using the rates (%) of phosphorus and nitrogen loss from the respective balances corresponding to each NUTS 2 (MAPA, 2018b, 2018c). N_2O emissions are calculated following IPCC Guidelines (Hergoualc'h et al., 2019; Paciornik et al., 2019), where Tier 2 emission factors to estimate direct N_2O emissions are taken from Cayuela et al. (2017), according to the irrigation management (rainfed or irrigated crops).

2.2.4.2. On-field pesticide emissions. To assess the impact of the toxicity potential of pesticide emissions, accurate estimations of the fraction of applied pesticide emitted to the different environmental compartments are required. The PestLCI model (Dijkman et al., 2012), which subsequently became the PestLCI Consensus (Fantke et al., 2017) is the pesticide emission model currently applicable for LCA, incorporating the state-of-the-art (Gentil et al., 2020).

Following the recommendations of Fantke et al. (2017), the primary distribution of pesticides emitted to the environmental compartments (namely air, field soil surface, field crop leaf surface and off-field surfaces) immediately after pesticide application is used as a direct input for the LCI. To this end, by using Eq. (4.1), the active substance (*AS*) emitted to compartment c ($E_{AS,\,c}$, kg *AS* in c·FU^{-1}) is calculated from the dose of *AS* applied ($E_{app,\,AS}$, kg *AS* FU^{-1}) and the fraction of *AS* that goes to compartment c ($EF_{AS,\,c}$, kg *AS* in c·kg *AS* applied^{-1}) obtained from Melero et al. (2020). Following personal communication with an expert, and considering that the PestLCI Consensus is configured just for modelling open field pesticide application (Gentil et al., 2020), 0.05 % of *AS* is assumed to be jointly emitted to air and off-field compartments in the case of greenhouse systems. This 0.05 % is then proportionally distributed between air and off-field compartments. Accordingly, the initial fraction of pesticide to air and off-field compartments is then distributed between the field soil surface and the crop leaf compartments.

$$E_{AS,c} = E_{app,AS} \cdot EF_{AS,c} \tag{4.1}$$

The results of the PestLCI Consensus are harmonised with the USEtox characterisation factors (CFs) (Gentil et al., 2020). To this end, the primary distribution to air ($E_{AS,air}$) and field soil ($E_{AS,field}$) from the PestLCI Consensus is related to USEtox CFs for continental rural air and agricultural soil, respectively. In addition, the primary distribution to off-field surfaces is related to USEtox CFs for continental agricultural soil, natural soil (including urban areas) and freshwater, according to the share of the surface area of each compartment in each NUTS 2.

The share of the surface area of agricultural soil (f_{agri}), freshwater (f_{fw}) and natural soil (f_{nat}) for each NUTS 2 is calculated by applying Eqs. (4.2) to (4.4), using the total surface area (A_{total}, ha), agricultural area (A_{agri}, ha) and freshwater area (A_{fw}, ha) of each NUTS 2, obtained from the Spanish Ministry of Agriculture, Food and Environment (MAGRAMA, 2012a, 2013b, 2013a, 2014a, 2015a; MAPA, 2016, 2017; MARM, 2011).

$$f_{agri} = \frac{A_{agri}}{A_{total}} \tag{4.2}$$

$$f_{fw} = \frac{A_{fw}}{A_{total}} \tag{4.3}$$

$$f_{nat} = 1 - f_{agri} - f_{fw} \tag{4.4}$$

The primary distribution of pesticide on crop leaf surface from the PestLCI Consensus was not taken into account because the toxicity caused by food intake is not modelled in USEtox.

2.2.5. Fuel consumption for machinery use

To estimate the consumption of type B diesel by machinery use (F_D, l·FU^{-1}) in on-field operations, the expense on fuel from ECREA-FADN (C, €·ha^{-1}·yr^{-1}) is divided by the market value (MV, €·l^{-1}) of type B diesel in each NUTS 2 obtained from MITECO (2022) and by the holding reference yield (Y, kg·ha^{-1}) (Eq. (5.1)):

$$F_D = \frac{C}{MV} \cdot \frac{1}{Y} \tag{5.1}$$

It must be noted that, in ECREA-FADN, fuel and lubricant expenses are gathered in the same item; nevertheless, considering expert recommendations, they are assumed to correspond to fuel expenses since the expense on lubricants tends to be irrelevant.

The consumption of fuel for irrigation purposes is not accounted for in this heading of ECREA-FADN. This may be due to the fact that electric pumps are mostly used nowadays in Spain (Espinosa-Tasón et al., 2020) and also because when water is supplied by irrigation consortiums (quite common in Spain) the energy cost is included in the price paid to them.

2.2.6. Irrigation

This section refers to the estimation of the activity data as regards irrigation (water requirements and energy consumption). In particular, the water requirement is estimated as the crop water requirement under soil water stress conditions, following Allen et al. (1998); and the energy needed for irrigating the crops is estimated by following Daccache et al. (2014) and Espinosa-Tasón et al. (2020). The procedure used to obtain these inventory data is detailed in SM-2.

2.3. Impact categories and impact assessment methods

The impact categories usually evaluated in agri-food LCAs (Sinisterra-Solís et al., 2020) are studied: these are climate change (CC), as kg CO_2 eq.; fine particulate matter formation (FPMF) as kg PM2.5 eq.; fossil depletion (FD), as kg oil eq.; metal depletion (MD), as kg Cu eq.; freshwater eutrophication (FwE), as kg P eq.; marine eutrophication (ME), as kg N eq.; terrestrial acidification (TA), as kg SO_2 eq.; photochemical ozone formation, ecosystems (POFe), as kg NO_x eq.; photochemical ozone formation, human health (POFh) as kg NO_x eq.; stratospheric ozone depletion (SOD), as kg CFC-11 eq.; land use (LU), as annual crop eq.·y; ionising radiation (IR), as Bq C-60 eq. to air; ecotoxicity (ET), as CTUe; human toxicity cancer and non-cancer (HTc and HTnc), as CTUh; and water scarcity (WS), as m^3 world eq. Toxicity related impact categories were characterised through USEtox 2.12 (Hauschild et al., 2008; Rosenbaum et al., 2008), water scarcity with AWARE 1.2c (Boulay et al., 2018), and ReCiPe 2016 v1.1 (Huijbregts et al., 2017) was used for the remaining categories. ReCiPe impact categories are assessed under the three perspectives: individualist (I), egalitarian (E) and hierarchist (H) (Huijbregts et al., 2017).

GaBi professional v10 software is used to estimate the impact categories associated with a unit of input consumed or on-field emission generated, except ET and HT from on-field emissions of pesticides and WS from irrigation activities. In particular, the interim CFs available in USEtox 2.12 (USEtox, 2019) are used to compute the effects of on-field pesticide emissions in HTc, HTnc and ET since for many of the active substances used there are no recommended CFs available. It must also be highlighted that the toxicity of some active substances is not assessed because no CFs were found in the literature (see Table TI-5 on SM-4).

For upstream processes, WS is evaluated by using the CFs corresponding to the OECD regional average for unspecified water. On the other hand, as this study is framed at subnational level and the main water consumption is for irrigation purposes, subnational CFs for agriculture, from Boulay and Lenoir (2020), are used to calculate the WS associated with irrigation; in this way, the representativeness of the CFs is improved and their uncertainty reduced (Sphera, 2022b).

2.4. Uncertainty analysis

The uncertainty associated to some input data is estimated so as to obtain comprehensive impact results. Many information sources, assumptions, and modelling choices are required to model the uncertainty, these are the main uncertainty sources in LCAs (Huijbregts, 1998). According to Sphera (2022a), the uncertainty of upstream processes and of the CFs is not considered because it is not practical and it is assumed they are developed through good practices.

The uncertainty analysis is carried out by using the Monte Carlo simulation technique, applying 1000 simulations for each input parameter. For the simulations, a 95 % confidence level and 5 % significance level are considered, which means that the confidence interval of each parameter is defined by the lower limit (LL) in the 2.5 percentile and the upper limit (UL) in the 97.5 percentile (Kuenen and Dore, 2019). As the distribution of many parameters is unknown and values lower than zero do not make practical sense, a triangle or uniform distribution is assumed; in fact, these are non-parametric distributions that allow the establishing of limits deterministically. The Monte Carlo simulation setting of each data and the input data sources are shown in Table 1.

2.5. Software

Excel spreadsheets (Microsoft Co.) are used to gather the information. Following Wickham and Grolemund (2016), R programming language (R Core Team, 2021) and RStudio interface (RStudio Team, 2022) are used to operate the data (tidying, transforming, visualisation and modelling operations). As well as R base functions, additional packages are used, namely "cowplot" v1.1.1 (Wilke, 2020), "DescTools v0.99.43" (Signorell et al., 2022), "effectsize" v0.5 (Ben-Shachar et al., 2020, 2022), "feather" v0.3.5 (Wickham et al., 2019b), "ggsci" v2.9 (Xiao and Li, 2018), "lawstat" v3.4 (Gastwirth et al., 2020), "linprog" v0.9.2 (Henningsen, 2022), "lmtest" v0.9.39 (Hothorn et al., 2022), "openxlsx" v4.2.4 (Schauberger et al., 2021), "rstatix" v0.7.0 (Kassambara, 2021), "showtext" v0.9.5 (Qiu, 2022), "tidyverse" v1.3.1 (Wickham et al., 2019a; Wickham and RStudio, 2021), "triangle" v0.12 (Carnell, 2019).

2.6. Data types and quality requirements

The input data used in this approach to estimate the LCIs come from different sources. As shown in Section 2.2, on-field activity data (i.e. dose of

Table 1
Data source and quality of the input data used to develop the LCI for the environmental assessment of the reference holdings at the NUTS 2 level in Spain, together with the Monte Carlo simulation setting of each data.

Data input	Related equation	Monte Carlo simulation setting	Source	Quality
Yield (Y)	Eqs. (5.1), (SM-2.5)	*	ECREAs	Very good
Infrastructure				
Material consumption		Triangle distribution [a, b, c]	Antón et al. (2014, 2013); Martin-Gorriz et al. (2020)	Good
Fertiliser consumption				
Market value of fertiliser products ($C_1 \ldots C_n$)	Eq. (2.1)	*	(MAPA, 2022a, 2022b)	Very good
Minimum N, P_2O_5 and K_2O supply to the crop and maximum fertiliser expense (b_1, b_2, b_3, b_4)	Eqs. (2.1) to (2.5)	*	ECREAs	Very good
N, P_2O_5 and K_2O content and cost of the fertiliser products (a_{11}, …, a_{4n})	Eqs. (2.1) to (2.5)	*	ECREAs	Very good
Pesticide consumption				
Dose of pesticide product ($E_{app,\ AS}$)	Eq. (4.1)	*	(MAPA, 2021)	Good
Fertiliser emissions				
Tier 2 NH_3 emission factors		Triangle distribution [a, b, c]	(Hutchings et al., 2019; Kuenen and Dore, 2019)	Very good
Tier 1 NOx emission factor		Triangle distribution [a, b, c]	(Stehfest and Bouwman, 2006)	Good
Tier 2 direct N_2O emission factors		Triangle distribution [a, b, c]	(Cayuela et al., 2017)	Very good
Tier 1 indirect N_2O emission factors		Triangle distribution [a, b, c]	(Hergoualc'h et al., 2019; Paciornik et al., 2019)	Good
NO_3^-		*	(MAPA, 2018b, 2018c)	Good
$PO4_3^-$		*		Good
Pesticide emissions				
Pesticide active substance ($E_{app,\ AS}$)	Eq. (4.1)	*	(MAPA, 2021)	Good
Total agricultural area in the respective NUTS 2 (A_{agri}), Eq. (4.2)	Eq. (4.2)	*	(MAGRAMA, 2012a, 2013b, 2013a, 2014a, 2015a; MAPA, 2016, 2017; MARM, 2011)	Very good
Total area of the respective NUTS 2 (A_{total}), Eqs. (4.2) and (4.3).	Eqs. (4.2) and (4.3)	*		Very good
Total area corresponds to surface water in the respective NUTS 2. Eq. (4.3)	Eq. (4.3)	*		Very good
Fraction of AS that goes to compartment c ($EF_{AS,\ c}$)	Eq. (4.1)	Replace random sample from the primary distribution values estimated by PestLCI Consensus model.	(Melero et al., 2020)	Very good
Machinery				
Fuel expenses (C)	Eq. (5.1)	*	ECREAs	Very good
Fuel market value (MV)	Eq. (5.1)	Uniform distribution [a, b]	(MITECO, 2022)	Very good
Water for irrigation				
Rooting depth (Z_r)	Eq. (SM-2.1)	Uniform distribution [a, b]	(Allen et al., 1998)	Very good
Water in the soil ($\theta_{FC} - \theta_{WP}$)	Eq. (SM-2.1)	Triangle distribution [a, b, c]	(ESDAC, 2020; Jones et al., 2020)	Very good
Soil water depletion fraction for no stress (p)	Eq. (SM-2.2)	Triangle distribution [a, b, c]	(Allen et al., 1998)	Good
Precipitations (P_i)	Eq. (SM-2.3)	Triangle distribution [a, b, c]	(SIAR, 2022)	Very good
Crop reference evapotranspiration (ET_o)	Eq. (SM-2.4)	Triangle distribution [a, b, c]		Very good
Crop coefficient (K_c)	Eq. (SM-2.4)	Triangle distribution [a, b, c]		Very good
Power for irrigation				
Pump efficiency (μ_{pump})	Eqs. (SM-2.7) and (SM-2.8)	Triangle distribution [a, b, c]	(Daccache et al., 2014)	Good
Friction losses (p_l)	Eq. (SM-2.9)	Triangle distribution [a, b, c]		Good
Pressure required to transport the water from the source because of gravity energy (p_{W_s})	Eq. (SM-2.9)	*	(Espinosa-Tasón et al., 2020)	Good
Standard operating pressure associated with furrow method (p_m)	Eq. (SM-2.9)	*		Good
Standard operating pressure associated with sprinkler method (p_m)	Eq. (SM-2.9)	*		Good
Standard operating pressure associated with drip method (p_m)	Eq. (SM-2.9)	*		Good
Pressure required to lift surface water (l_{W_s})	Eq. (SM-2.10)	*		Good
Pressure required to lift groundwater (l_{W_s})	Eq. (SM-2.10)	Triangle distribution [a, b, c]		Good
Efficiency of diesel motor (μ_{Dm})	Eq. (SM-2.11)	Triangle distribution [a, b, c]	(Daccache et al., 2014)	Good
Efficiency of electric motor (μ_{Em})	Eq. (SM-2.11)	Triangle distribution [a, b, c]		Good
Conveyance efficiency (μ_{conv})	Eq. (SM-2.22)	Triangle distribution [a, b, c]	(Espinosa-Tasón et al., 2020)	Good
Distribution efficiency (μ_{dis})	Eq. (SM-2.22)	Triangle distribution [a, b, c]		Good
Furrow efficiency method (μ_{fs})	Eq. (SM-2.21)	Triangle distribution [a, b, c]	(Berbel et al., 2018; Daccache et al., 2014;	Good
Sprinkler efficiency method (μ_{ss})	Eq. (SM-2.21)	Triangle distribution [a, b, c]	Espinosa-Tasón et al., 2020; Phocaides, 2007)	Good
Drip efficiency method (μ_{ds})	Eq. (SM-2.21)	Triangle distribution [a, b, c]		Good
Number of diesel engines for irrigation ($Diesel\_motors$)	Eqs. (SM-2.12) and (SM-2.13)	*	(Espinosa-Tasón et al., 2020)	Good
Number of electric engines for irrigation ($Electric\_motors$)	Eqs. (SM-2.12) and (SM-2.13)	*		Good
Desalinated water used in agriculture (W_d)	Eqs. (SM-2.15) and (SM-2.16)	*		Good
Reclaimed water used in agriculture (W_r)	Eqs. (SM-2.15) and (SM-2.16)	*		Good
Energy consumption for the use of desalinated water (E_d)	Eq. (SM-2.14)	*		Good
Energy consumption for the use of reclaimed water (E_r)	Eq. (SM-2.14)	*		Good
Available water from surface source (W_s)	Eqs. (SM-2.10) and (SM-2.20)	*	(INE, 2022a, 2022b)	Very good

Table 1 (*continued*)

Data input	Related equation	Monte Carlo simulation setting	Source	Quality
Available water from ground source (W_g)	Eqs. (SM-2.10) and (SM-2.20)	*		Very good
Desalinated and reclaimed water for irrigation (W_{treat})	Eq. (SM-2.17)	*		Very good
Total water availability ($W_{total\_sources}$)	Eq. (SM-2.17)	*		Very good
Water irrigated using furrow method (W_{fm})	Eq. (SM-2.17)	*		Very good
Water irrigated using sprinkler method (W_{sm})	Eq. (SM-2.17)	*		Very good
Water irrigated using drip method (W_{dm})	Eq. (SM-2.17)	*		Very good
Total water irrigated (W_{tm})	Eq. (SM-2.17)	*		Very good
Area irrigated using furrow method (A_{fm})	Eq. (SM-2.21)	*	(MAGRAMA, 2012a, 2013b, 2013a, 2014a, 2015a; MAPA, 2016, 2017; MARM, 2011)	Very good
Area irrigated using sprinkler method (A_{sm})	Eq. (SM-2.21)	*		Very good
Area irrigated using drip method (μ_{dm})	Eq. (SM-2.21)	*		Very good
Total irrigated area (A_{total})	Eq. (SM-2.21)	*		Very good
Characterisation factors (CF)				
USEtox characterisation factors for on-field pesticide emissions		*	(USEtox, 2019)	Very good

a = Lower limit; b = Upper limit; c = Recommended value.
* Parameter uncertainty not assessed.

inputs used and on-field emissions) are obtained from official sources, current scientific literature, and consensus models for on-field emissions. Upstream processes (production of the different inputs used) are modelled by using Ecoinvent v3.8 (Wernet et al., 2016) and GaBi DB (SPHERA, 2022a) databases (see SM-2). When assessing the quality of input data following the recommendations from the European Commission (EU, 2013; Hauschild et al., 2011), the quality of most of the data is generally classified as very good and good; nevertheless, the data from Ecoinvent and GaBi DB are classified as being of basic quality. Table 1 summarises the features of the input data used to develop the LCI. The Data in Brief article associated is an integral part of this study, as it shows both the dataset used and the comprehensive procedure employed to model the approach proposed in this article.

2.7. Description of the case studies as regards tomato and orange production

Eight reference holdings have been configured from the ECREA reports corresponding to the years studied. Three of them correspond to orange production in Andalucia (AN), Murcia (MC) and Comunidad Valenciana (VC); four to the production of greenhouse tomatoes in AN, Castilla-La Mancha (CM), MC and VC; and the last holding corresponds to the production of open-field tomatoes in CM. Although the period under study ranges from 2010 to 2017, due to data availability, the number of years considered to evaluate the reference holdings varies depending on the crop (see the last column in Table 2).

Table 2 shows that orange reference holdings display an average yield ranging from 30.7 t of oranges·ha^{-1}·yr^{-1} in AN to 23.1 t of oranges·ha^{-1}·yr^{-1} in VC; likewise, the mean surface area of the holdings in AN and MC is 13.71 ha·holding^{-1} and 20.92 ha·holding^{-1}, respectively; in VC, whereas, smallholdings prevail, with 2.96 ha·holding^{-1}. As to the tomato crop, in the case of the greenhouse system, the average yield ranges from 114.15 t of tomato·ha^{-1}·yr^{-1} in MC to 41.99 t of tomato·ha^{-1}·yr^{-1} in VC with an average holding surface of 2.08 ha·holding^{-1} in AN and 0.33 ha·holding^{-1} in VC. Open-field tomatoes in CM show an average yield of 37.8 t of tomato·ha^{-1}·yr^{-1}, lower than in the case of the greenhouse system, and an average surface area of 1.69 ha·holding^{-1}.

Table 2
The main characteristics of the tomato and orange cropping systems in the principal Spanish NUTS 2 producers, 2010–2017. Data retrieved from SM-1.

NUTS 2	System	Yield (kg·ha^{-1}·yr^{-1})		Surface (ha)		Number of years
		Mean	Sd	Mean	Sd	
Orange						
Andalucía (AN)	Open-field	30,668	3006	13.71	7.40	8
Comunidad Valenciana (VC)	Open-field	23,101	2357	2.96	0.35	8
Región de Murcia (MC)	Open-field	27,237	9731	20.92	7.79	8
Tomato						
Andalucía (AN)	Greenhouse	88,255	6502	2.08	0.47	7
Castilla-La Mancha (CM)	Greenhouse	87,942	7151	0.48	0.07	5
Comunidad Valenciana (VC)	Greenhouse	41,993	202	0.33	0.06	7
Región de Murcia (MC)	Greenhouse	114,146	13,389	1.73	1.16	7
Castilla-La Mancha (CM)	Open-field	37,806	8332	1.69	0.29	5

Sd: standard deviation.

The results of the activity data for the reference holdings obtained by applying the approach explained in Section 2.2 are shown in SM-3. This data is subsequently used to estimate the midpoint impact categories described in Section 2.4. To simplify the analysis, only CC (for hierarchic perspective), ET, HTnc and SW scores are analysed in the following section since the greatest effort in the LCI stage has been devoted to setting the inventory items with explicit and meaningful influence in these impact categories. The impact results for the remaining categories listed in Section 2.4 are detailed in SM-4.

The results of the environmental impacts are shown below. As the uncertainty of the impacts has been modelled from non-parametrical distributions in the input data, the results are assumed to be non-normally distributed. Therefore, besides the mean and standard deviation or variance (mainly used as central tendency and dispersion indicators), the median and interquartile ranges are shown, as they will be used to express the reference results and their uncertainty, respectively.

3. Results of the case studies on tomatoes and oranges and discussion

3.1. Average environmental impacts of orange production

The average environmental impact scores of orange production in the reference holdings defined for the main producing NUTS 2 in Spain are summarised in Table 3 and Fig. 2. These results include the uncertainty simulated from the LCI parameters, which is detailed in SM-2, as well as the interannual variability according to the years studied. Descriptively, it may be observed that MC exhibits the highest WS score, 53 % greater than AN (the lowest). As for ET, HTnc and CC, VC impacts the most, 25 %, 5 %, and 34 % greater than the lowest (AN for ET and HTnc, and MC for CC). These differences can be explained by the different marginal resource consumption of the reference holdings (yield differentials), as well as by the differences in the precipitation and reference evapotranspiration between the NUTS 2, particularly in the case of WS. As to the uncertainty, analysed by using the interquartile range relative to the median, it may be seen that the orange crop in MC shows the greatest dispersion in terms of WS, ET, and HTnc, whereas as regards CC, AN has the most widely dispersed values.

The contribution analysis (Fig. 3) shows that, on average, 99 % of the WS is caused by irrigation, and 92 % and 97 % of ET and HTnc, respectively, are due to pesticide on-field emissions. The contribution of each stage to CC is different depending on the NUTS 2; the stages that contribute most are machinery use (32 %), fertiliser production (27 %) and on-field operations (17 %) in AN; fertiliser production (32 %), on-field operation

Table 3
Average impacts of orange crops in the main NUTS 2 producers in Spain, years 2010 to 2017.

Impact category	NUTS 2	Impact per kg of product^{-1}							
		Mean	Median	SD	IQR	RSD	RIQR	$P_{2.5}$	$P_{97.5}$
Blue water scarcity (WS: m^3 world eq.·FU^{-1})	Andalucía (AN)	$1.14 \cdot 10^{1}$	$1.14 \cdot 10^{1}$	2.12	3.02	19 %	26 %	7.34	$1.55 \cdot 10^{1}$
	Comunidad Valenciana (VC)	$1.35 \cdot 10^{1}$	$1.34 \cdot 10^{1}$	2.37	3.23	18 %	24 %	9.4	$1.87 \cdot 10^{1}$
	Región de Murcia (MC)	$1.67 \cdot 10^{1}$	$1.74 \cdot 10^{1}$	4.79	7.45	29 %	43 %	8.19	$2.52 \cdot 10^{1}$
Freshwater ecotoxicity (ET: CTUe·FU^{-1})	Andalucía (AN)	$5.83 \cdot 10^{-3}$	$5.61 \cdot 10^{-3}$	$1.93 \cdot 10^{-3}$	$2.54 \cdot 10^{-3}$	33 %	45 %	$2.88 \cdot 10^{-3}$	$1.05 \cdot 10^{-2}$
	Comunidad Valenciana (VC)	$7.45 \cdot 10^{-3}$	$7.03 \cdot 10^{-3}$	$2.54 \cdot 10^{-3}$	$3.24 \cdot 10^{-3}$	34 %	46 %	$3.59 \cdot 10^{-3}$	$1.35 \cdot 10^{-2}$
	Región de Murcia (MC)	$6.53 \cdot 10^{-3}$	$6.30 \cdot 10^{-3}$	$2.59 \cdot 10^{-3}$	$3.57 \cdot 10^{-3}$	40 %	57 %	$2.46 \cdot 10^{-3}$	$1.28 \cdot 10^{-2}$
Climate change (CC: kg CO_2 eq.·FU^{-1})	Andalucía (AN)	$1.96 \cdot 10^{-1}$	$1.89 \cdot 10^{-1}$	$3.55 \cdot 10^{-2}$	$6.62 \cdot 10^{-2}$	18 %	35 %	$1.47 \cdot 10^{-1}$	$2.57 \cdot 10^{-1}$
	Comunidad Valenciana (VC)	$1.99 \cdot 10^{-1}$	$1.94 \cdot 10^{-1}$	$2.39 \cdot 10^{-2}$	$3.00 \cdot 10^{-2}$	12 %	15 %	$1.62 \cdot 10^{-1}$	$2.56 \cdot 10^{-1}$
	Región de Murcia (MC)	$1.84 \cdot 10^{-1}$	$1.86 \cdot 10^{-1}$	$2.34 \cdot 10^{-2}$	$3.60 \cdot 10^{-2}$	13 %	19 %	$1.42 \cdot 10^{-1}$	$2.25 \cdot 10^{-1}$
Human toxicity non-cancer (HTnc: CTUh·FU^{-1})	Andalucía (AN)	$3.16 \cdot 10^{-11}$	$3.10 \cdot 10^{-11}$	$8.87 \cdot 10^{-12}$	$1.41 \cdot 10^{-11}$	28 %	46 %	$1.70 \cdot 10^{-11}$	$4.92 \cdot 10^{-11}$
	Comunidad Valenciana (VC)	$4.17 \cdot 10^{-11}$	$4.16 \cdot 10^{-11}$	$1.20 \cdot 10^{-11}$	$1.75 \cdot 10^{-11}$	29 %	42 %	$2.26 \cdot 10^{-11}$	$6.60 \cdot 10^{-11}$
	Región de Murcia (MC)	$3.82 \cdot 10^{-11}$	$3.72 \cdot 10^{-11}$	$1.39 \cdot 10^{-11}$	$2.33 \cdot 10^{-11}$	36 %	63 %	$1.43 \cdot 10^{-11}$	$6.41 \cdot 10^{-11}$

SD: standard deviation; IQR: interquartile range, RSD: relative standard deviation; RIQR: relative interquartile range, $P_{2.5}$: percentile 2.5; $P_{97.5}$: percentile 97.5.

(24 %) and infrastructure (18 %) in VC; and fertiliser production (33 %), irrigation (21 %), infrastructure (19 %) and on-field operations (19 %) in MC.

The interannual variability of the impacts of the reference holdings in each NUTS 2 does not show a clear trend through the years analysed (Fig. 4). In MC, WS and CC tend to increase during the first few years and then decrease from 2015 onwards; in AN, however, although CC scores decrease from 2010 to 2017, they do recover somewhat in 2015. These behaviours mainly respond to changes in the yield of the reference holdings. Other influential parameters are the precipitation in WS for every NUTS 2, the fuel consumption in CC for AN, and the nitrogen applied in CC for MC.

3.2. Environmental impacts of tomato production

The environmental impact scores resulting from tomato production in the reference holdings defined for the main NUTS 2 producers in Spain are summarised in Table 4 and Fig. 5. When comparing the NUTS 2 impact scores obtained for the greenhouse system in the four categories analysed, the impacts in VC are greater than in the other NUTS 2. Specifically, the medians obtained in VC for WS, ET, CC and HTnc scores are 383 %, 200 %, 136 % and 200 % greater, respectively, than those obtained in the NUTS 2 with the lowest impact, namely AN in the case of WS, and MC for ET, CC and HTnc. The impact scores from tomato production in CM show that the median scores are greater in the open-field system for WS, ET and HTnc (124 %, 200 % and 128 %, respectively), whereas the median of the CC score in the greenhouse system is 43 % greater. The differences between the CC, ET and HTnc scores of greenhouse tomato crops in the studied NUTS 2 and between WS, ET and HTnc of the two tomato cropping systems in CM mainly respond to the yields of the reference holdings. In addition to the yield of the reference holdings, evapotranspiration is a parameter that exerts an influence on the differences in the WS scores of

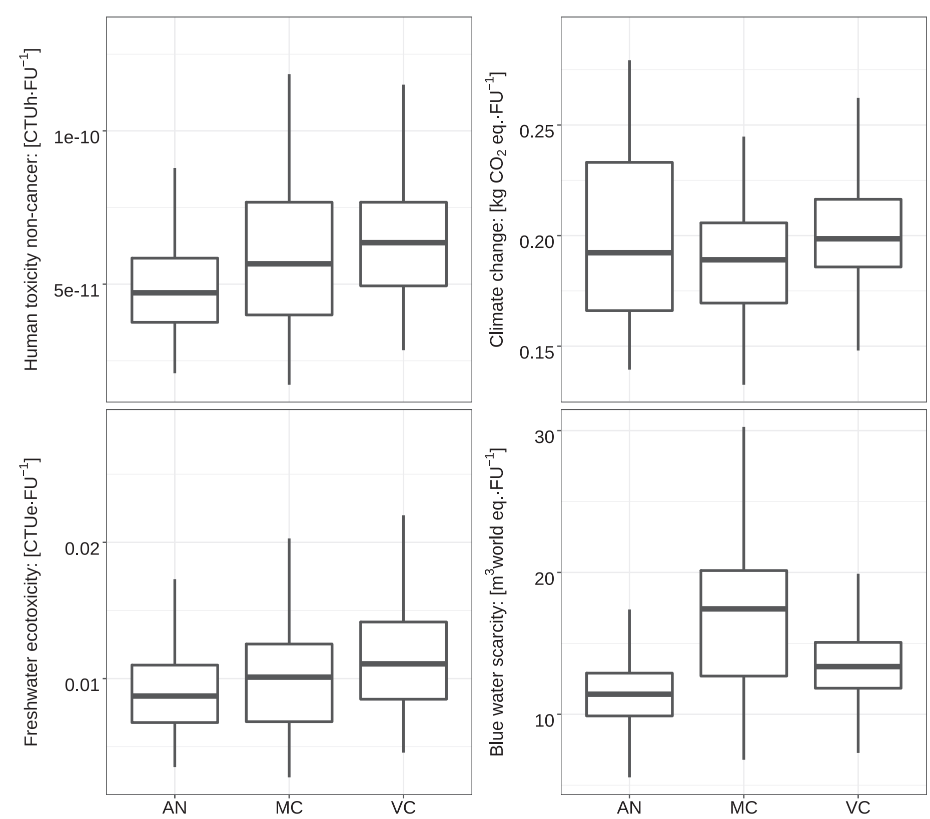

Fig. 2. Box and whisker plots of the aggregated environmental impacts of orange crops in the main NUTS 2 producers in Spain, in the period 2010–2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

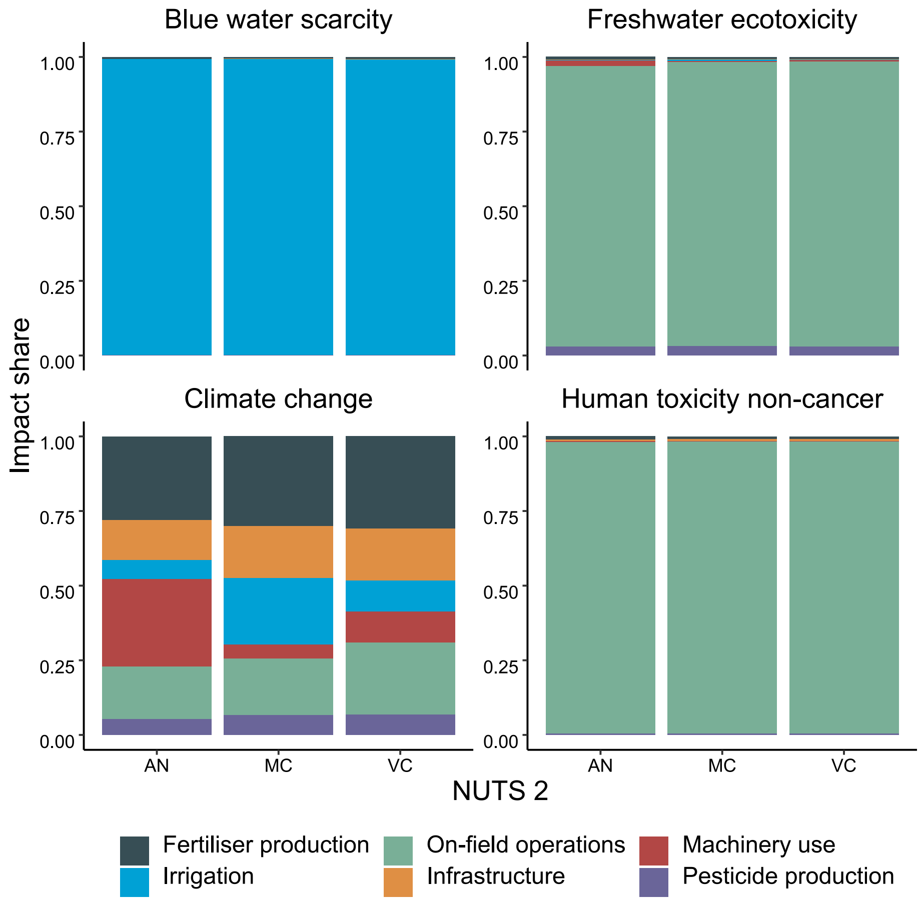

Fig. 3. Relative contribution of life cycle stages to the environmental impacts of orange crop in the main NUTS 2 producers in Spain, in the period 2010–2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

greenhouse tomato crops, while the infrastructure has a bearing on the differences in the CC scores of open-field tomatoes compared to greenhouse tomato crops in CM. When the uncertainty is analysed by using the interquartile range relative to the median, it may be observed that for greenhouse systems, the reference holdings of tomato cultivation with the greatest dispersion in their impact scores are those located in VC for WS, AN for ET and HTnc, and CM for CC. As to the reference holdings of CM, corresponding to the greenhouse and open field systems, the impact scores of open-field cropping present greater dispersion in every impact category analysed.

The contribution analysis (Fig. 6) shows that, as is the case with the orange crop, irrigation is the stage contributing the most to WS (98 % in the greenhouse systems and 99 % in the open-field system). Similarly, due to the on-field emissions of pesticide, on-field operations contribute the greatest share both in ET and HTnc (99 %). For the reference holdings in the greenhouse system, infrastructure (38 % in AN, 61 % in VC, 56 % in MC and 69 % in CM), fertiliser production (27 % in AN, 17 % in VC, 20 % in MC and 8 % in CM), and on-field operations (20 % in AN, 13 % in VC, 15 % in MC and 6 % in CM), are the stages that contribute the most to CC. On the other hand, for open-field tomatoes in CM, machinery use (31 %), infrastructure (23 %) and irrigation (22 %) are the stages with the greatest share in CC.

When analysing the evolution of the impact results in the years studied (Fig. 7), it may be clearly observed that WS, ET and HTnc scores for open-field tomato cropping in CM tend to increase from 2010 to 2013 and then decrease slightly in 2014. CC scores for on-field tomato cropping in CM, as well as the impact results in the remaining tomato reference holdings, do not show a consistent trend and instead suggest stationary behaviour around the average value.

3.3. Inferential statistics analysis of the environmental impacts of the reference holdings analysed

The analyses of both orange and tomato crops so far suggest differences between the results obtained for the different reference holdings when these are compared with other feasible alternatives. However, both visually and descriptively, it is not convenient to validate whether these differences become statistically significant. For instance, as can be seen in Figs. 2, 4, 5, and 7, many of the impact results of the reference holdings overlap, making it difficult to identify any potential differences. Thus, to assess the significance of the effect of the NUTS 2 and the type of cropping system on the estimated impact scores, one-way ANOVAs are designed. Orange reference holdings correspond to the open-field system, whereas tomatoes are grown in greenhouses in the four NUTS 2 and open-field in CM. Therefore, three tests are developed to analyse the global differences. The first evaluates the significance of the differences between the impacts of orange crops in the three NUTS 2. The second is the same but applied to greenhouse tomatoes. The third tests the significance of the differences between greenhouse tomatoes and those grown in the open-field system in CM.

Previous to the ANOVAs, non-extreme outlier values have been identified following Kassambara (2019), as the data come from simulations. Next, a residual analysis has been performed to test for the assumptions of a parametric one-way ANOVA. In addition, normality has been assessed using the Kolmogorov-Smirnov normality test for large samples, and the homogeneity of variances has been assessed using the Breusch-Pagan test. By considering a 5 % significance level in all comparisons, residuals show no normality distribution and there is no homogeneity of variances. As these assumptions are not fulfilled, the non-parametric Kruskal-Wallis test is used to assess, individually, the effects of both

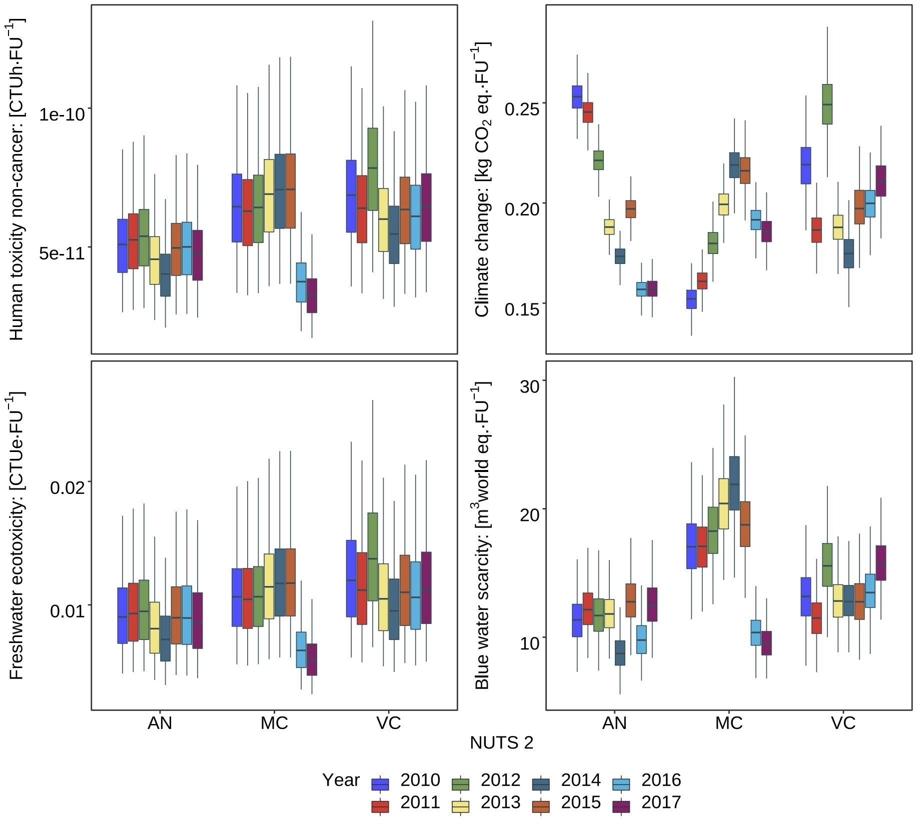

Fig. 4. Box and whisker plots of the aggregated environmental impacts of orange crops in the main NUTS 2 producers in Spain, in the period 2010–2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

the NUTS 2 and the system on the environmental impacts of orange and tomato reference holdings.

All Kruskal-Wallis tests are significant (p-value < 0.05), validating that, at least one of the alternatives evaluated shows results that are significantly different from the others. Following Ben-Shachar et al. (2022), rank epsilon squared (ε^2) is used as an indicator to evaluate the effect size of the differences found using the Kruskal-Wallis tests (Ben-Shachar et al., 2022). Table 5 shows that the largest effect size corresponds to comparisons between CC scores for greenhouse tomato holdings ($\varepsilon^2 = 0.81$), whereas the lowest corresponds to comparisons between CC scores for orange holdings ($\varepsilon^2 = 0.04$). Applying the rules proposed by Field (2013) and Ben-Shachar et al. (2022), the size of the differences found using the Kruskal-Wallis tests (effect size) is categorised as large, except in CC for orange crops in which case it is small and in WS and ET for orange crops in which cases it is medium.

In a post hoc analysis, multiple Dunn's pairwise comparisons tests to a 1 % significance level, with an applied Bonferroni adjustment, are run between

Table 4
Average impacts of tomato crops in the main NUTS 2 producers in Spain, in 2010–2017.

Impact category	NUTS 2	System	Impact per kg of tomato^{-1}							
			Mean	Median	SD	IQR	RSD	RIQR	$P_{2.5}$	$P_{97.5}$
Blue water scarcity (WS: m^3 world eq.·FU^{-1})	Andalucía (AN)	IG	2.82	2.74	$8.01 \cdot 10^{-1}$	1.13	28 %	41 %	1.5	4.53
	Castilla-La Mancha (CM)	IG	4.65	4.53	1.32	1.83	28 %	40 %	2.43	7.43
	Comunidad Valenciana (VC)	IG	$1.37 \cdot 10^{1}$	$1.33 \cdot 10^{1}$	4.14	5.74	30 %	43 %	6.93	$2.26 \cdot 10^{1}$
	Región de Murcia (MC)	IG	4.84	4.74	1.42	2.03	29 %	43 %	2.49	7.79
	Castilla-La Mancha (CM)	IO	$1.07 \cdot 10^{1}$	$1.01 \cdot 10^{1}$	3.8	5.31	36 %	52 %	4.95	$1.94 \cdot 10^{1}$
Freshwater ecotoxicity (ET: CTUe·FU^{-1})	Andalucía (AN)	IG	$7.38 \cdot 10^{-1}$	$6.77 \cdot 10^{-1}$	$2.46 \cdot 10^{-1}$	$3.49 \cdot 10^{-1}$	33 %	52 %	$4.14 \cdot 10^{-1}$	1.22
	Castilla-La Mancha (CM)	IG	$7.41 \cdot 10^{-1}$	$6.86 \cdot 10^{-1}$	$2.48 \cdot 10^{-1}$	$3.48 \cdot 10^{-1}$	33 %	51 %	$4.23 \cdot 10^{-1}$	1.23
	Comunidad Valenciana (VC)	IG	1.57	1.5	$5.49 \cdot 10^{-1}$	$7.20 \cdot 10^{-1}$	35 %	48 %	$7.62 \cdot 10^{-1}$	2.75
	Región de Murcia (MC)	IG	$5.74 \cdot 10^{-1}$	$5.00 \cdot 10^{-1}$	$1.94 \cdot 10^{-1}$	$2.45 \cdot 10^{-1}$	34 %	49 %	$2.87 \cdot 10^{-1}$	$9.01 \cdot 10^{-1}$
	Castilla-La Mancha (CM)	IO	2.21	2.06	$7.66 \cdot 10^{-1}$	1.05	35 %	51 %	1.07	3.97
Climate change (CC: kg CO_2 eq.·FU^{-1})	Andalucía (AN)	IG	$1.88 \cdot 10^{-1}$	$1.78 \cdot 10^{-1}$	$3.11 \cdot 10^{-2}$	$2.74 \cdot 10^{-2}$	17 %	15 %	$1.50 \cdot 10^{-1}$	$2.65 \cdot 10^{-1}$
	Castilla-La Mancha (CM)	IG	$1.37 \cdot 10^{-1}$	$1.35 \cdot 10^{-1}$	$2.04 \cdot 10^{-2}$	$3.12 \cdot 10^{-2}$	15 %	23 %	$1.04 \cdot 10^{-1}$	$1.77 \cdot 10^{-1}$
	Comunidad Valenciana (VC)	IG	$3.18 \cdot 10^{-1}$	$3.18 \cdot 10^{-1}$	$3.50 \cdot 10^{-2}$	$4.87 \cdot 10^{-2}$	11 %	15 %	$2.53 \cdot 10^{-1}$	$3.89 \cdot 10^{-1}$
	Región de Murcia (MC)	IG	$1.35 \cdot 10^{-1}$	$1.31 \cdot 10^{-1}$	$1.62 \cdot 10^{-2}$	$1.42 \cdot 10^{-2}$	12 %	11 %	$1.14 \cdot 10^{-1}$	$1.76 \cdot 10^{-1}$
	Castilla-La Mancha (CM)	IO	$9.65 \cdot 10^{-2}$	$9.44 \cdot 10^{-2}$	$1.82 \cdot 10^{-2}$	$2.34 \cdot 10^{-2}$	19 %	25 %	$6.60 \cdot 10^{-2}$	$1.30 \cdot 10^{-1}$
Human toxicity non-cancer (HTnc: CTUh·FU^{-1})	Andalucía (AN)	IG	$4.82 \cdot 10^{-9}$	$4.42 \cdot 10^{-9}$	$1.61 \cdot 10^{-9}$	$2.29 \cdot 10^{-9}$	33 %	52 %	$2.70 \cdot 10^{-9}$	$8.01 \cdot 10^{-9}$
	Castilla-La Mancha (CM)	IG	$4.84 \cdot 10^{-9}$	$4.48 \cdot 10^{-9}$	$1.63 \cdot 10^{-9}$	$2.28 \cdot 10^{-9}$	34 %	51 %	$2.76 \cdot 10^{-9}$	$8.07 \cdot 10^{-9}$
	Comunidad Valenciana (VC)	IG	$1.03 \cdot 10^{-8}$	$9.80 \cdot 10^{-9}$	$3.60 \cdot 10^{-9}$	$4.71 \cdot 10^{-9}$	35 %	48 %	$4.96 \cdot 10^{-9}$	$1.80 \cdot 10^{-8}$
	Región de Murcia (MC)	IG	$3.75 \cdot 10^{-9}$	$3.26 \cdot 10^{-9}$	$1.27 \cdot 10^{-9}$	$1.61 \cdot 10^{-9}$	34 %	49 %	$1.87 \cdot 10^{-9}$	$5.89 \cdot 10^{-9}$
	Castilla-La Mancha (CM)	IO	$1.12 \cdot 10^{-8}$	$1.02 \cdot 10^{-8}$	$4.29 \cdot 10^{-9}$	$5.51 \cdot 10^{-9}$	38 %	54 %	$5.42 \cdot 10^{-9}$	$2.23 \cdot 10^{-8}$

SD: standard deviation; IQR: interquartile range, RSD: relative standard deviation; RIQR: relative interquartile range, $P_{2.5}$: percentile 2.5; $P_{97.5}$: percentile 97.5.

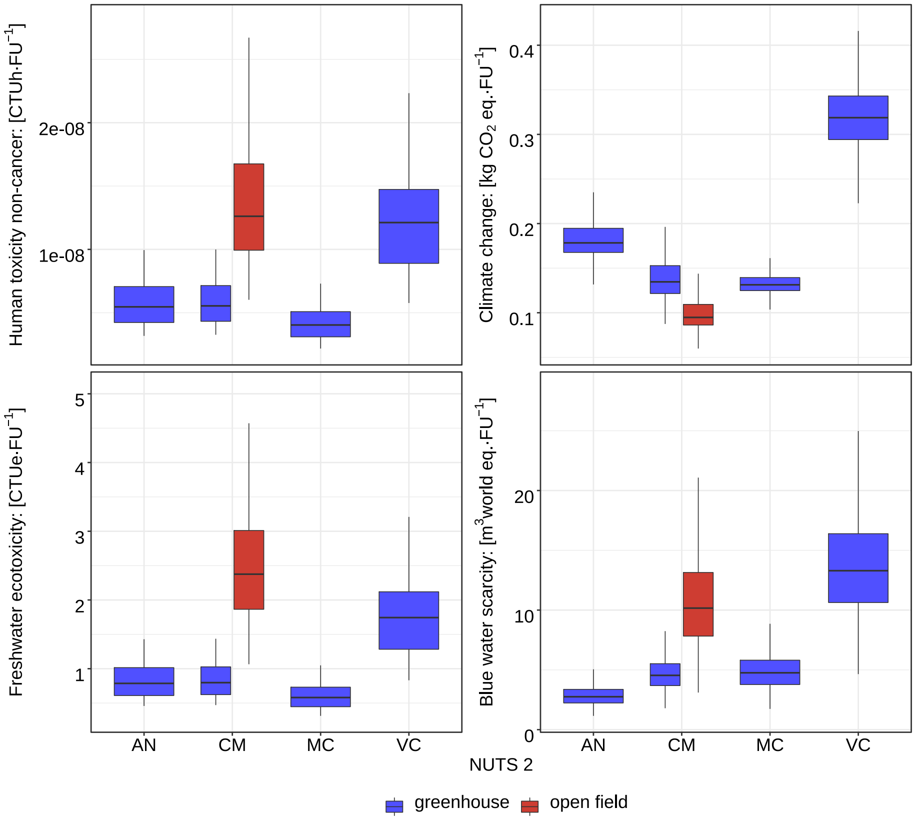

Fig. 5. Aggregated environmental impacts of tomato crops in the main NUTS 2 producers in Spain, in the period 2010–2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

different NUTS 2 and cropping systems in each year. Table 6 shows the results of the Dunn's tests. Negative Z-values mean that the average rank sum of the scores of the first group (Group 1) is significantly greater than that of the second group (Group 2), whereas positive Z-values have the opposite meaning, and "ns" means that non-significant differences are found in the pairwise comparison.

Table 6 shows that most of the pairwise comparisons of the environmental impact scores of the reference holdings are significant, showing differential results both between the lowest and highest scores and between the intermediate. Only for ET and HTnc scores do Dunn's tests suggest that there is not sufficient evidence to state that the impacts of the reference holdings of greenhouse tomatoes in CM are different from those in AN. These results complement the previously developed descriptive analysis and confirm that in the case of orange reference holdings, the worst environmental scores are those of MC in terms of WS and VC in the categories of ET, CC and HTnc, whereas the best results are those obtained by AN in the categories of WS, ET, and HTnc, and MC in that of CC. Similarly, it may be observed that the tomato reference holding in VC is a significantly worst environmental option in the greenhouse system, whereas the best option in the greenhouse system is AN in the case of WS and MC in the categories of ET, HTnc and in CC. When comparing reference holdings corresponding to open-field tomatoes vs greenhouse tomatoes in CM, the greenhouse system shows significantly lower scores in WS, ET and HTnc, and greater scores in CC.

3.4. Discussion and comparison with other LCA studies on tomato and orange crops in Spain

Some criticism as to the use of aggregated economic data with which to estimate environmental impacts can be found in the literature. In particular, Pradeleix et al. (2022) state that on-field emissions from fertiliser application cannot be estimated from FADNs since, although the expense on fertilisers is explicit, the type of fertiliser applied is not and these can contain different quantities of macronutrients. Notwithstanding this, the proposed approach allows the fertiliser consumption to be estimated by using linear programming in which the expense on fertilisers, the quantity of macronutrients applied in the reference holdings, as well as the fertilisers purchase value are taken into account. Similarly, the fuel consumed by the machinery for on-field operations is calculated by considering the expense of the fuel of the reference holdings and the uniform distribution of diesel B market value.

To validate the proposed approach to the obtaining of site-specific inventories for the reference holdings in the NUTS 2, the environmental impacts calculated in this study are compared with those from literature for the same crops in Spain (Table 7). Beforehand, it must be noted that the epistemic uncertainty concerning the differences found in the reviewed studies is implicit; however, an attempt is made to identify the objective issues that can generate these potential differences. As the environmental impact scores of this study are not normally distributed and there is no homogeneity of variances in their distribution, instead of presenting the results in the traditional way as "mean ± margin of error", the notation "mean, standard deviation" is used to perform the comparisons. CC is the most widely studied midpoint impact category for agri-food products in the available literature (Table 7) and also the one with the greatest methodological standardisation. As to the other impact categories, they are either not found in the literature reviewed or they are not compiled in the table because they are assessed by using a different impact indicator. It must also be highlighted that, although throughout the present study HTnc and HTc are assessed separately, in Table 7, they are replaced by human toxicity (HT) calculated as the sum of the HTc plus HTnc scores (as detailed in SM-4, TM-4), due to the fact that just the HT score may be found in the literature reviewed.

When the environmental impacts estimated in this study are compared with those found in the literature, the differences found exhibit a different order of magnitude. This can be explained by the marked influence of the origin, quantity and quality of the data on the LCA results and the uncertainty

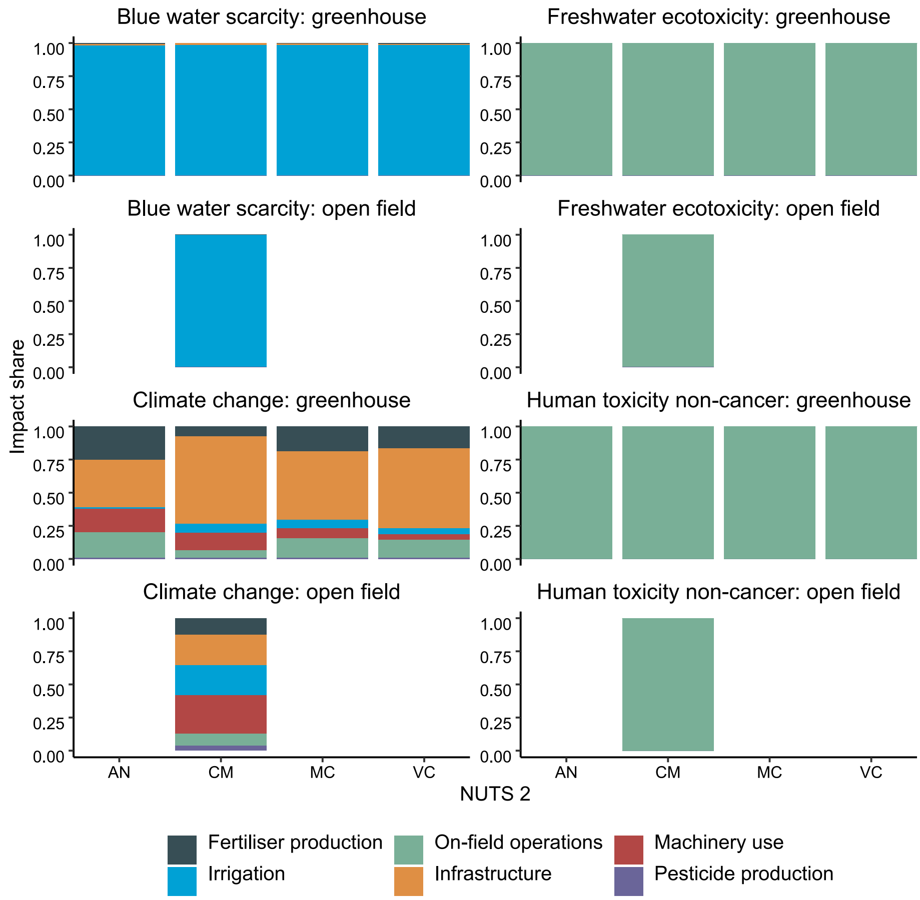

Fig. 6. Relative contribution of life cycle stages to the environmental impacts of the tomato crop in the main NUTS 2 producers in Spain in the period 2010–2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

due to methodological choices. For instance, the uncertainty associated with the choice of the activity data (temporal and geography representativeness of data, data sources, etc.), the impact characterisation method, or the upstream processes used greatly influence the LCA results. The temporal variability considered in this study also influences the impact results, as differences may be observed between the impacts of each assessed year.

As regards orange crops, the average CC and WS scores estimated in this study for the orange reference holding in MC are 56 % lower than those estimated by Martin-Gorriz et al. (2020) for the same NUTS 2. Those higher CC scores in Martin-Gorriz et al. (2020) could be explained by the yield (10.52 % greater); however, there are two other possible explanations. One is that the amount of fuel consumed in the transportation of the raw material from the local storehouse to farms is not considered in this study. In addition, to estimate direct N_2O emissions from fertiliser application a Tier 2 emission factor is used in this study, which is lower than the Tier 1 emission factor used in Martin-Gorriz et al. (2020), as the N applied is the same because it was taken from the same source. The CC, HTnc and ET scores estimated by Ribal et al. (2017) for VC show a higher variation coefficient than those from this study, suggesting a greater scattering of the impact results. It must be noted that in Ribal et al. (2017) data variability comes from a transversal sample of orange holdings for a specific season, whereas, in this study, both temporal variability and the uncertainty from some input parameters is modelled. In addition, the average CC score of this study is 35.8 % lower, whereas the average HT and ET scores are not only lower but also outside the order of magnitude. Besides the different uncertainty sources modelled in both studies, and despite the greater N application rate considered in this study and the lower yield (18.56 % lower), differences in the CC scores can be explained by the lower direct N_2O emissions from fertiliser application in this study, estimated using a Tier 2 emission factor instead of a Tier 1 as in Ribal et al. (2017). The different order of magnitude of HT and ET scores may be due to the fact that in Ribal et al. (2017) recommended plus interim CFs are applied in every stage, whereas, in this study, those CFs are used only in the on-field operation stage and in the other stages only the recommended CFs are applied. The CC score from the study by Aguilera et al. (2015), which corresponds to the average citrus crop produced in Spain in a specific year (data correspond to 2010), is close to the average values obtained in this study for orange production. In fact, the average CC scores of the present study in MC, AN and VC are 15.72 %, 23.27 % and 25.16 %, respectively, higher than the average CC score obtained by Aguilera et al. (2015). This could be partially explained by the lower orange yields considered in this study; for instance, the orange yield in AN (the highest orange yield) is 28.11 % lower than that of Aguilera et al. (2015).

For tomato crops, the available literature only permits a comparison of CC and WS. For greenhouse tomatoes, the average CC score estimated in this study for AN is 28.8 % lower than that obtained in Torrellas et al. (2012) for the same NUTS 2, despite the greater yield of the present study (twice as big). In relation to this, it is important to highlight that the greenhouse infrastructure makes a significant contribution in CC (see Section 3.2) and the result from Torrellas et al. (2012) corresponds to a multi-tunnel greenhouse, which requires greater material consumption than "*Parral*" greenhouse, the one considered in this study in AN. The average CC score obtained by Romero-Gámez et al. (2017) is 48.46 % lower and less scattered than in VC (the NUTS 2 with the highest CC score for the greenhouse system) and 56.30 % lower and slightly more scattered for the open-field system in CM. Along these lines, Romero-Gámez et al. (2017) assess a specific tomato cultivar (Cherry) in a generic Mediterranean context, whereas the present study assesses a generic tomato cultivar in specific Spanish NUTS 2. Moreover, different emission factors for on-field emissions are used in both studies; for instance, Romero-Gámez

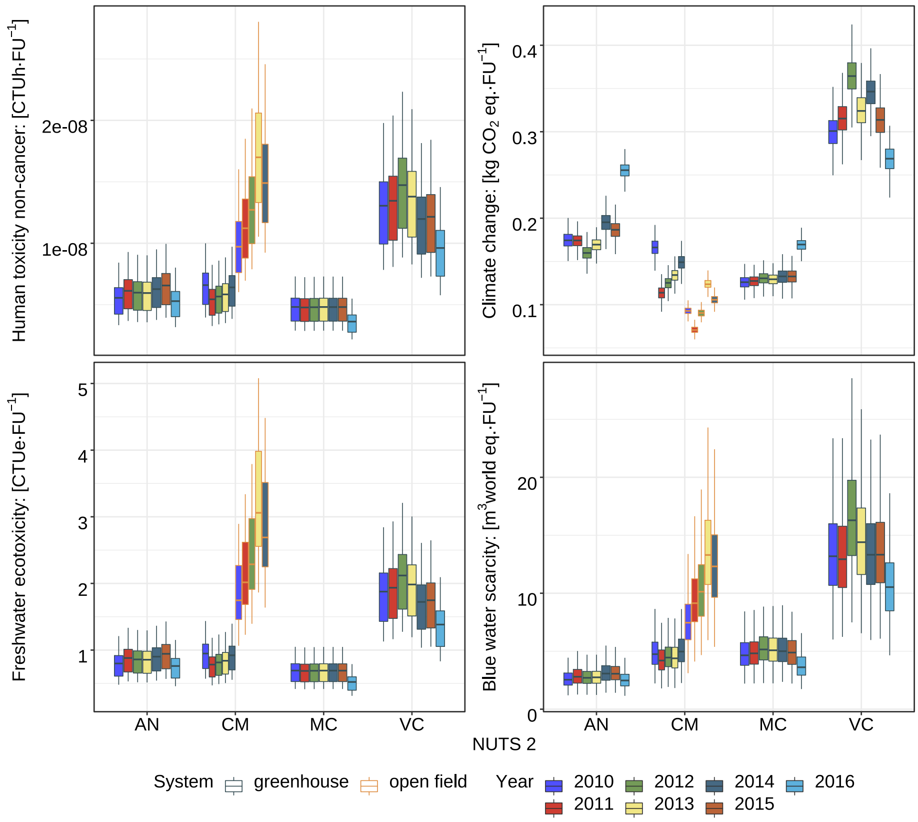

Fig. 7. Aggregate environmental impacts of tomato crops in the main NUTS 2 producers in Spain, in the period 2010–2017. AN: Andalucía; CM: Castilla-La Mancha; VC: Comunidad Valenciana; MC: Región de Murcia.

et al. (2017) consider a 1.25 % emission factor for direct N_2O-N, whereas in this study it is 0.5 % (Cayuela et al., 2017). Martínez-Blanco et al. (2011) WS scores shown in Table 7 are estimated by multiplying the respective subnational CF of WS by the water use calculated in Martínez-Blanco et al. (2011). The CC and WS scores of Martínez-Blanco et al. (2011) are within the range of those estimated in this study for greenhouse tomato in MC and AN (the NUTS 2 with the lowest values in these categories, respectively) and VC (the highest). For the open-field system in CM, the CC and WS scores are 39.49 % lower and 75.96 % higher than those from the study by Martínez-Blanco et al. (2011), respectively. These differences can be explained by the different regional and temporal aspects considered in each study. It is highlighted that Martínez-Blanco et al. (2011) study specific tomato cultivars (Caramba in the greenhouse system and El Virado in the open-field), in Catalonia, a different NUTS 2 but also located along the Mediterranean coast as are MC and VC, their tomato yield is bigger (around twice as big as in AN and CM and four times bigger than in VC).

4. Conclusion and further research

Assessing the environmental impacts of agricultural systems is a first step to improve the environmental profile of crops. This study proposes a methodological approach to developing LCIs for the purposes of calculating the impacts of representative reference holdings at the NUTS 2 subnational level from average economic and operational information available in official sources, mainly from ECREA-FADN. The developed case studies on orange and tomato production in the main NUTS 2 producers showed that the proposed methodology can be helpful in obtaining a representative

Table 5
Effect sizes of the Kruskal-Wallis tests applied to the impacts of orange and tomato crops using different systems and in differing NUTS 2.

Reference holdings	Epsilon square ~ ε^2			
	CC	WS	HTnc	ET
Orange	$3.85{\cdot}10^{-2}$	$1.08{\cdot}10^{-1}$	$2.58{\cdot}10^{-1}$	$7.02{\cdot}10^{-2}$
Greenhouse tomato	$8.08{\cdot}10^{-1}$	$5.39{\cdot}10^{-1}$	$7.50{\cdot}10^{-1}$	$5.41{\cdot}10^{-1}$
Castilla-La Mancha tomato crops	$5.60{\cdot}10^{-1}$	$6.10{\cdot}10^{-1}$	$6.36{\cdot}10^{-1}$	$7.16{\cdot}10^{-1}$

CC: climate change; WS: water scarcity; ET: freshwater ecotoxicity; HTnc: human toxicity non-cancer.

Table 6
Pairwise comparisons between orange and tomato farming impacts in the main NUTS 2 producers in Spain from 2010 to 2017.

Group 1	Group 2	Z-value			
		WS	ET	CC	HTnc
Orange reference holdings					
Andalucía (AN)	Comunidad Valenciana (VC)	42.33	40.88	12.52	50.23
Andalucía (AN)	Región de Murcia (MC)	78.59	17.17	−17.73	32.15
Región de Murcia (MC)	Comunidad Valenciana (VC)	−36.27	23.72	30.26	18.08
Greenhouse tomato reference holdings					
Andalucía (AN)	Castilla-La Mancha (CM)	51.48	ns	−59.69	ns
Andalucía (AN)	Región de Murcia (MC)	60.60	−32.71	−69.21	−32.62
Andalucía (AN)	Comunidad Valenciana (VC)	138.85	81.28	59.34	81.17
Castilla-La Mancha (CM)	Región de Murcia (MC)	3.84	−30.12	−3.49	−30.02
Castilla-La Mancha (CM)	Comunidad Valenciana (VC)	75.27	73.94	113.86	73.85
Región de Murcia (MC)	Comunidad Valenciana (VC)	78.24	113.99	128.55	113.79
Castilla-La Mancha tomato reference holdings					
Irrigated greenhouse	Irrigated open field	79.72	84.62	−74.80	78.12

CC: climate change; WS: water scarcity; ET: freshwater ecotoxicity; HTnc: human toxicity non-cancer; ns: non-significant differences are found.

Table 7
Environmental impact scores of 1 kg of tomatoes or oranges under different production systems in Spain. Scores are expressed as "mean, standard deviation".

Product	System[a]	NUTS 2	Yield [$t{\cdot}ha^{-1}\ yr^{-1}$]	CC[d]	HT[e]	ET[f]	WS[g]	Source
Orange	OS	Andalucía	$3.07{\cdot}10^{1}$, 3.01	$1.96{\cdot}10^{-1}$, $3.55{\cdot}10^{-2}$	$3.11{\cdot}10^{-9}$, $3.10{\cdot}10^{-10}$	$5.83{\cdot}10^{-3}$, $1.93{\cdot}10^{-3}$	$1.14{\cdot}10^{1}$, 2.12	This study
Orange	OS	Region de Murcia	$2.31{\cdot}10^{1}$, 9.73	$1.84{\cdot}10^{-1}$, $2.34{\cdot}10^{-2}$	$3.78{\cdot}10^{-10}$, $9.39{\cdot}10^{-10}$	$6.53{\cdot}10^{-3}$, $2.59{\cdot}10^{-3}$	$1.67{\cdot}10^{1}$, 4.79	This study
Orange	OS	Comunidad Valenciana	$2.72{\cdot}10^{1}$, 2.36	$1.99{\cdot}10^{-1}$, $2.39{\cdot}10^{-2}$	$4.13{\cdot}10^{-9}$, $4.73{\cdot}10^{-10}$	$7.45{\cdot}10^{-3}$, $2.54{\cdot}10^{-3}$	$1.35{\cdot}10^{1}$, 2.37	This study
Orange	OS	Region de Murcia	$2.09{\cdot}10^{1}$	$4.16{\cdot}10^{-1}$	–	–	$3.79{\cdot}10^{1}$[b]	Martin-Gorriz et al. (2020)
Orange	OS	Comunidad Valenciana	$3.34{\cdot}10^{1}$, 9.93	$3.10{\cdot}10^{-1}$, $7.93{\cdot}10^{-1}$	$2.49{\cdot}10^{-8}$, $2.65{\cdot}10^{-8}$	$1.28{\cdot}10^{1}$, $1.44{\cdot}10^{1}$	–	Ribal et al. (2017)
Citrus	OS	Spain	$4.20{\cdot}10^{1}$, 8.62	$1.59{\cdot}10^{-1}$, $4.98{\cdot}10^{-2}$[c]	–	–	–	Aguilera et al. (2015)
Tomato	GS	Andalucía	$8.83{\cdot}10^{1}$, 6.50	$1.78{\cdot}10^{-1}$, $3.11{\cdot}10^{-2}$	$4.94{\cdot}10^{-9}$, $1.62{\cdot}10^{-9}$	$6.77{\cdot}10^{-1}$, $2.46{\cdot}10^{-1}$	2.74, $8.01{\cdot}10^{-1}$	This study
Tomato	GS	Region de Murcia	$1.14{\cdot}10^{2}$, $1.34{\cdot}10^{1}$	$1.31{\cdot}10^{-1}$, $1.62{\cdot}10^{-2}$	$3.85{\cdot}10^{-9}$, $1.28{\cdot}10^{-9}$	$5{\cdot}10^{-1}$, $1.94{\cdot}10^{-1}$	4.74, 1.42	This study
Tomato	GS	Comunidad Valenciana	$4.20{\cdot}10^{1}$, 6.20	$3.18{\cdot}10^{-1}$, $3.5{\cdot}10^{-2}$	$1.05{\cdot}10^{-8}$, $3.63{\cdot}10^{-9}$	1.5, $5.49{\cdot}10^{-1}$	$1.33{\cdot}10^{1}$, 4.14	This study
Tomato	GS	Castilla - La Mancha	$8.79{\cdot}10^{1}$, 7.15	$1.35{\cdot}10^{-1}$, $2.04{\cdot}10^{-2}$	$4.97{\cdot}10^{-9}$, $1.64{\cdot}10^{-9}$	$6.86{\cdot}10^{-1}$, $2.48{\cdot}10^{-1}$	4.53, 1.32	This study
Tomato	GS	Catalonia	$1.59{\cdot}10^{2}$	$1.53{\cdot}10^{-1}$	–	–	3.31[b]	Martínez-Blanco et al. (2011)
Tomato	GS	Mediterranean conditions	$8.83{\cdot}10^{1}$	$6.17{\cdot}10^{-1}$, $2.02{\cdot}10^{-1}$	–	–	–	Romero-Gámez et al. (2017)
Tomato	GS	Andalucía	$1.65{\cdot}10^{2}$	$2.50{\cdot}10^{-1}$	–	–	–	Torrellas et al. (2012)
Tomato	OS	Castilla - La Mancha	$3.78{\cdot}10^{1}$, 8.33	$9.44{\cdot}10^{-2}$, $1.82{\cdot}10^{-2}$	$1.38{\cdot}10^{-8}$, $4.82{\cdot}10^{-9}$	2.06, $7.66{\cdot}10^{-1}$	$1.01{\cdot}10^{1}$, 3.8	This study
Tomato	OS	Catalonia	$1.03{\cdot}10^{2}$	$1.56{\cdot}10^{-1}$	–	–	5.74[b]	Martínez-Blanco et al. (2011)
Tomato	OS	Mediterranean conditions	$6.23{\cdot}10^{1}$	$2.16{\cdot}10^{-1}$, $3.34{\cdot}10^{-2}$	–	–	–	Romero-Gámez et al. (2017)

[a] OS: open-field system; GS: greenhouse system.
[b] WS score is calculated from the water use for irrigation from this literature source.
[c] Results without accounting for C sequestration are considered. A rule of three is applied to calculate the standard deviation before discounting C sequestration.
[d] Climate change [kg CO_2 eq.]
[e] Human toxicity [CTUh].
[f] Freshwater ecotoxicity [CTUe].
[g] Blue water scarcity [m^3 world eq.]

description of the environmental profile of crops, giving results consistent with those from the literature.

To consider interannual variability, data from different years have been gathered, while ranges for the input parameters have been used to tackle technological representability whenever possible instead of deterministic values. However, as far as fertiliser consumption is concerned, only the temporal representability was represented, whereas it was not possible to represent the temporal and technological uncertainty of the pesticides. The uncertainty associated with the emission factors used to model on-field emissions from pesticides and fertilisers has also been considered. In this way, impact results have been obtained as value ranges; however, it has been extremely difficult to obtain up-to-date information so as to represent the above-mentioned uncertainty, which requires an effort from official institutions.

Despite the validity of the results obtained, as corroborated by the comparison with the literature, extending the current monitoring system to include a broader range of sustainability issues is recommended in line with EC (2020), as suggested by Poppe et al. (2016). Changes in the data included in Spanish ECREA-FADNs are, thus, required to comply with the EU farm-to-fork strategy requirements. Along these lines, it is necessary to distinguish between conventional and organic agriculture, as the aforementioned strategy suggests organic agriculture as a feasible alternative for the fulfilment of its objectives. As shown in both Antón et al. (2014) and in this study, the greenhouse structure exerts a significant influence on the environmental impacts of greenhouse crops. Therefore, specifying the type of greenhouse structure in ECREA-FADN would improve the estimation of the environmental impacts. Improvements to the additional data sources used in this study are also required to increase the reliability of the impact results. In particular, the survey on the use of pesticides should be carried out more often and take into consideration a wider range of crops.

In an attempt to estimate the representative environmental impacts of Spanish agriculture, further studies on other crops are needed so as to validate the approach and generate subnational life cycle inventories. In addition, other functional units linked to the farmer's economic interests should be considered, as they determine the production decision. The estimation of endpoint indicators would also permit a broader environmental crop profile, considering the areas of protection as recognisable societal values. It must be borne in mind that this represents a partial approach as it focuses on one of the three sustainability pillars. Hence, it would be useful to integrate environmental indicators with economic and social to holistically assess crop sustainability.

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CRediT authorship contribution statement

Nelson Sinisterra-Solís: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Investigation. **Neus Sanjuán:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – review & editing. **Javier Ribal:** Conceptualization, Methodology, Software, Writing – review & editing, Supervision. **Vicent Estruch:** Methodology, Validation, Formal analysis, Investigation. **Gabriela Clemente:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – review & editing.

Data availability

Data will be made available on request.

Declaration of competing interest

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

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